Hegemonic Distraction and

Abstract

We do stuff, its pretty cool.

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

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; see Palmer et al. (2021)) and the Alliance Treaty Obligations and Provisions project (focused on formal alliances between nations; see Leeds et al. (2002)). Without risk of exaggeration, explaining the causes of military conflict – or predicting future conflict – is the biggest show in town (Ward et al., 2013). Substantive findings from this literature continue to be well-cited, ranging from democratic peace (Maoz and Russett, 1993) to Bennett and Allan C. Stam, III (2003)'s comprehensive approach to explaining the causes of war.

While contributions made by this vast literature are important, questions about generalizability remain (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 (IID). Unfortunately (for research, though not for world peace), 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 different data generating processes – see de Marchi, Gelpi and Grynaviski (2004)). Within any given regime, many of these conflicts are geographically concentrated – in the post-WW2 period, disproportionately many of the conflicts occur in the Middle East.

We are thus faced 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 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 thus 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.

Importantly, 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.

Here, we focus on a particular type of shock to the international system: 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 other actors of interest such as China. We are thus interested in a relatively straight-forward model that investigates the proximity of cooperative relationships between state 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 study these interdependencies between states (Minhas, Hoff and Ward, 2019; Hoff, 2021). Here we employ this general framework to develop a latent measurement of how a state relates to other states in a network context. The factor analysis we employ seeks to take as an input the interactions that actors have with others across a variety of dimensions and project this onto a low-dimensional space. In many ways this goal 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).

We seek to model state interactions on a network, where there are specific types of patterns that often occur and that should be captured 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 ij 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 places actors it summarizes the interdependencies between actors in a relational k-dimensional latent vector space.

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 economic shocks, could have two divergent effects. On the one hand, one could think of US attention and resources as scarce, and the mechanism would be that while the US 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. Our expectation is that both types of constraint – military and economic – would have the same effect. 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. Obviously, this causal mechanism relies on military constraint only and does not depend on economic conditions. We call this *the Credibility Model*.

The 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 or ...) 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 US's 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. In the research presented here, our focus here is on third party actors and their relationship with China (i.e., a US 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 US military entanglement is also a measure of US 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 US constraint. This leads to our second hypothesis – as above, we are focused on third party relations with China:

Hypothesis 2: When the US 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 US constraint to capture a variety of mechanisms that might limit US action. In broad terms, we believe (based on SME input and prior research) that constraint is a function of three 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
3. US political or economic distraction caused by either foreign or domestic shocks.

To population these categories, we relied on sixteen variables distributed across the following broader categories:

Variables	Source
Defense spending	World Bank, US DoD
Troop levels, by region	US DoD, Kane
US Casualties	US DoD, Kane
Market Crises	Frieden and Lake
Economic variables	Trading Economics

Table 1: Variables for generation of US Distraction Index

The main source of constraint that is incomplete in the above framework is domestic political crises (i.e., apart from a response to economic shocks, which is captured).[1]

A simple latent variable model of the above variables produced three features, representing active US conflicts (F1), US defense spending / commitments (F2), and the economic shocks (F3). A PCA with three latent variables explained 89% of the variance in the raw data, which is very good. Scree plots / an examination of eigenvalues supported the use of three latent variables:

[1]Prior work has shown that political crises of this sort are rare / not likely consequential (Frieden et al., 2017) and we leave the inclusion of political measures to future work.

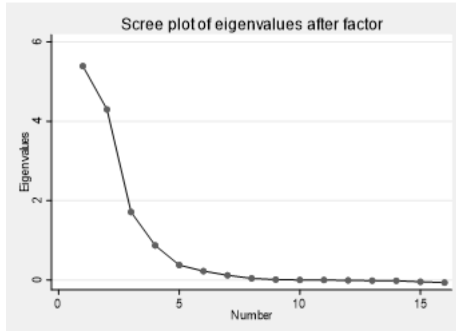

Figure 1: Scree plot of constraint PCA

A possible fourth factor, which we did not include, focuses on variance from GDP growth and changes in the stock market.

Graphs of the three factors through time show considerable variance that tracks with our priors on United States military conflicts and economic shocks over the past two decades:

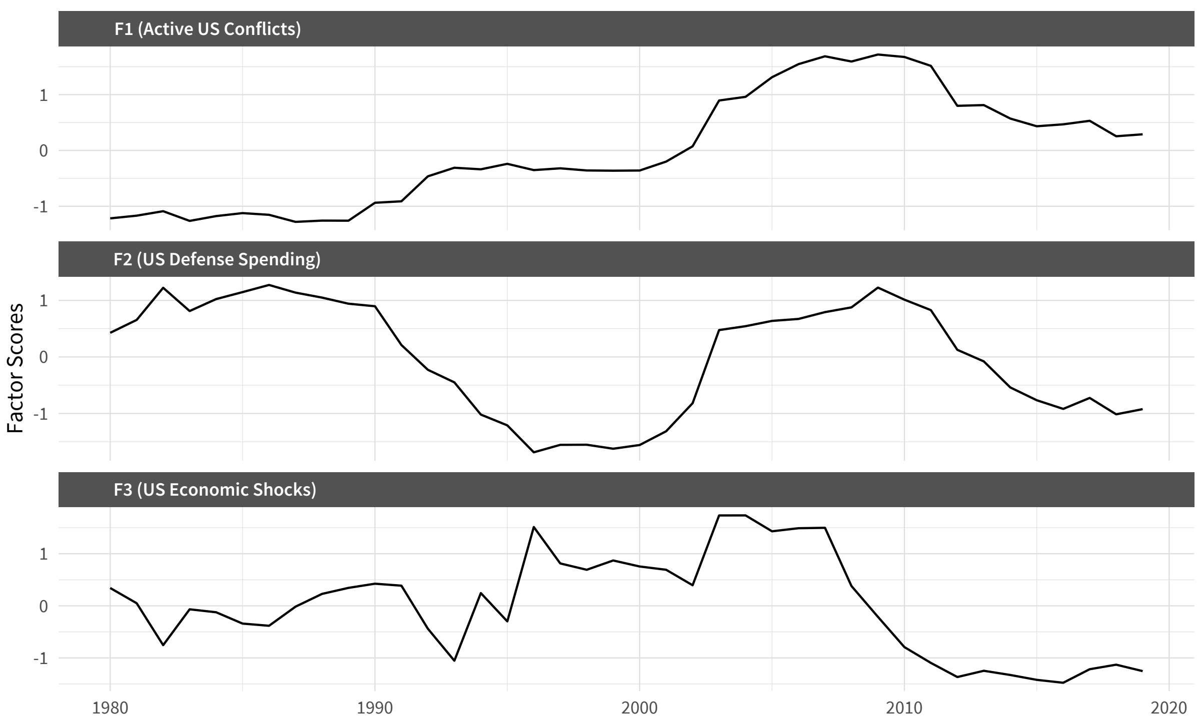

Figure 2: PCA Viz.

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. E.g., 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. This is named the Latent Factor Model (LFM).

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 trade between states for a given dyad and divide that by the total volume for one state in the dyad. 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.[2] In particular, we take X years of balance of trade data / UN voting data and each of them forms one slice of our multilayer network.

[2] See (cite) for other attempts to use the latent factor model to infer alignments in different contexts.

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. The LFM handles these third order dependencies with a multiplicative random effect based on the Singular Value Decomposition.[3] 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. The equations underlying the latent factor model are as follows:

$$
\begin{aligned}
y_{ij} \;&=\; f(\theta_{ij}), \text{ where} \\
\theta_{ij} \;&= \boldsymbol{\beta}_d^\top \mathbf{X}_{ij} + \boldsymbol{\beta}_s^\top \mathbf{X}_i + \boldsymbol{\beta}_r^\top \mathbf{X}_j \\
&\quad + a_i + b_j + \epsilon_{ij} \\
&\quad + \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j
\end{aligned} \tag{1}
$$

[3] This 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.

$$
\begin{aligned}
\{(a_1, b_1), \ldots, (a_n, b_n)\} &\overset{\text{iid}}{\sim} N(0, \Sigma_{ab}) \\
\{(\epsilon_{ij}, \epsilon_{ji}) : \ i \neq j\} &\overset{\text{iid}}{\sim} N(0, \Sigma_{\epsilon}), \text{ where} \\
\Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} & \quad \Sigma_{\epsilon} = \sigma_{\epsilon}^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}
\end{aligned} \tag{2}
$$

In particular, we argue that the $\mathbf{u_i}^T \mathbf{D} \mathbf{v_j}$ term, which is included in the model to capture third order dependencies, also is useful for us as a measure of economic alignment. We run an LFM without covariates on the economic data, and then take this term for every pair of countries in every year, as a measure of economic alignment and one with UN voting similarity as a measure of diplomatic alignment.[4]

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.

The latent factor model which underpins our measures of relationships maps each state into a k dimensional 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 5-8.

[4] We 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.

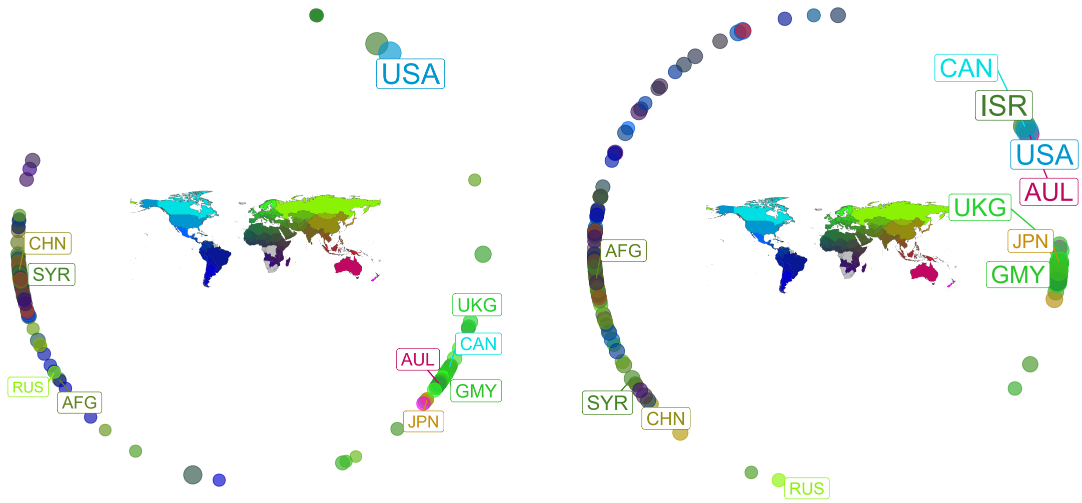

Figure 3: Visualization of multiplicative effects for our measure of diplomatic influence in 2000 (left) and 2019 (right). Each circle designates a country and the color corresponds to the legend at the center of the visualization. Countries that cluster together are those that were found by the model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

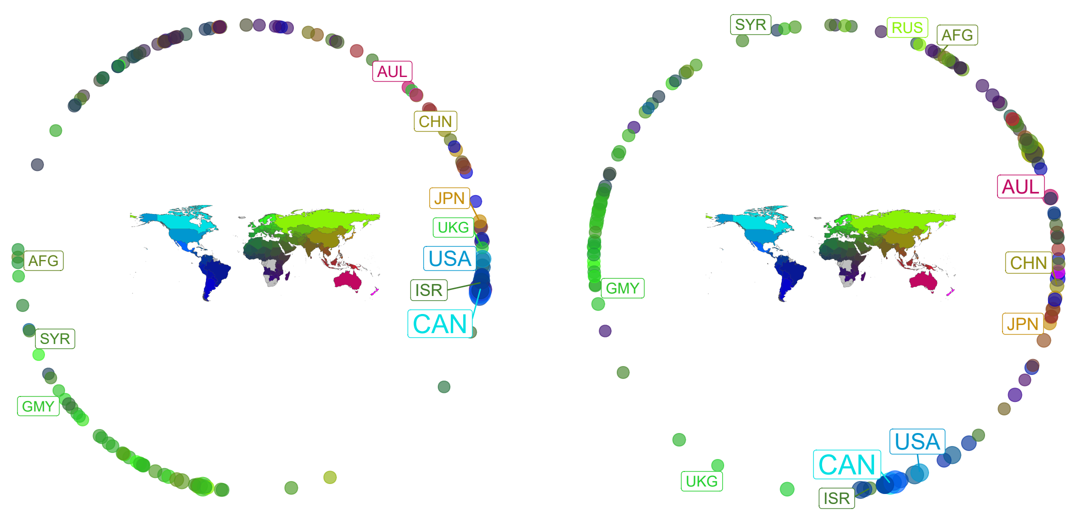

Figure 4: Visualization of multiplicative effects for our measure of trade influence in 2000 (left) and 2020 (right). Each circle designates a country and the color corresponds to the legend at the center of the visualization. Countries that cluster together are those that were found by the model to 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 influence measure based on UN voting shows three pretty clear 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. This is true whether we are looking at a latent factor model with 2 or 5 dimensional latent factors. 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 influence correspond to many of 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 a trio of important relationships. 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 9, 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, as shown in figure 10, while our measure of economic influence 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.

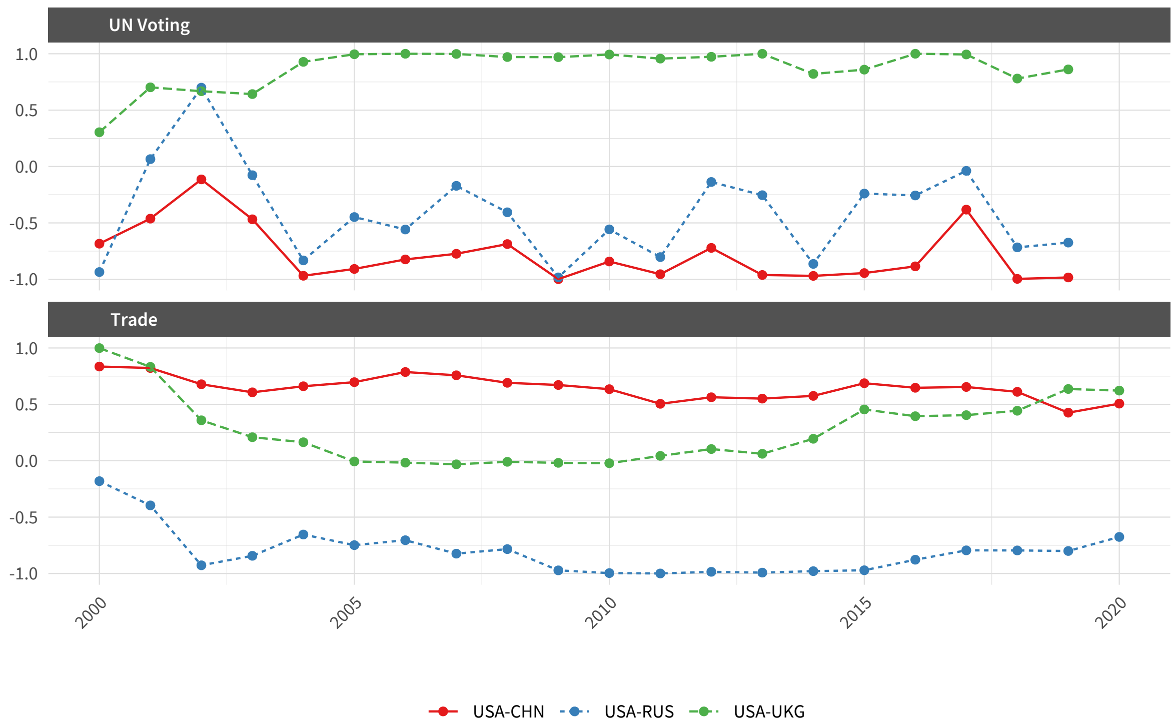

Figure 5: Cosine distance in latent factor space.

Regression Models

Given the forgoing meaures, 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), F_2 (US Defense Spending / Commitments) and F_3 (Economic Shocks).[5]

$$\text{DV}_i = a + j\beta_1 F_1 + (1-j)\beta_2 F_2 + \beta_3 F_3 + e_i \tag{3}$$

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

We should indicate that we havea vector of controls, and also be clearer about what we're doing with F3.

Our unit of observation here is at the country year level with a sample of 118 countries measured annually between 2000 and 2020. The countries excluded from the analysis are 1) those countries 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. To generate our dependent variable, we take our measure of a country's economic alignment with China and we measure the change in it from one year to the next. Based on our hypotheses H1 and H2, we test whether this movement 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), US defense expenditures and force commitments (F_2), and economic crises (F_3). 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 a country's closeness of economic alignment with China. 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 coun-

[5] Note that F_1 and F_2 have sufficient correlation that we run multiple models using either F_1 or F_2, rather than include them in a model together.

try 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 random effects based on a state's domestic political institutions.

0.1. Main Results

For our first pass at these models, we focus on the two largest factors of US constraint:

- F_1 US casualties
- F_2 US force commitments and military spending
- F_3 US economic shocks

In the first set of models depicted in figures **??** and **??** 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. 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, as seen in figures **??** and **??** – we see a similar pattern – diplomatic alignment with China increases with our measures of US distraction, economic alignment does not.

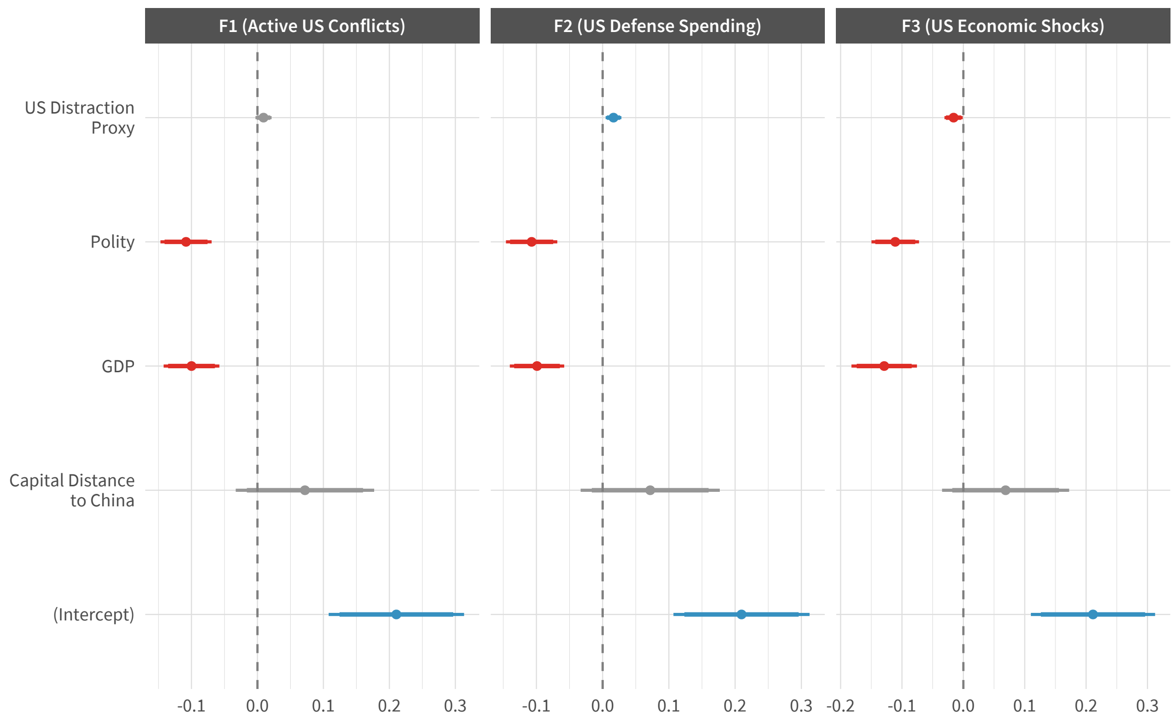

Figure 6: Parameter estimates from hierarchical model on diplomatic similarity with random country effects. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

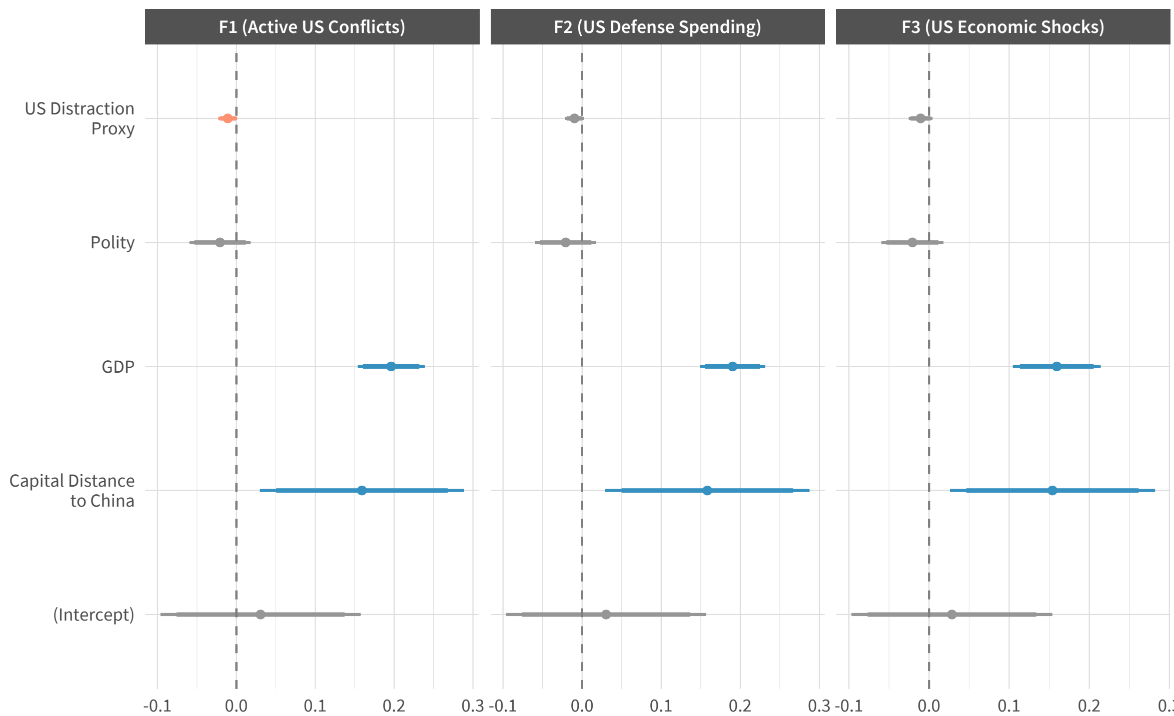

Figure 7: Parameter estimates from hierarchical model on economic similarity with random country effects. Each column shows the results with a different distraction measure that is labeled in the facet on the top of the plots. Points represent average value of parameters, thicker line represents the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

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 four models, indicating that there is interestingly, closer alignment between China and more distant states.

0.2. Heterogeneous Effect

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 examine this, we modify our hierarchical model to not just allow random intercepts, but also random slopes, and rather than using countries as our random effect, we group states using their 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 F1 or F2 in each tranche of the polity score.

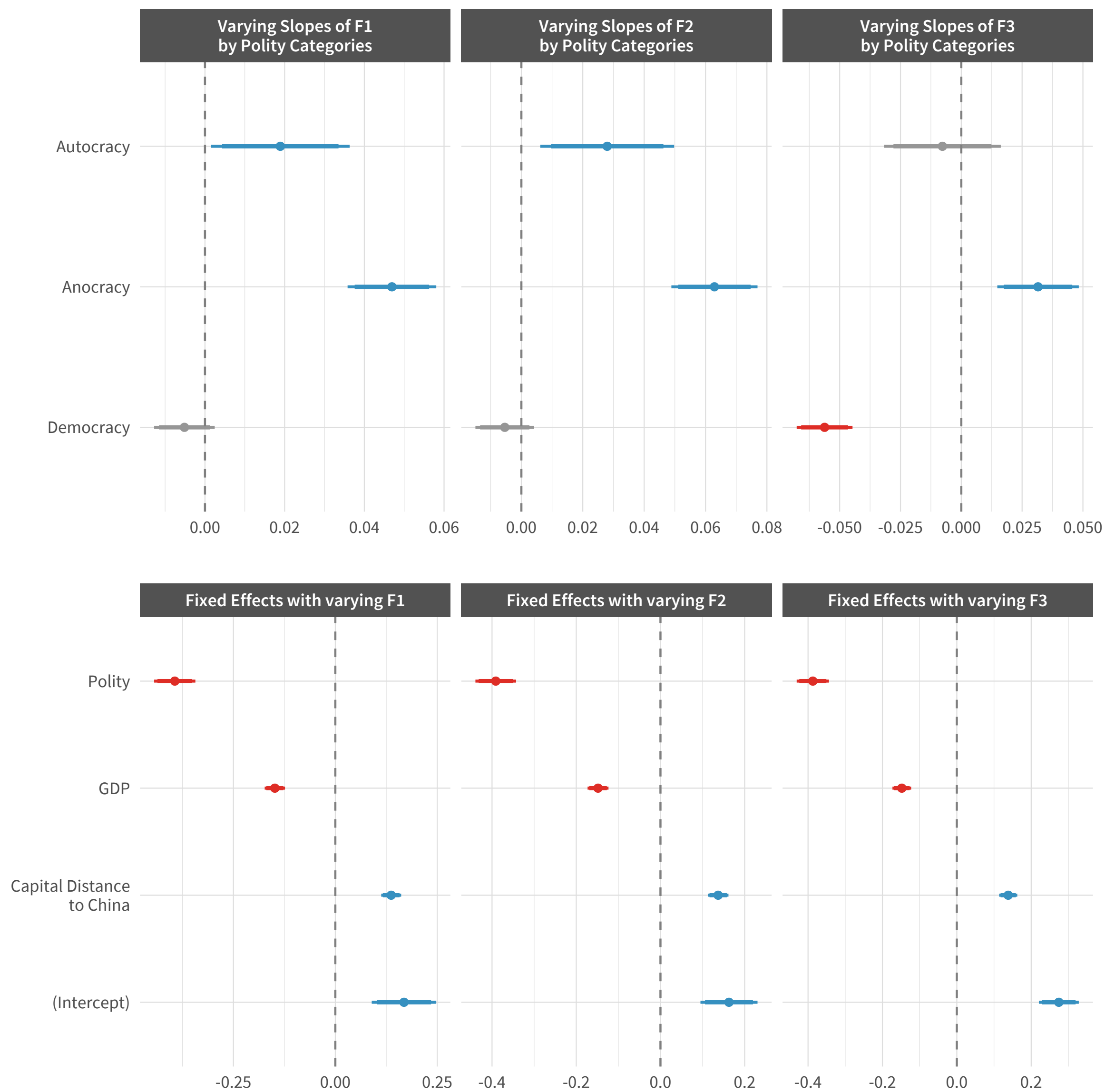

Figure 8: Parameter estimates from hierarchical model on diplomatic similarity with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects. Points represent average value of parameters, thicker line represents the 90% confidence interval, and thinner the 95%.

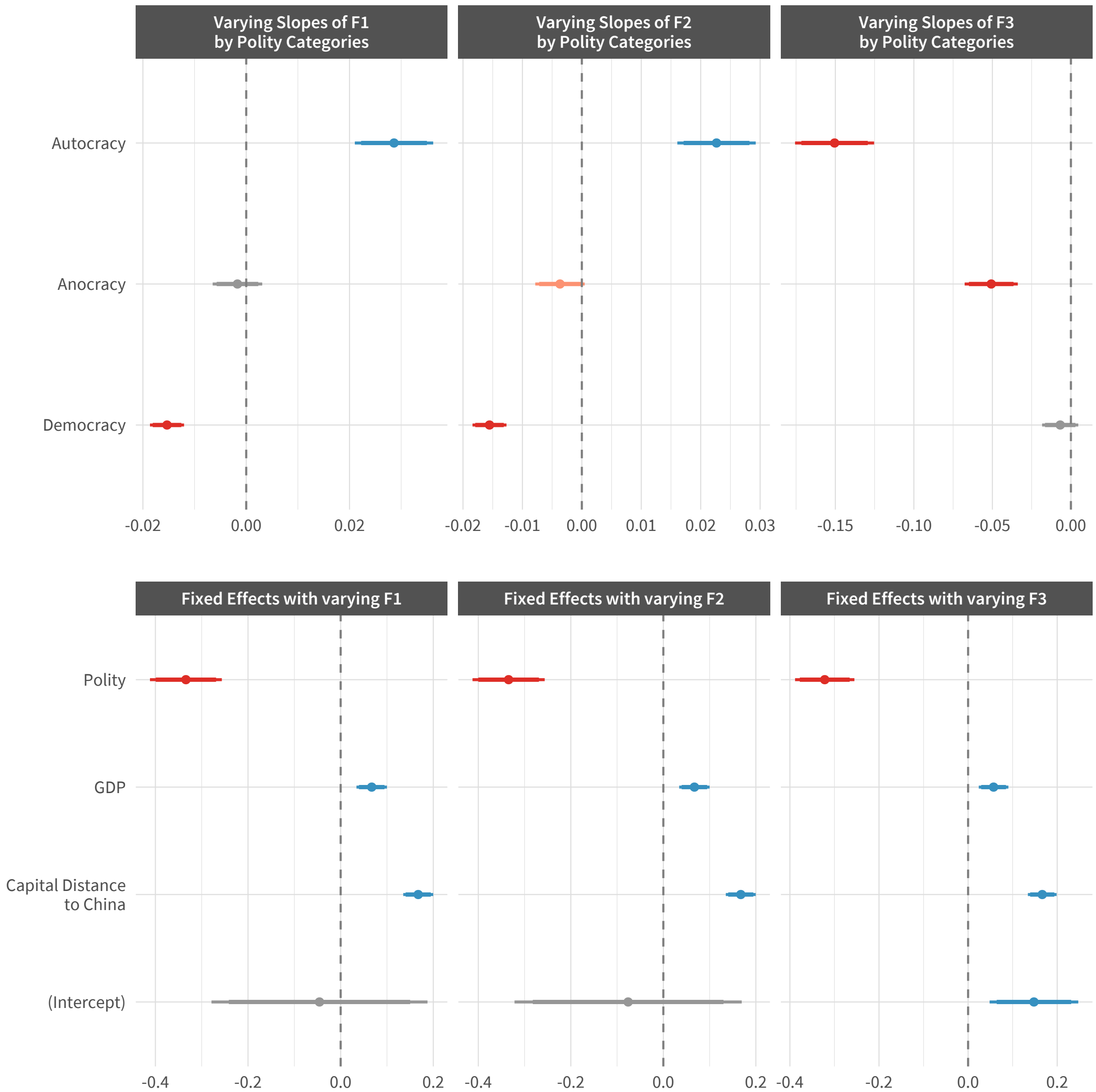

Figure 9: Parameter estimates from hierarchical model on economic similarity with varying effects of the distraction measures by polity categories. Top panel shows how the distraction measures vary by polity categories and bottom the fixed effects. Points represent average value of parameters, thicker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

For F1 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 F2, 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

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