Hegemonic Distraction and

Abstract

We do stuff, its pretty cool.

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

Introduction

- Basic question: Does US distraction due to wars, particularly in the Middle East lead to adverse outcomes in the rest of the world.
- Contributions:
    1. . Novel and superior measure of economic alignment
    2. Novel measure of US distraction
    3. . Findings about how US distraction leads states to cozy up/distance themselves from China
- Can use US withdrawal from Afghanistan and implications for US/China competition as an easy hook

Literature Review

1. Measure of US distraction – ?????
2. Measure of Alignment
    - Signorino S scores
    - Axelrod and Bennett
    - Gartzke UN voting S scores
    - Bailey, Voeten, Strezhnev ideal points
    - Gallop and Minhas
    - McManus and Neiman

Theoretical Intuition

US distraction, as measured by a larger share of resources and battle deaths in the Middle East, could be argued to have two divergent effects. On the one hand, we could think of US attention and resources as scarce, and the claim would be that while the US is distracted, say with a conflict in Afghanistan, they have less bandwidth and freedom of action to respond to a crisis in East Asia, we call this *the Distraction Model*. An alternative perspective relies on work that has been done on reputation and credibility, and this perspective argues that by spending blood and treasure in Iraq or Afghanistan, the United States demonstrates their resolve and willingness to spend blood and treasure elsewhere, we call this the *Credibility Model*.

Distraction Model

The basic insight of the Distraction Model is that both resources and attention are finite. The United States is a historically rich and powerful country, but that each successive conflict or intervention will have less resources, less oversight, and less political capital, and so all else being equal, the United States is less likely to get involved in a third (or fourth or tenth) conflict while it is, for example, involved in occupation and counterinsurgency in Iraq and Afghanistan. This has important implications for the behavior of third parties–if you are considering actions contrary to the interests of the United States, whether this be development of illicit weapons systems, invasion of a neighboring state, or simply a country choosing to align more closely with the US's strategic rivals, you are less likely to face consequences the more the United States is distracted. When applied to our measurement of state affinity, this naturally leads to our first hypothesis.

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. The basic idea behind 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 given goal, because the ration of the cost of these actions to their benefit is unobservable. However, we can make inferences about states' willingness to pursue costly actions using their past behavior–so if a state is willing to spend blood and treasure in one context, we should increase our belief that they are willing to do so in another context, and our measure of US distraction is also a measure of US demonstration of resolve. Now an important caveat here 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 being said, this leads us to a diametrically opposite view of how third parties will respond to our measure of US distraction. If the US demonstrates their willingness to bear heavy costs to achieve more congenial political outcomes in one context, we should update our belief about their willingness to bear costs in other contexts, leading to our second hypothesis.

Hypothesis 2: When the US is more distracted, they will have demonstrated more resolve, and states will be less willing to align closely with the People's Republic of China.

Should we discuss our theory of heterogeneous effects here with its own hypothesis, or wait for the results section?

Methods

Measuring Distraction

We have developed a measure of US constraint / distraction 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:

- Defense spending (World Bank, DoD)
- Troops levels, by region (DoD, Kane)
- US Casualties (DoD, Kane)
- Market Crises (Frieden and Lake)
- Economic variables (Trading Economics)

The main source of constraint that is incomplete in the above is domestic political crises (i.e., apart from a response to economic shocks, which is captured). Prior work has shown that political crises of this sort are rare / not likely consequential (Frieden, et al., 2017), but we will add an improved measure if we continue the project. A simple latent variable model of the above variables produced three variables, representing active US conflicts, US defense spending / commitments, and the economy.

These latent variables define the level of US constraint; in what follows, we will however focus on the first two latent variables because they more narrowly affect the US (and not other members of our sample). Go into more detail about the PCA, and add pictures.

Measuring Economic Alignment

/textcolorredRewrite with 2 DVs To test our theories, we want a measure of how closely states are aligned, and how this changes 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 – 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 they 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 eachother because of antipathy and neutrality: the difference between the US having no trade with Cuba or Iran, and having almost no trade with Slovenia is much greater than the trade data makes it appear. We believe that both of these issues can be ameliorated by treating measures of cooperation as a form of relational data, and using a network approach, called the Latent Factor Model, to infer our latent measure of alignment.

We use two different raw measures of cooperation: 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 states for a given dyad, and dividing 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 (**??**).[1]

[1]See **?** and **?** for other attempts to use the latent factor model to infer alignments in different contexts.

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. 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.[2] 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:

[2]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.

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

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

In particular, we argue that the $\mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j$ term, which is included in the model to capture third order dependencies, also is useful for us as a measure of economic alignment. So 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. In each case, we also allow the order of the multiplicative effect (k) to take on a value of either 2, representing a 2 dimensional latent factor space, or 5, to account for different levels of complexity in this space. In figure **??** we show a map with each countries economic alignment with China in 2000 and 2020, in figure **??** we show the evolution of our measure for a number of prominent dyads, and in figure **??** we show the network of econic alignment highlighting the role of geographic proximity.

SM could you insert pretty pictures

- Pick some dyad time series for **??**
- Map with proximity to either China or the US in 2000 and 2020.
- Circle plot with US, China, UK, Israel, Russia, India and maybe some other states labeled.

Downstream Modeling

Our unit of observation here is at the country year level. We do this for 118 countries, for every year 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, to see how countries move towards or away from China given the distraction or demonstrated resolve of the United States.

Our key independent variable, as discussed in section **??**, is our measures of US distraction based either on active US conflicts (called f1) and US defense expenditures and force commitments (called f2). 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 country more or less closely aligned with China, we include both Polity's measure of a country's level of democracy (the intuition being that autocratic regimes will be more close 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 states domestic political institutions.

Main Results

In the first set of models depicted in **??** we see a marked divergence between our measures of diplomatic and economic alignment. As F1 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 (F2 based on troop deployments and military spending, as seen in **??**), we see a similar pattern – diplomatic alignment with China increases with our measures of US distraction, economic alignment does not.

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. SM: can you add some way of depicting these model results, don't care if coeff plot, table, whatever

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 get at 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 do this in two ways: first we use the canonical division into consolidated democracies (Polity Score >= 7), consolidated autocracies (< -6) and mixed regimes (all other states). We also divide country years into 4 quartiles from the least to the most democratic, and in these models we allow a random slope for F1 or F2 in each tranche of the polity score.

For F1 and the canonical polity categories, we find a similar effect across our dependent variables. There is a consistent positive effect of US distraction among autocracies, meaning that autocracies are more aligned with China when 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 3 of the 4 dependent variables 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.[3]

SM: can you add some way of depicting these model results, don't care if coeff plot, table, whatever

Discussion

Look how much science we did, we in fact did a science!!!!

[3]The result also generally holds when we let the data determine the size of the institutional groupings, rather than prespecifying these canonical groups