

Decisive or Distracted: the Effects of United States Constraint on Security Networks*

Ha Eun Choi^b, Scott de Marchi^c, Max Gallop^a, Shahryar Minhas^b

^a*University of Strathclyde, Glasgow, 16 Richmond St., Glasgow, UK G1 1XQ*

^b*Department of Political Science, Michigan State University, East Lansing, MI 48824, USA*

^c*Department of Political Science, Duke University, Durham, NC 27703, USA*

Abstract

The United States spent much of the last two decades involved in a pair of wars in the Middle East. These actions required large commitments, not just of blood and treasure, but also of attention and resolve. We thus try to understand the consequences of what one could call either US distraction or a demonstration of US commitment. In particular, we look at how third parties respond to the US's focus on conflicts in one region of the world, in terms of their cooperation in the economic and diplomatic spheres. To do so, we develop a novel measure of US distraction, as well as novel network based measures of economic and diplomatic cooperation or alignment. We seek to test the theory that when the US is more distracted, other states will be more likely to cooperate with the United States's principle rival, China. We find that such cooperation is more likely in the diplomatic sphere than the economic one. However, when we look at how different types of states react to US distraction, we find that across both measures democracies generally respond by moving farther away from China, while non-democracies move closer to the PRC.

keywords: methods; hegemonic distraction; Sino-US relations; state preferences

*Alphabetical order signifies equal authorship, all mistakes are our own. Replication material and instructions will be made available at <https://github.com/s7minhas/plutonium>.

Email addresses: choiha3@msu.edu (Ha Eun Choi), scott.demarchi@gmail.com (Scott de Marchi), max.gallop@strath.ac.uk (Max Gallop), minhassh@msu.edu (Shahryar Minhas)

Introduction

An abiding concern of the interstate security literature has been conflict between nations. To a large degree, this approach has been facilitated by the availability of data – notably, the Correlates of War dataset (focused primarily on militarized interstate disputes Palmer et al., 2021) and the Alliance Treaty Obligations and Provisions project (focused on formal alliances between nations Leeds et al., 2002). Without risk of exaggeration, explaining the causes of military conflict – or predicting future conflict – is an area of considerable interest (Ward et al., 2013; Mueller and Rauh, 2018; Terechshenko, 2020). Substantive findings from this literature continue to be well-cited, ranging from the democratic peace (Maoz and Russett, 1993) to comprehensive approaches explaining the causes of war (Bennett and Allan C. Stam, III, 2003; Cranmer, Menninga and Mucha, 2015).

With the end of the Cold War concerns about interstate conflict seemed to wane – at least in the popular press – but they have returned to the conversation on the heels of the Russian invasion of Ukraine. There are obviously many questions that remain for Europe and future conflicts given Russia's aggressions, however, many have also speculated about what this might portend for Chinese aggression in Taiwan and the broader East Asian theatre. Related to this is the fact of China's broader emergence in the international system and the question of whether the United States and China can escape the so-called Thucydides trap.

Exploring this question from an empirical perspective comes with a number of difficulties. First, there are concerns about how generalizable our models of conflict are across time periods (Jenke and Gelpi, 2017). What researchers would like to do is to limit studies of war to time periods in which the causes of war spring from the same data generating process. For example, the ability of nations to project force and maintain

units in the field has changed dramatically over time, and as a result, any dyadic examination of war should limit models to observations of conflict that are independent and identically distributed. Compounding this difficulty is that only 4% of dyad years have a military conflict and the majority of those are continuations of conflict rather than the initiation of conflict, which are two distinct data generating processes de Marchi, Gelpi and Grynaviski, 2004; Metzger and Jones, 2018. Additionally, in the post World War 2 period, a disproportionate number of interstate conflicts occur in the Middle East, which would have made predicting the Ukraine-Russia conflict difficult much less the risk of one involving China.

Making empirical claims about the likelihood of conflict between China and the United States requires us to deal with two competing constraints: either we broaden the sample and inappropriately treat non-IID observations together, or we can limit our sample to a particular regime but end up with geographically limited and rare event data. There are, in short, no easy answers to this problem. War in general is an event of obvious importance, but it is difficult to study given its infrequency and the changing nature of warfare across time. In this article, we propose to study the other side of the coin: cooperation between states. While the causal mechanisms that lead to war and cooperation are likely distinct, it is reasonable to assume that, all else equal, states that are embedded in a cooperative relationship are much less likely to engage in military conflict. By understanding the causes of cooperation between states we can sidestep the statistical issues involved with studying conflict directly and can instead focus on the more plentiful data generated by varying levels of cooperation between states. The relatively plentiful supply of data on cooperation between states also gives us considerable flexibility in the types of questions we can answer. There is genuine year to year variance in the relationships between states and this allows us to examine a broader set of mechanisms that explain cooperation. Most importantly, understand-

ing the ways states are connected to one another on cooperative dimensions can shed light on changes in China's ability to potentially influence the international system.

Here, we focus on how a particular type of shock to the international system may have paved the way for China to expand its influence: the level of economic and military constraint faced by the United States. The United States, especially in the last two decades, has been a pivotal actor in the international system; constraints on the United States' capacity should impact the actions taken by other states – both with respect to cooperation with the United States directly but also cooperation with a rising actor such as China. We are thus interested in a model that investigates the proximity of cooperative relationships between states as a function of United States economic and military constraint.

Just as alliances (Warren, 2010; Cranmer, Desmarais and Menninga, 2012) and conflict (Maoz, 2012; Ward, Siverson and Cao, 2007) occur in networks between states, so does cooperation. Accordingly, we rely on a latent factor model (LFM) to measure these interdependencies between states (Hoff et al., 2013; Minhas, Hoff and Ward, 2019). Here we employ this general framework to develop a latent measurement of how a state relates to each other in a network context. The factor analysis we employ seeks to take as an input the interactions that actors have with others across a cooperative measure and project this onto a lower-dimensional space. Actors are positioned closer together in this estimated space not only if they frequently cooperate, but also if they high high levels of cooperation with similar third parties. The underlying goal of our approach to measuring cooperation is no different than how others have sought to find simpler representations of legislators and bills (Poole and Rosenthal, 1985) or topic models for text (Roberts, Stewart and Tingley, 2016).

In developing our measure of cooperation we want to capture specific types of patterns that often occur when reducing the dimensionality of a network. One such pattern

is stochastic equivalence. Stochastic equivalence refers to the idea that there are communities of nodes in a network, and actors within a community act similarly towards those in other communities. Thus, the community membership of an actor provides us with information on how that actor will act towards others in the network. Put more concretely, a pair of actors i, j are stochastically equivalent if the probability of i relating to, and being related to, by every other actor is the same as the probability for j (Anderson, Wasserman and Faust, 1992). For example, in an international cooperation network, we might see relatively isolated rogue states, like North Korea and Iran, as being stochastically equivalent, because they have limited cooperation with states like China and Russia, and generally conflictual relations with rich Western states. Similarly, close allies of the United States (for example Canada and the United Kingdom) will exhibit high degrees of stochastic equivalence, likely to cooperate with other rich Western states, and direct conflictual acts towards said rogue states. This concept simply speaks to the assertion that we can learn something about how an actor will interact with an entire network based on, for example, the existing set of relationships that they are enmeshed in.

An additional dependence pattern that often manifests in networks is homophily – the tendency of actors to form transitive links. The presence of homophily in a network implies that actors may cluster together because they share some latent attribute. In the context of clustering in alliance relationships, we are likely to find that states like the United States, United Kingdom, and Germany may cluster together because they share some latent state level attribute. We would ignore salient information if we did not use, for example, the United Kingdom's behavior towards third parties, when trying to understand the United States' preference similarity with those parties. Doing so is likely to paint an incomplete picture of the preferences that states share with one another.

The LFM accounts for these higher order dependence patterns and ensures that

similarity in preferences is likely to be transitive, for example, if the United States has similar preferences to the United Kingdom, and the United Kingdom to France, the United States' preferences should be relatively close to France's. Further the most useful feature of the LFM for our purpose is that it summarizes the interdependencies between actors in a relational k-dimensional latent vector space. From this vector space we can both understand how states in the system are tied to others in the system, but can also ask more specific questions about the dominance of particular actors in the system such as China.

Our plan for the rest of the article is straight-forward. First, we will sketch the two competing theories for how the United States' constraint could affect relationships in the international system. Second, we will establish our measure of the level of constraint of the United States during the period 2000 – 2020. Third, we will detail the LFM and output measures for this time period. Last, we will present the results of our downstream regressions that detail the impact on cooperation as a function of constraint.

Theoretical Intuition

Constraints on the United States, represented by military entanglements and shocks, could have two divergent effects. On the one hand, one could think of United States attention and resources as scarce, and the mechanism would be that while the United States is distracted (e.g., with a conflict in Afghanistan or Iraq), they have less bandwidth and freedom of action to respond to a crisis in East Asia. We call this the *Distraction Model*.

An alternative mechanism relies on research that has been done on reputation and credibility and this perspective argues that by spending blood and treasure in contexts like Iraq or Afghanistan, the United States demonstrates their resolve and willingness to commit elsewhere. We call this the *Credibility Model*.

Distraction Model

The basic insight of the Distraction Model is that both resources and attention are finite (Deutsch and Singer, 1964; Haass, 2008; Bilmes, 2013). The United States is a historically rich and powerful country, but each successive conflict or intervention will reduce available resources, especially in an increasingly multipolar world. All else equal, the United States may have been less likely to get involved in a second (or third, etc.) conflict while it was, for example, involved in Iraq and Afghanistan. This has important implications for the behavior of third parties, especially if they are considering actions contrary to the interests of the United States. For example, a state developing illicit weapons systems, invading a neighboring state, or simply aligning more closely with the United States' strategic rivals, may face fewer consequences while the United States is distracted.

When applied to our measurement of state affinity capturing both military and economic conditions, this naturally leads to our first hypothesis. Our focus is on third party actors and their relationship with China (i.e., a United States adversary). We are obviously not including the entire range of hostile actions that third parties might take:

Hypothesis 1: When the United States is more distracted, states will align more closely with the People's Republic of China

Credibility Model

The second model draws on a long history of research about credibility and resolve (Schelling, 1966; Walter, 2006; Crescenzi, 2007; Gibler, 2008; Weisiger and Yarhi-Milo, 2015). The idea motivating this model is that we do not know a state's willingness to take costly actions (for example, kinetic military actions or coercive economic measures) to achieve a goal because the ratio of the cost of these actions to their benefit is unobservable. We can, however, make inferences about states' willingness to pursue costly

actions using their past behavior as a guide. Put simply, if the United States demonstrates willingness to bear heavy costs to achieve desirable political outcomes in one context, third party actors should update beliefs about the United States' willingness to bear costs in other contexts. Accordingly, our measure of United States military entanglement is also a measure of demonstration of resolve.

An important caveat is that credibility and resolve are contextual: states are more willing to pay a high cost to avoid conquest by a genocidal tyrant than they would be to secure lower tariffs on agricultural goods. That said, this leads us to a diametrically opposite view of how third parties will respond to our measure of United States constraint, which leads to our second hypothesis – as above, we are focused on third party relations with China:

Hypothesis 2: When the United States is constrained due to military commitments, they will have demonstrated more resolve, and states will be less willing to align closely with the People's Republic of China.

Methods

As noted above, we have developed a measure of constraint to capture a variety of mechanisms that might limit the actions of the United States. In broad terms, we operationalize constraint as a function of two possible sources:

1. Active conflicts that the US is involved in with an emphasis on those conflicts that represent significant materiel commitment and US casualties
2. US force commitments around the globe

To populate these categories, we rely on sixteen variables distributed across the following broad categories:

Variables	Source
Defense spending	World Bank, 2021, US Department of Defense, 2020
Troop levels, by region	US Department of Defense, 2020, Kane, 2016
US Casualties	US Department of Defense, 2020, Kane, 2016
Market Crises	Frieden et al., 2017
Economic variables	Trading Economics, 2021

Table 1: Variables for generation of US Distraction Index

A source of constraint that is incomplete in the above framework are political shocks. Prior work has shown that political crises of this sort are rare and not likely consequential (Frieden et al., 2017). We leave exploration of the inclusion of political measures to future work. A simple latent variable model of the categories show in Table 1 produced two features, representing active US conflicts (F_1) and US defense spending / commitments (F_2).¹ Figure 1 illustrates the cumulative proportion of variance accounted for by each of the factors in the top panel, and in the bottom the variance of each factor. A PCA with two latent variables explained over 75% of the variance in the raw data.²

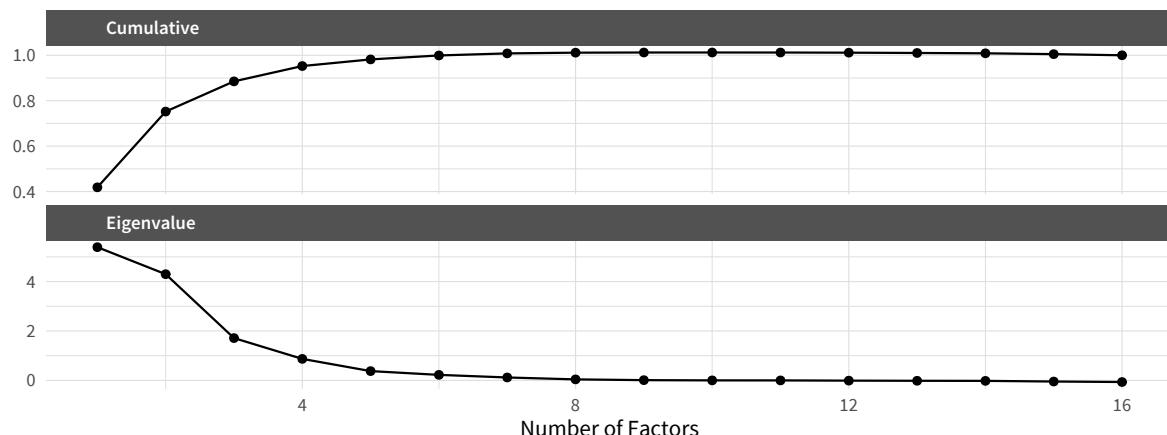


Figure 1: Scree plot of constraint PCA.

¹In the appendix, we have included a discussion of the variable weights for each factor.

²A possible third factor, which we did not include has as its most component employment rate, but the interpretation of that factor as representing economic difficulties faced by the US is not at all clear given the other factor loadings.

Figure 2 visualizes how the three factors have changed through time. They show considerable variance that tracks with our priors on constraints resulting from United States military conflicts over the past two decades.

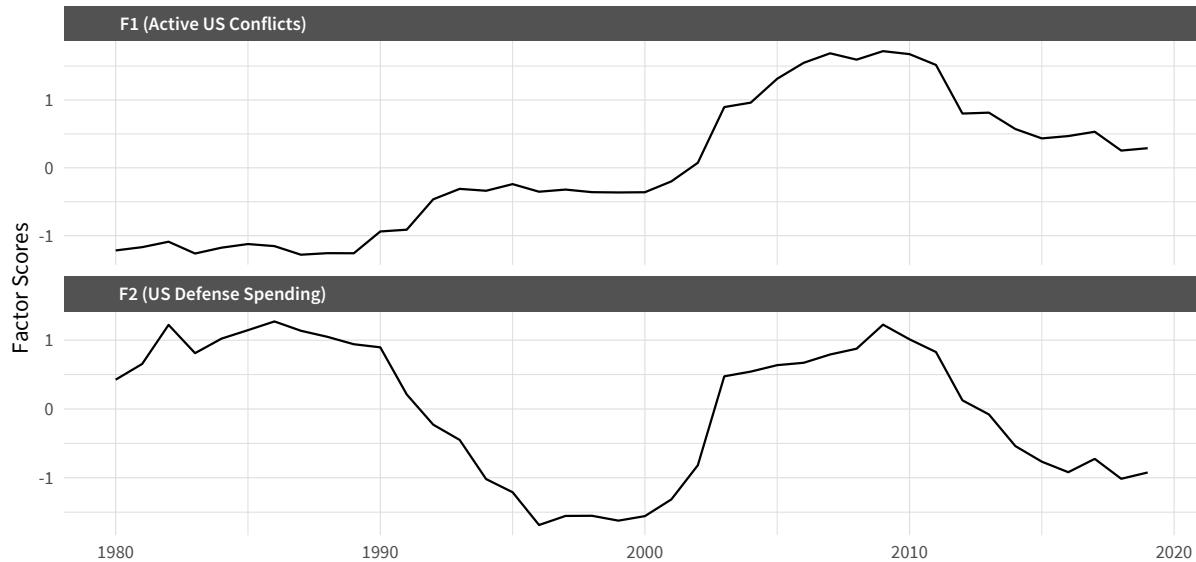


Figure 2: Visualization of F_1 and F_2 over time.

Measuring Alignment

To test our theories, we require a measure of how closely states are aligned and how these relationships change over time. One way to do this would simply be to look at a raw measure of cooperation between states, but this has a number of issues. First, states have very different overall levels of cooperative activity – e.g., the fact that there is much more trade between the United States and China than between China and Mongolia does not mean that there is closer alignment between those two states. Rather, it means that the US and China trade more with everybody. Second, there would be difficulties of left censorship. If we take trade, for example, to be the consequence of a latent measure of economic alignment, it is important to distinguish between states that do not trade with each other because of antipathy versus neutrality. For example,

the US has little with Cuba or Iran due to antipathy; it has almost no trade with Slovenia for quite different reasons. We believe that both of these issues can be ameliorated by treating measures of cooperation as a form of relational data using a network approach to infer our latent measure of alignment.

We use two different raw measures of cooperation as input data: the balance of trade between states (as measured by the IMF) and similarity in states' UN voting records. For the balance of trade, we take the volume of trade between states for a given dyad and divide that by the total volume for one state in the dyad. This gives us a directed measure of how dependent one state's trade is on another. These form the links in our network of economic alignment. For our measure of diplomatic alignment, we look at the percent of votes at the United Nations General Assembly in which states voted in the same way. We use these two networks to estimate state affinity using the Latent Factor Model.³

The latent factor model is a network model that is designed to account for three different orders of interdependencies in relational data. First, it accounts for the tendency of some actors to trade more and agree to more economic agreements by including sender and receiver random effects. Second it accounts for the fact that economic cooperation is often reciprocal in the composition of the error term. Finally, the area that sets the LFM apart from other network estimators is how it handles third order dependencies. Two particular types of third order dependencies which the LFM can handle are homophily – the tendency for actors that share an unobserved characteristic – to interact more with each other, and stochastic equivalence, the idea that actors which play similar roles in a network are more likely to cooperate with the same third party.

³See Cranmer, Menninga and Mucha (2015); Cheng and Minhas (Forthcoming); Huhe, Gallop and Minhas (2021); Dorff, Gallop and Minhas (2021) for other attempts to use the latent factor model to infer alignments in different contexts.

The LFM handles these third order dependencies with a multiplicative random effect based on the Singular Value Decomposition.⁴ This third order term is useful in allowing us to cope with left censoring in this data, since we can use their trade with common third parties to determine if they are in the same realm of the global economic network, or if their opposition runs deeper. We formulate the latent factor model as follows:

$$y_{ij} = f(\theta_{ij}), \text{ where}$$

$$\begin{aligned} \theta_{ij} = & \beta_0 + a_i + b_j + \epsilon_{ij} \\ & + \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j \end{aligned} \tag{1}$$

Our focus for measuring cooperation across economic and diplomatic dimensions is on the $\mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j$ term, which is included in the model to capture third order dependencies. We run an LFM without covariates on both sets of cooperation data separately, and then take this term for every pair of countries in every year as a measure of alignment.⁵

Face Validity

With a measure like this, it is important to investigate whether it is giving us leverage over the unobserved relationships that we are trying to estimate. We examine face validity in two ways – first by looking at the overall network of relationships uncovered, and then by looking in more detail at the time series of certain prominent relationships.

⁴This effect needs to be multiplicative because by multiplying random variables, we can preserve the third order residuals which would have 0 expectation if they were simply added.

⁵We ran models with both a 2 and a 5 dimensional latent factor space, and found the results to be relatively consistent, and so for the sake of clarity, we focus on the easier to interpret 2 dimensional results. In the appendix we have included a section showing that our results are consistent with a 5 dimensional latent factor space.

The latent factor model which underpins our measures of relationships maps each state into a latent vector space. States that have their vectors pointed in similar directions are more likely to influence each other and common third parties, whereas states whose vectors point in opposite directions have limited influence on each other, and in many cases antipathy. We plot the overall distribution of the network in both 2000 and 2019 (for UN voting data) or 2020 (for trade data), in figures 3 and 4.

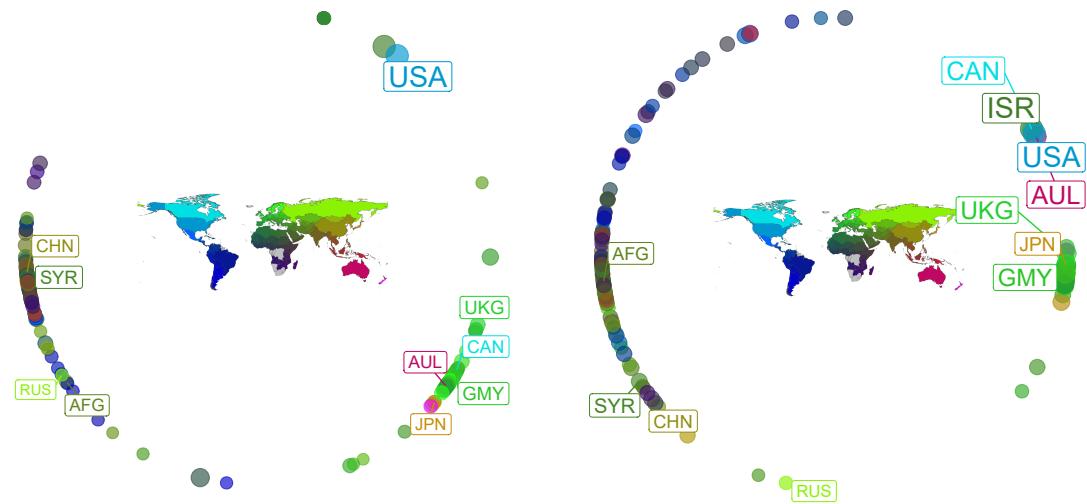


Figure 3: Visualization of multiplicative effects for our measure of diplomatic alignment in 2000 (left) and 2019 (right). Each circle designates a country and the color corresponds to the legend at the center of the visualization. Countries that cluster together are those that were found by the model to have similar sending patterns, meaning that they tend to influence one another.

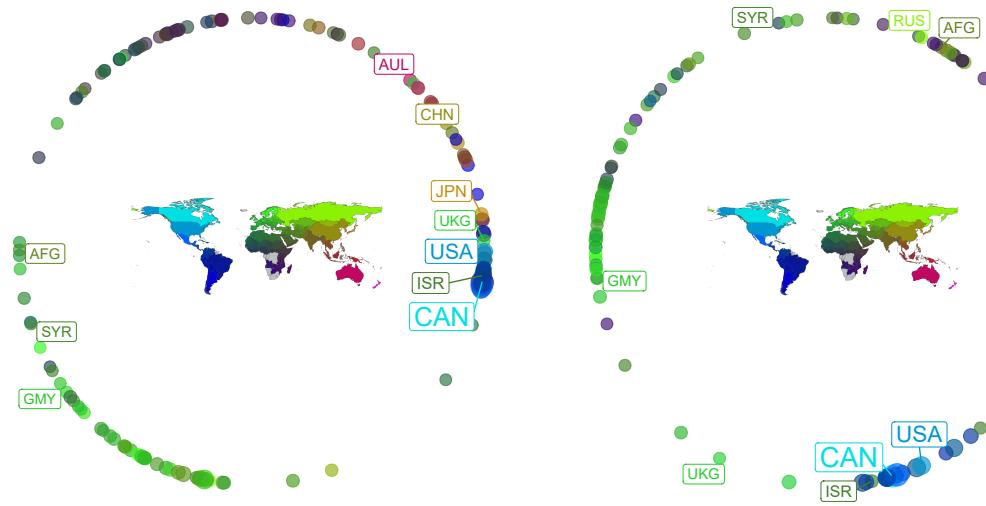


Figure 4: Visualization of multiplicative effects for our measure of trade alignment in 2000 (left) and 2020 (right). Each circle designates a country and the color corresponds to the legend at the center of the visualization. Countries that cluster together are those that were found by the model to have similar sending patterns, meaning that they tend to influence one another.

There are a few immediate takeaways from these networks – first is that the diplomatic alignment measure based on UN voting shows three discernible clusters: the US and Israel (and Canada in 2020) are relatively isolated, but generally close to a larger cluster with most of the other major European powers, along with Japan, Australia, and New Zealand. The third cluster contains the vast majority of the global South.⁶ The network for trade in 2000 paints a somewhat different story. While we still see clustering of many of the major western powers, there is a much stronger role played by geography here – the US is close to many other states in the Americas, and Russia is close to many European states. We also, as one might expect, see much closer alignment between the US and China. In 2020, the geographic clustering remains, but Russia has drifted away from Europe, and US/China economic relations are somewhat less close. These figures show that the measures of diplomatic and economic alignment correspond to many of

⁶This is true whether we are looking at a latent factor model with 2 or 5 dimensional latent factors.

our intuitions about influence in world politics, while also maintaining important and novel characteristics based on the data used to generate them.

We also test the face validity of these measures by looking at how they characterize three important dyads. We choose the relationship between the US and UK, which we expect to be generally close and amicable, and the US's relations with its two major competitors China and Russia. As shown in Figure 5, this measure captures the general tenor of the relationships – the US and UK have a consistently positive relationship, whereas the relationship the US has with both China and Russia, based on UN voting, is characterized as more adversarial – the time series interestingly points to generally positive relationships in the immediate aftermath of 9/11, which deteriorate precipitously starting in 2003 with the Iraq war, and while there are some marginal improvements, the relationship stays quite negative. On the other hand, while our measure of economic alignment pinpoints the positive US/UK relationship, and the negative US/Russia relationship, it finds that the US has a relationship with China that is at times even more closely aligned than that with the United Kingdom. This makes a degree of sense given that the volume of US/China trade dwarfs the trade in the so-called special relationship.

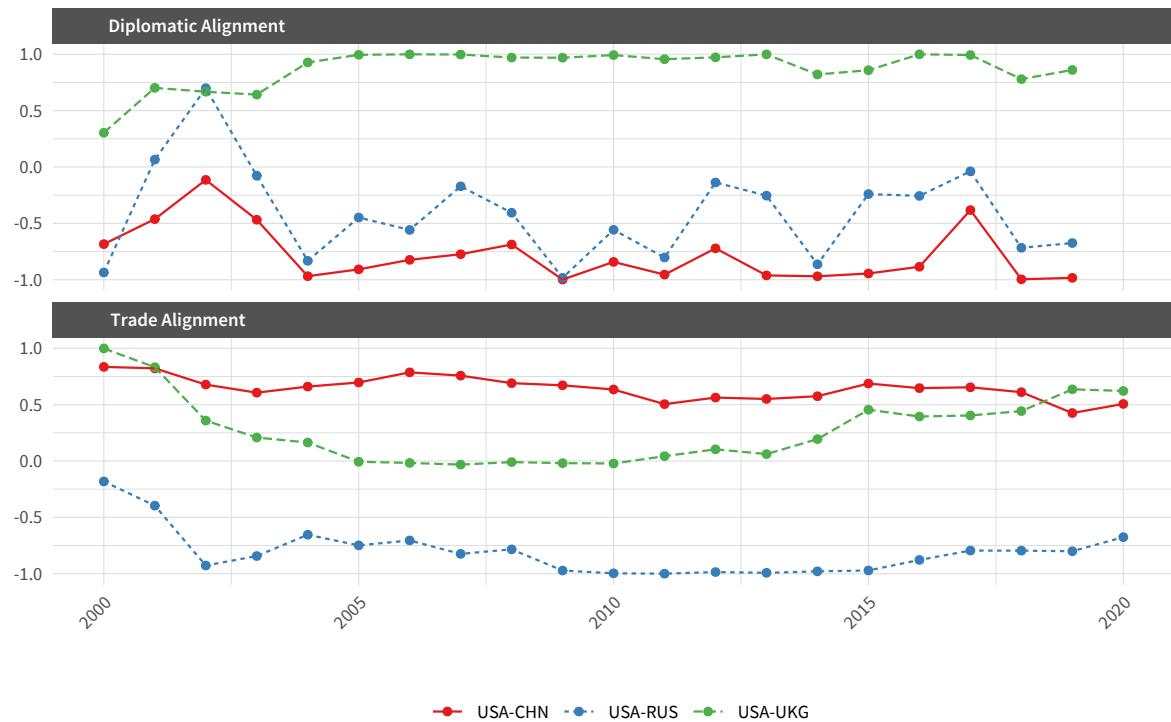


Figure 5: Level of alignment across diplomatic and economic types of cooperation for selected dyads over time.

Regression Models

Given the forgoing measures, our empirical approach to testing H₁ and H₂ is straightforward. The dependent variable (DV) is proximity of actors to China; our main independent variables (IVs) are United States constraint. These latent factors are F_1 (Active US Conflicts) and F_2 (US Defense Spending / Commitments).⁷

$$DV_i = a + j\beta_1 F_1 + (1 - j)\beta_2 F_2 + \beta_3 F_3 + e_i, \quad (2)$$

where j is an indicator variable for whether the model is using F_1 or F_2 .

Our unit of observation here is at the country-year with a sample of 118 countries

⁷Note that F_1 and F_2 have sufficient correlation that we run multiple models using the variables separately rather than including them together.

measured annually between 2000 and 2020. The countries excluded from the analysis are 1) those where the IMF has no data on their trade flows, 2) the United States and China, since we are interested in the effects of US distraction on economic alignment with China. We have two dependent variables, one focused on the level of economic alignment with China and another on the level of diplomatic alignment with China. Based on our hypotheses H₁ and H₂, we test whether the level of alignment is a function of distraction or the demonstrated resolve of the United States.

Our key independent variable, as discussed in the previous section, is our measures of US distraction based either on active US conflicts (F_1) and US defense expenditures & force commitments (F_2). For each country-year observation, we include the value of US distraction in the previous year to see how it relates to that country's alignment with China. We also include a number of country level controls that might influence how closely a country is aligned to China diplomatically or economically. Following the insights of the gravity model of trade, we control for a country's population, their GDP, and the distance between their capital and Beijing. To account for political factors that might make a country more or less closely aligned with China, we include Polity's measure of a country's level of democracy (the intuition being that autocratic regimes will be closer to other autocracies, like China, and democracies will be less close, all else being equal). To account for other structural factors, we estimate our models within a hierarchical framework which allows for both the fixed effects discussed above, as well as random effects. In the first set of results, we rely on random effects for country, and later we look at how the effect of our key independent variables vary based on a state's domestic political institutions.

0.1. Empirical Results

In the first set of models depicted in Figures 6 and 7 we see a marked divergence between our measures of diplomatic and economic alignment. As F_1 increases, denoting a higher level of US attention and resources devoted to the Middle East, states have a consistent increase in their diplomatic alignment with China (though our estimate of this result is measured with a high degree of uncertainty). The opposite, however, seems to be the case for economic alignment , as US distraction seems to be associated with an aggregate move away from China. When we move from one measure of US distraction to another – F_2 based on troop deployments and military spending – we see a similar pattern, diplomatic alignment with China increases with our measures of US distraction, economic alignment does not.

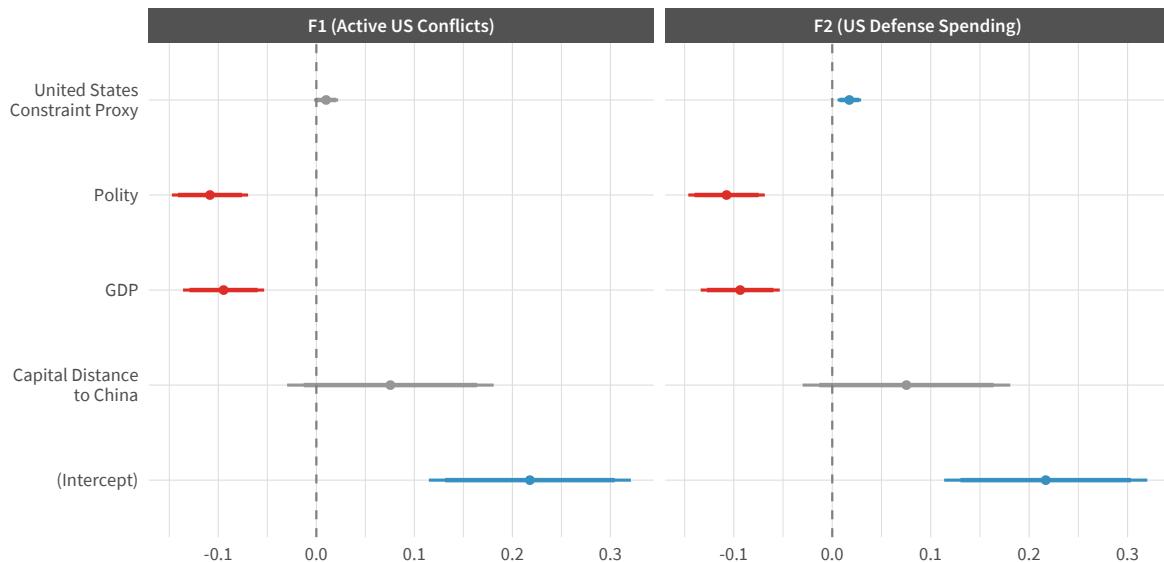


Figure 6: Parameter estimates from hierarchical model on diplomatic alignment with random country effects. Each column shows the results with a different distraction measure that is labeled in the facet on the top of the plots. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

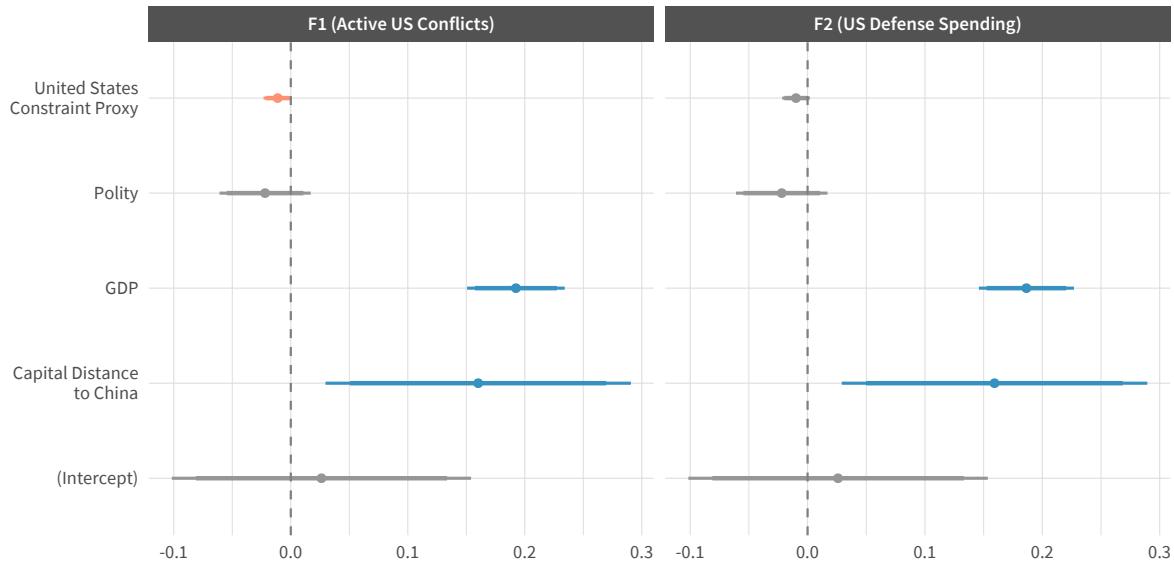


Figure 7: Parameter estimates from hierarchical model on economic alignment with random country effects. Each column shows the results with a different distraction measure that is labeled in the facet on the top of the plots. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

For control variables, we see a similar division between the two types of dependent variable. Democracies are less likely to be aligned diplomatically with China, but more likely to be aligned economically, and the same is true for rich states. The distance to Beijing has a consistent positive effect across all models (though it is more precisely estimated when focusing on diplomatic alignment), indicating that there is closer alignment between China and more distant states, on average, which might speak to the weariness that some of China's neighbors feels with regards to its growing importance.

One possible explanation for these ambiguous results is that these models show the aggregate effect, but beneath the surface, different states react to US distraction in different ways. To understand whether or not we can find evidence of variation in how countries are responding to China, we visualize the country random effect estimates from the diplomatic and trade alignment models in Figure 8. For both measures of alignment we see notable variation in country random effect estimates.

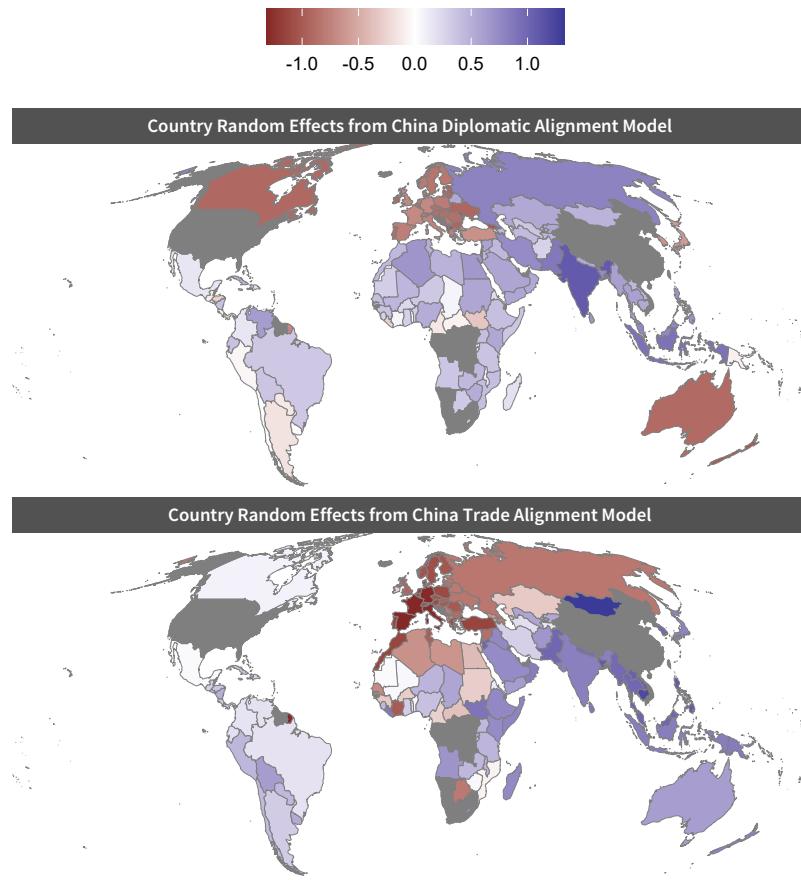


Figure 8: Country Random Effect Estimates, where the lower values in red indicate less alignment with China and higher values in blue indicate greater alignment. Countries in grey are those that were omitted from the model.

To further examine this, we modify our hierarchical model to allow the effect of our US distraction variables to vary across types of political institutions. We measure political institutions using polity scores. We use the canonical division into consolidated democracies (Polity Score ≥ 7), consolidated autocracies (< -6) and mixed regimes (all other states). In these models, we allow a random slope for the three distraction proxies in each tranche of the polity score.

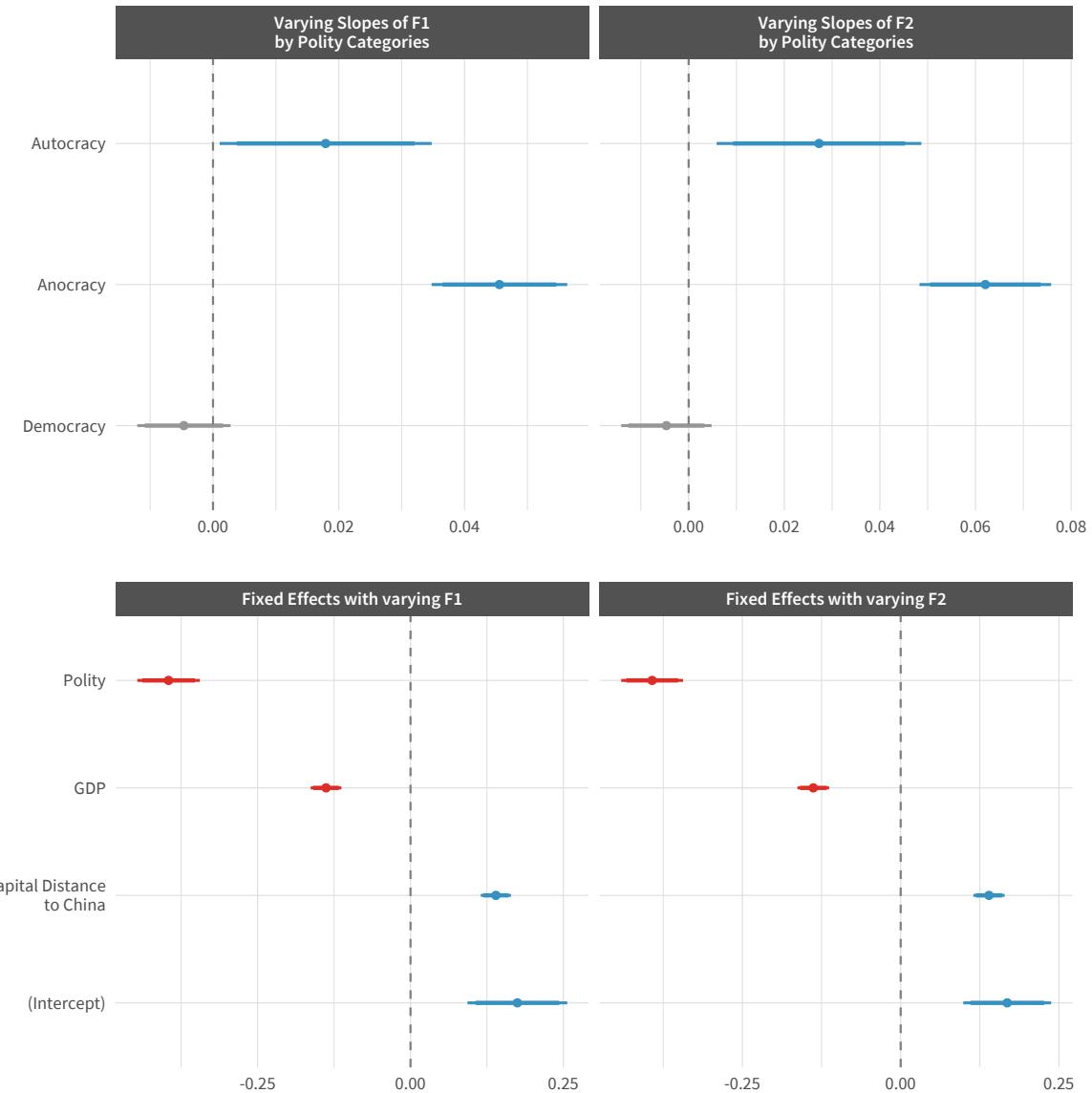


Figure 9: Parameter estimates from hierarchical model on diplomatic alignment with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects, each column again represents the results of one model. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

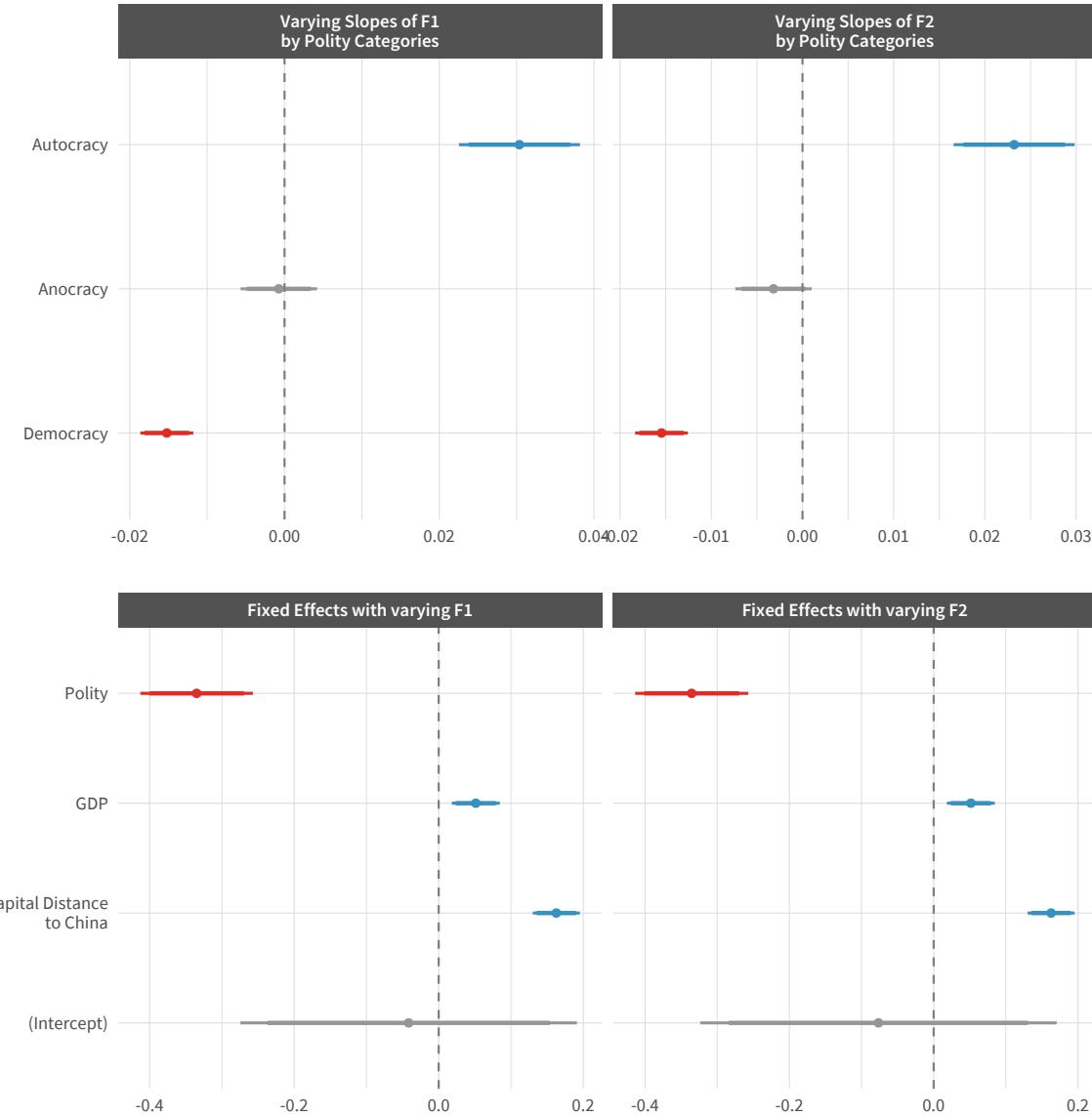


Figure 10: Parameter estimates from hierarchical model on economic alignment with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects, each column again represents the results of one model. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

For F_1 , we find a similar effect across our dependent variables. There is a consistent positive effect of US distraction among autocracies, meaning that autocracies grow more aligned with China while the US is distracted, but as we move from consolidated autocracy to mixed regime, and to democracy, this effect shrinks, and in many cases changes direction, such that consolidated democracies, across both economic and diplomatic measures become less aligned with China when the US is more distracted. For F_2 , there is a consistent positive effect of US distraction for both autocracies and mixed regimes, but the effect again reverses itself in consolidated democracies.

Conclusion

In this paper, we develop a theory of how constraints faced by the US have realigned cooperation networks in the international system. Specifically, during times of US distraction, we find that the level of cooperation between China and non-democratic countries has notably increased. To arrive at this finding we not only developed a factor based measures of US distraction, but also a network based approach to understanding how cooperation with China is changing in the diplomatic and economic realms. Our distraction measure show notable variation over time and we provide face validity evidence for our estimated measures of cooperation. The implications from our findings highlight what simply examining conflict data cannot. China's role in the international system is changing in measurable ways and its ability to potentially exert influence has become more notable in periods of US distraction.

References

- Anderson, Carolyn J., Stanley Wasserman and Katherine Faust. 1992. "Building Stochastic Blockmodels." *Social Networks* 14(1):137–161.
- Bennett, D. Scott and Allan C. Stam, III. 2003. *The Behavioral Origins of War*. Ann Arbor, MI, USA: University of Michigan Press.
- Bilmes, Linda. 2013. "The financial legacy of Iraq and Afghanistan: How wartime spending decisions will constrain future national security budgets."
- Cheng, Cindy and Shahryar Minhas. Forthcoming. "Keeping Friends Close, but Enemies Closer: Foreign Aid Responses to Natural Disasters." *British Journal of Political Science*.
- Cranmer, Skyler J., Bruce A. Desmarais and Elizabeth J. Menninga. 2012. "Complex dependencies in the alliance network." *Conflict Management and Peace Science* 29(3):279–313.
- Cranmer, Skyler J., Elizabeth Menninga and Peter Mucha. 2015. "Kantian fractionalization predicts the conflict propensity of the international system." *Proceedings of the National Academy of Sciences* 112(38):11812–11816.
- Crescenzi, Mark J. C. 2007. "Reputation and interstate conflict." *American Journal of Political Science* 51(2):382–396.
- de Marchi, Scott, Christopher Gelpi and Jeffrey D. Grynaviski. 2004. "Untangling Neural Nets." *American Political Science Review* 98(02):371–378.
- Deutsch, Karl Wolfgang and Joel David Singer. 1964. "Multipolar Power Systems and International Stability." *World Politics* 16(3):390–406.
- Dorff, Cassy, Max Gallop and Shahryar Minhas. 2021. "[W]hat Lies Beneath: Using Latent Networks to Improve Spatial Predictions." *International Studies Quarterly* 66(1).
URL: <https://doi.org/10.1093/isq/sqab086>
- Frieden, Jeffry A., David A. Lake, Michael Nicholson and Aditya Ranganath. 2017. "Economic Crisis and Political Change in the United States, 1900 to the Present." *Unpublished manuscript, University of California, San Diego* .
- Gibler, Douglas M. 2008. "The Costs of Reneging: Reputation and Alliance Formation." *Journal of Conflict Resolution* 52(3):426–454.
- Haass, Richard N. 2008. "The age of nonpolarity: what will follow US dominance." *Foreign affairs* pp. 44–56.

- Hoff, Peter D., Bailey Fosdick, Alex Volfovsky and Katherine Stovel. 2013. "Likelihoods for fixed rank nomination networks." *Network Science* 1(3):253–277.
- Huhe, Narisong, Max Gallop and Shahryar Minhas. 2021. "Who are in charge, who do I work with, and who are my friends: A latent space approach to understanding elite coappearances in China." *Social Networks* 66:26–37.
- Jenke, Libby and Christopher Gelpi. 2017. "Theme and variations: Historical contingencies in the causal model of interstate conflict." *Journal of Conflict Resolution* 61(10):2262–2284.
- Kane, Tim. 2016. "The decline of American engagement: Patterns in US troop deployments." *Economics working paper* 16101.
- Leeds, Brett Ashley, Jeffrey M Ritter, Sara McLaughlin Mitchell and Andrew G. Long. 2002. "Alliance Treaty Obligations and Provisions, 1815-1944." *International Interactions* 28:237–260.
- Maoz, Zeev. 2012. "Preferential Attachment, Homophily, and the Structure of International Networks, 1816-2003." *Conflict Management and Peace Science* 29(3):341–369.
- Maoz, Zeev and Bruce M. Russett. 1993. "Normative and Structural Causes of Democratic Peace, 1946-1986." *American Political Science Review* 87(3):624–38.
- Metzger, Shawna K and Benjamin T Jones. 2018. "Getting time right: Using Cox models and probabilities to interpret binary panel data." *Political Analysis* pp. 1–16.
- Minhas, Shahryar, Peter D. Hoff and Michael D. Ward. 2019. "Inferential Approaches for Network Analysis: AMEN for Latent Factor Models." *Political Analysis* 27(2):208–222.
- Mueller, Hans Felix and Christopher Rauh. 2018. "Reading Between the Lines: Prediction of Political Violence Using Newspaper Text." *American Political Science Review* 112(2):358—375.
- Palmer, Glenn, Roseanne W McManus, Vito D'Orazio, Michael R Kenwick, Mikaela Karstens, Chase Bloch, Nick Dietrich, Kayla Kahn, Kellan Ritter and Michael J Soules. 2021. "The MID5 Dataset, 2011-2014: Procedures, coding rules, and description." *Conflict Management and Peace Science* p. 0738894221995743.
- Poole, Keith T. and Howard Rosenthal. 1985. "A Spatial Model for Legislative Roll Call Analysis." *American Journal of Political Science* 29(2):357–384.
- Roberts, Margaret E, Brandon M Stewart and Dustin Tingley. 2016. "Navigating the local modes of big data." *Computational social science* 51.
- Schelling, Thomas C. 1966. *Arms and influence*. Yale University Press.

- Terechshenko, Zhanna. 2020. "Hot under the collar: A latent measure of interstate hostility." *Journal of Peace Research* 57(6):764–776.
- Trading Economics. 2021. "Trading Economics Data.".
URL: <https://tradingeconomics.com/>
- US Department of Defense. 2020. "National Defense Budget Estimates for Fiscal Year 2021." *Office of the Under Secretary of Defense (Comptroller)* .
URL: https://comptroller.defense.gov/Portals/45/Documents/defbudget/fy2021/FY21_Green_Book.pdf
- Walter, Barbara F. 2006. "Information, uncertainty, and the decision to secede." *International Organization* 60(1):105–135.
- Ward, Michael D., Nils W. Metternich, Cassy L. Dorff, Max Gallop, Florian M. Hollenbach, Anna Schultz and Simon Weschle. 2013. "Learning from the Past and Stepping into the Future: Toward a New Generation of Conflict Prediction." *International Studies Review* 16(4):473–644.
- Ward, Michael D., Randolph M. Siverson and Xun Cao. 2007. "Disputes, Democracies, and Dependencies: A Reexamination of the Kantian Peace." *American Journal of Political Science* 51(3):583–601.
- Warren, T. Camber. 2010. "The geometry of security: Modeling interstate alliances as evolving networks." *Journal of Peace Research* 47(6):697–709.
- Weisiger, Alex and Keren Yarhi-Milo. 2015. "Revisiting reputation: How past actions matter in international politics." *International Organization* 69(2):473–495.
- World Bank. 2021. "World Bank Open Data.".
URL: <https://data.worldbank.org/>

Contents

0.1	Empirical Results	17
A.1	Factor Loadings	27
A.2	Results with k=5	27

A.1. Factor Loadings

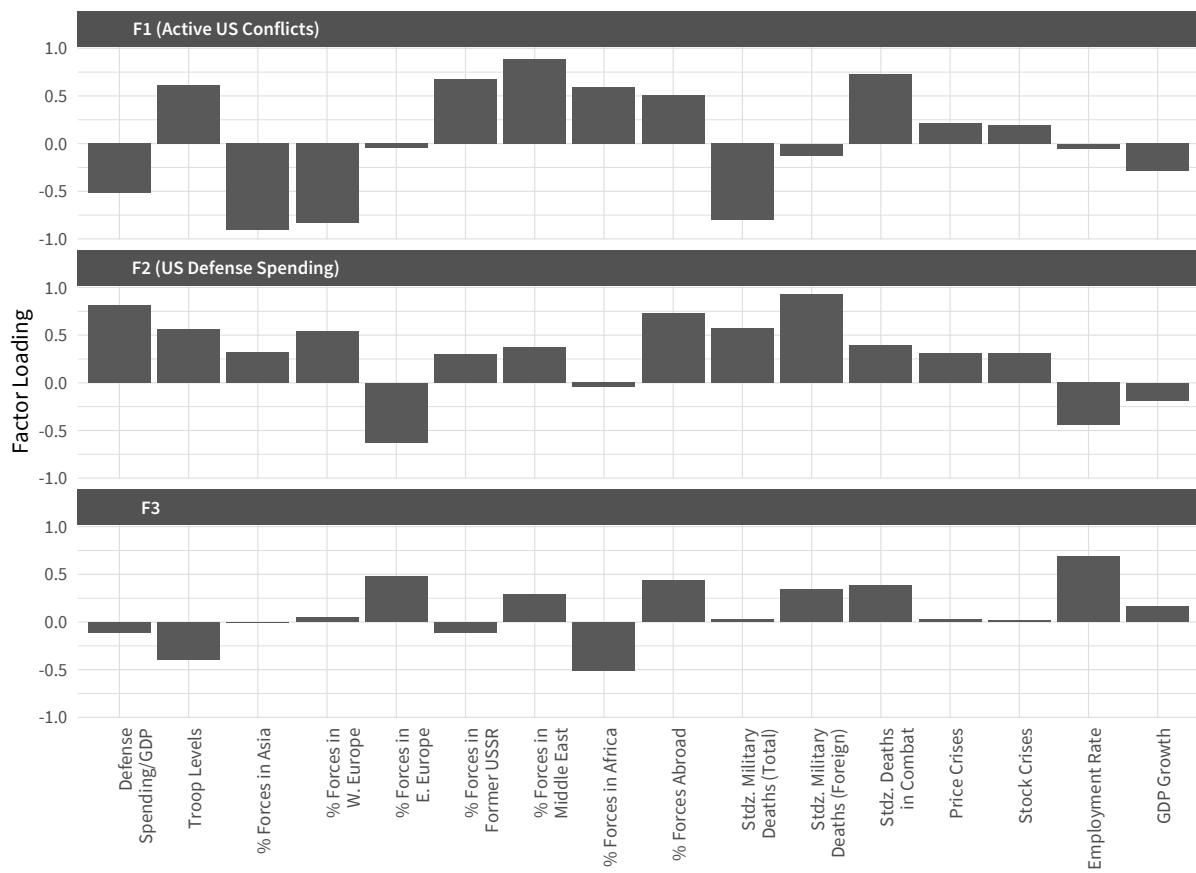


Figure A1: Loadings of constraint PCA

A.2. Results with k=5

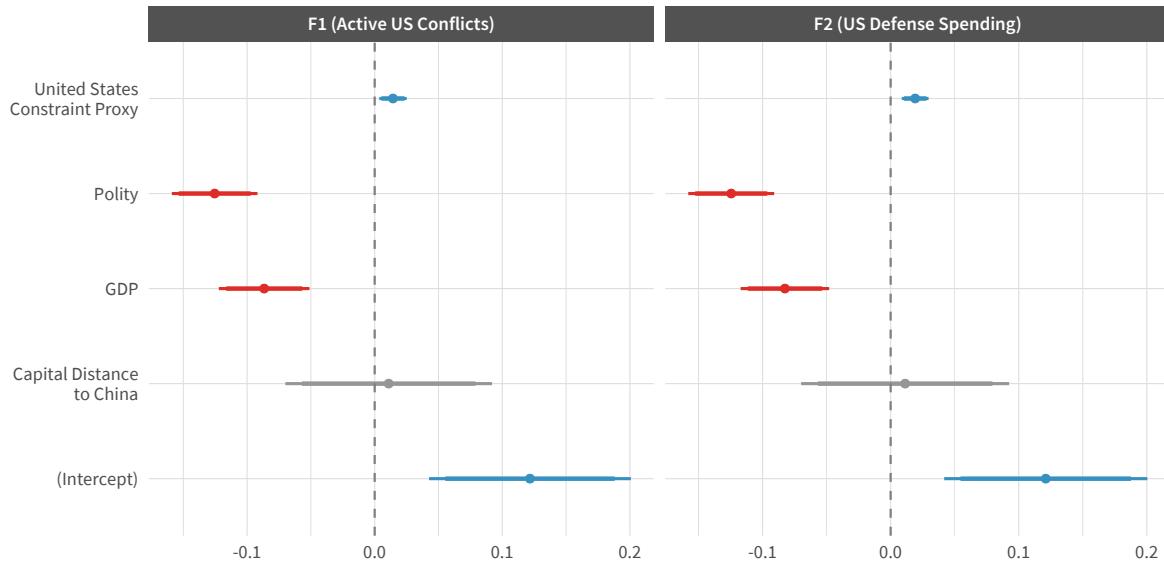


Figure A2: Parameter estimates from hierarchical model on diplomatic similarity with random country effects. Each column shows the results with a different distraction measure that is labeled in the facet on the top of the plots. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

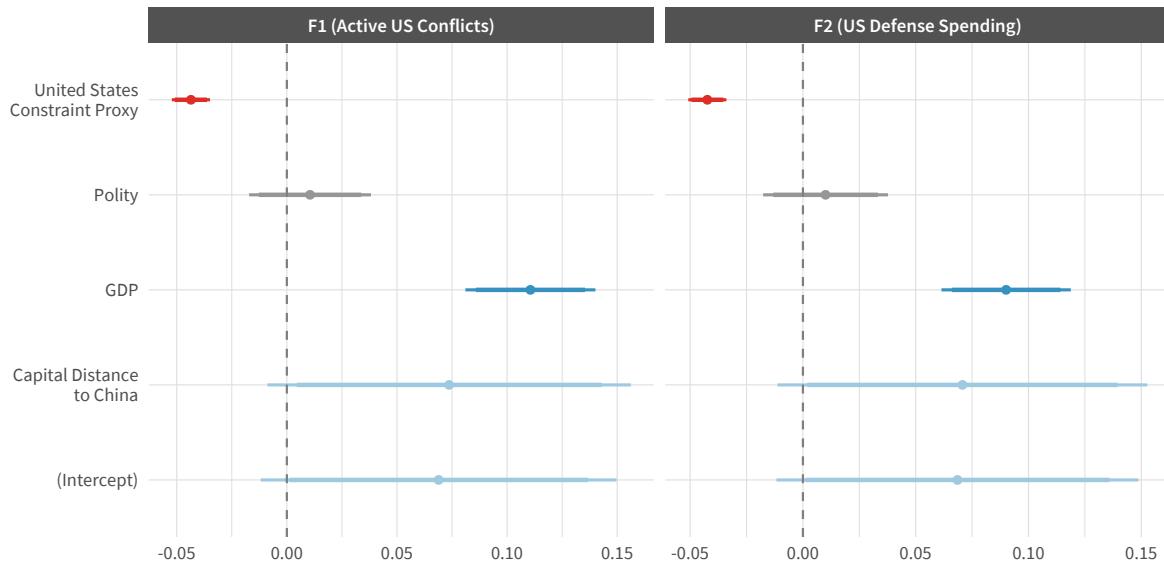


Figure A3: Parameter estimates from hierarchical model on economic similarity with random country effects. Each column shows the results with a different distraction measure that is labeled in the facet on the top of the plots. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

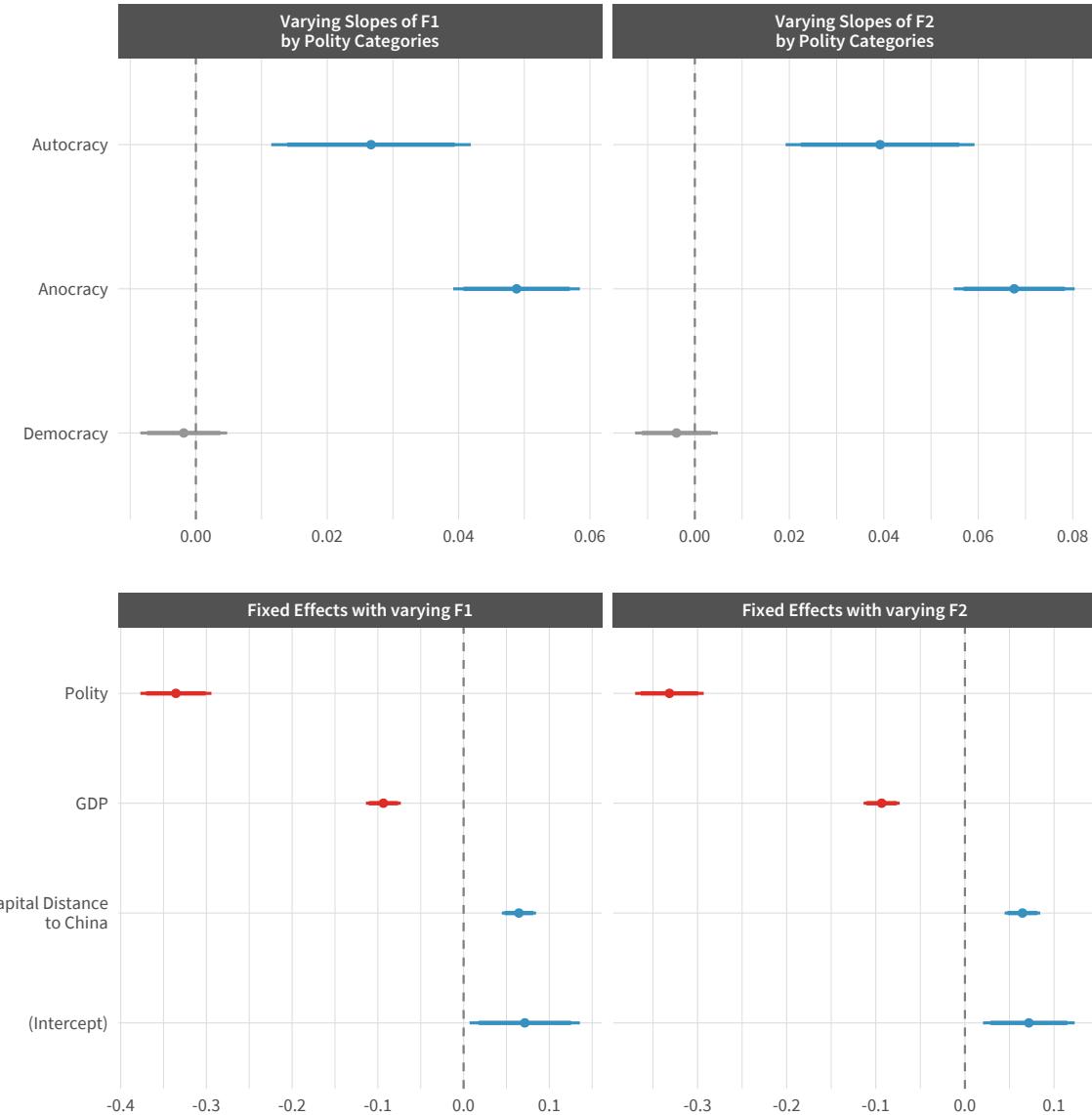


Figure A4: Parameter estimates from hierarchical model on diplomatic similarity with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects, each column again represents the results of one model. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

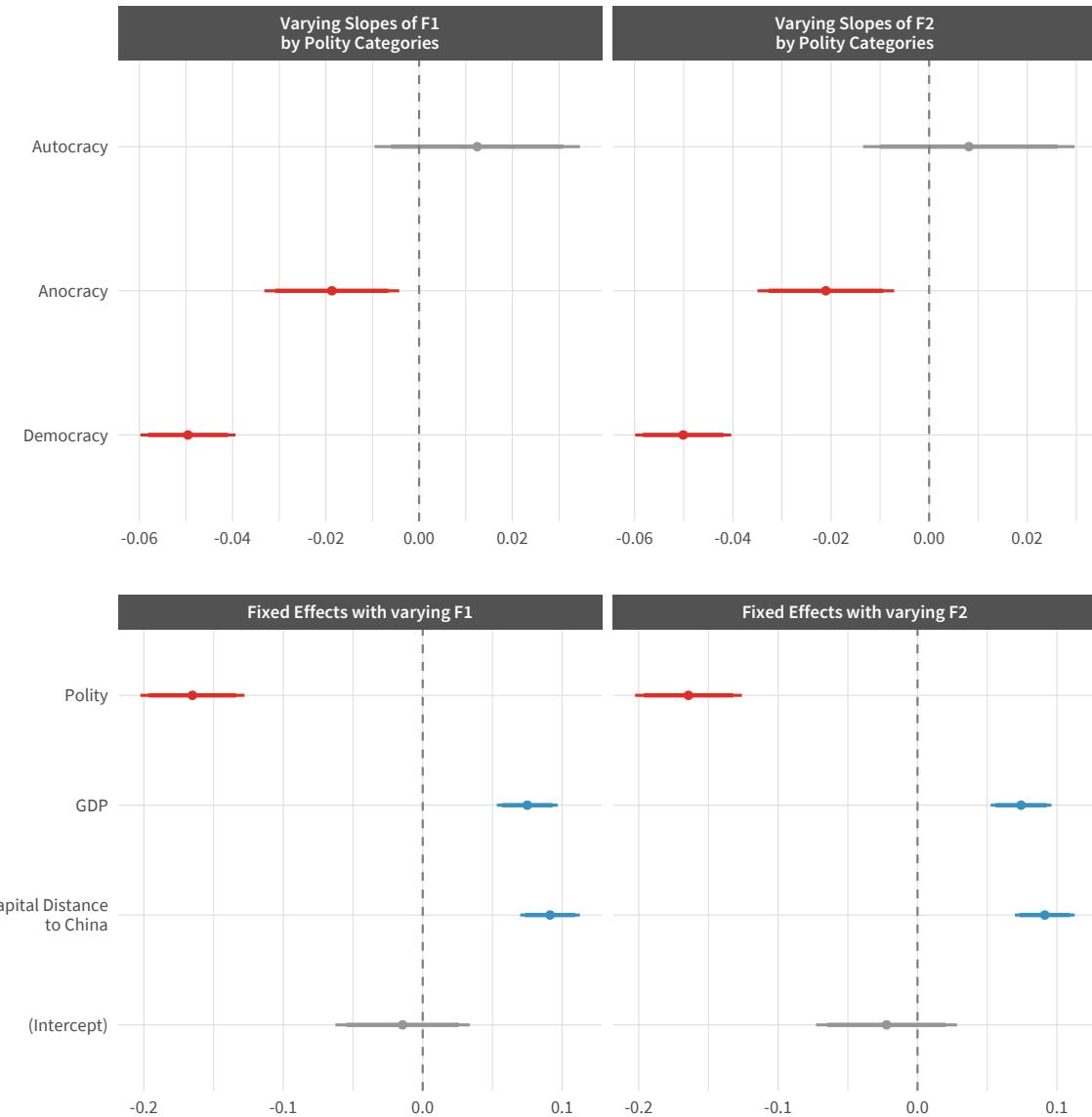


Figure A5: Parameter estimates from hierarchical model on economic similarity with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects, each column again represents the results of one model. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.