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Identifying the level of major power support signaled for protégés: A latent measure approach

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Abstract

Major powers signal support for protégés in order to reassure them and deter harm against them. Yet, it is not always clear how to identify who a major power's protégés are or the degree of support signaled. Major powers have a variety of complementary signals to choose among, including alliances, arms transfers, joint military exercises, and others. It can be difficult to weigh the importance of individual signals, especially since different major powers do not deploy each signal in the same way. We address this challenge using a Bayesian latent measurement model, which provides a theoretically coherent means of identifying the overall level of support signaled by a major power for a protégé. Our approach yields a cross-sectional time-series dataset, providing a continuous measure of the degree of support signaled by major powers for all minor powers from 1950 to 2012. Our model also provides insights regarding which signals of support are most informative when sent by each major power. We find considerable variation among major powers regarding which of their signals are most meaningful, but in general alliances and military exercises tend to be among the most important signals. In further applications using our latent measure, we also assess under which conditions major powers are likely to increase their signals of support for protégés, as well as predict whether a major power will intervene in conflicts involving its protégés.

Keywords

alliances, hierarchy, latent variable, measurement model, military intervention, signaling

Introduction

Major powers typically sit atop networks of protégés, weaker states that share a major power's foreign policy orientation and whose security the major power wishes to ensure. Understanding major power–protégé relations is key to studying many topics in international relations, including hierarchy, balance of power, signaling, and deterrence. But who exactly are a major powers' protégés, and how do major powers signal support for their security?

Early research on major powers and protégés focused on alliance relationships (e.g. Waltz, 1979; Morrow, 2000), meaning that alliances were the only signal of support that received analytical attention. By not considering that major powers might wish to ensure the security of countries other than their formal allies, this approach implicitly treated a major power's set of protégés as equivalent to its alliance partners. More recently, scholars have noted how other gestures, such as nuclear deployments (Fuhrmann & Sechser, 2014), troop deployments (Martinez Machain & Morgan, 2013; Allen, Bell & Clay, 2018), arms transfers (Yarhi-Milo, Lanoszka & Cooper, 2016), military exercises (Blankenship & Kuo, n.d.), and even leadership visits and statements (McManus, 2018), can also function as signals of

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a major power's support for a protégé's security. This increasing interest in other signals offers a more realistic view of the full foreign policy toolkit available to major powers (Most & Starr, 1989; Palmer & Morgan, 2006). However, it also raises important theoretical and empirical questions.

First, are all of these gestures truly intended as signals of support for a protégé's security, or are some of them driven by other motivations? Second, how can we rank the relative informational value of these signals? Third, is the same signal equally informative when sent by different major powers? Finally, how can we estimate the *overall* level of support that major powers signal and identify which protégés a major power signals the most support for? Previous research has made little progress in addressing these questions, and existing theories offer little guidance regarding how to make the apples-to-oranges comparisons that are necessary for weighting the relative importance of different signals.

We offer a new tool for addressing these questions, using a Bayesian latent measurement model to construct a latent variable measuring the overall level of support signaled by major powers for the security of each potential protégé state in the international system. Our model yields a cross-sectional time-series dataset, providing continuous measures of the degree of support signaled by the USA, Russia,[1] China, Britain, and France for all minor powers from 1950 to 2012. Rather than making assumptions about the relative importance of each signal, our approach provides estimates of this based on the dataset itself.

Our approach makes several contributions. First, it provides new insight into which signals are likely to have the most informational value as indicators of a major power's interest in a protégé's security. Our results suggest that all of the signaling mechanisms identified by previous research are indeed driven by a desire to signal support, meaning that they should all carry some informational value. However, variation in signaling strategies suggests that certain signals are likely to be more informative when sent by some major powers than by others. For example, US alliances appear to be less indicative of genuine interest in a protégé's security than alliances offered by other major powers.

Second, our latent variable can rank protégés in terms of the overall level of support that each major power signals for their security. This offers a clearer view of major powers' foreign policy priorities and what their global protégé networks look like. We find, for example, that the US has consistently signaled support for protégés around the globe, while Russian signals have a narrower geographic focus. We also find that major powers signal uneven levels of support for their formal alliance partners.

Third, we provide new insights into questions of when major powers send signals of support and whether these signals actually lead to military intervention in time of need. We address these questions in two applications using our latent variable in statistical regressions. Our findings offer new insights regarding how major powers weigh long-term interests versus short-term threats in their signaling decisions and the extent to which signals tie a major power's hands and reveal its intentions.

A final benefit is that the latent variable can be used in follow-on research. Our variable better captures the level of support signaled by major powers than only accounting for one type of signaling, and it is less cumbersome than controlling for each signal individually. For studying many questions about strategic behavior, our measure is more theoretically appropriate than those of foreign policy similarity, which may capture homophily rather than deliberate signaling.

How major powers signal support

Maintaining a network of protégé states is beneficial to major powers because protégés can host the major power's forces, grant economic or political concessions to the major power, and promote the major power's values and legitimacy (Lake, 2009; McDonald, 2015; Nieman, 2016). Therefore, major powers have an interest in the security of their protégés, and they have the incentive to signal their support for their protégés' security to the world, for purposes of both deterrence and reassurance. There has been considerable academic interest in how major powers signal support and what makes signals credible.

Nonetheless, it can be unclear what exactly constitutes a signal of support for a protégé's security. When we say that a major power 'supports' a protégé's security, we simply mean that the major power wishes for the protégé to remain secure and free from harm. The term 'signal' refers to a deliberate public indication of a private preference or intention. Therefore, when a major power signals support for a protégé's security, it uses words or gestures to publicly convey that it desires the protégé to remain secure.

A signal of support does not necessarily mean an absolute commitment to defend a protégé militarily, but

[1] We use Russia to refer to both the USSR and Russia.

it should raise expectations of some form of intervention. While alliances often contain explicit defensive commitments, other signals can also raise expectations that a major power will somehow assist the protégé if it is harmed. Of course, signaling decisions are strategic. Some signals may be bluffs, in the sense that a major power seeks to convey that it cares more about a protégé's security than it truly does. Yet, if signals are costly to send – in terms of either sunk financial costs or hand-tying reputational costs – then bluffing should be limited. Therefore, the level of support publicly signaled is likely to be correlated with, though not identical to, the level of support privately felt.

The most obvious signal of support is an *alliance*. An alliance explicitly commits a major power to intervene if a protégé is attacked, creating a hand-tying effect due to probable reputational damage if the major power shirks its commitment (Morrow, 2000; Gibler, 2008). Many scholars have found a deterrent effect of defensive alliances, at least under some circumstances (Johnson & Leeds, 2011; Kenwick, Vasquez & Powers, 2015). Alliances have been the focus of much previous research, but they are not the only signal of support.

Recent research has identified additional signals that a major power can send to convey support for a protégé's security. Fuhrmann & Sechser (2014) note that *nuclear deployments* function as signals of support because of the monetary expense associated with them and the risk that the major power will automatically be drawn into war. Similarly, it is argued that a *troop deployment* constitutes a credible signal of support because of the likelihood that the troops will automatically become involved if the protégé is attacked (Schelling, 1966). In keeping with this argument, Martinez Machain & Morgan (2013) and Allen, Bell & Clay (2018) show that troop deployments deter attacks against host states.

Additional military gestures that have been proposed as signals of support for a protégé's security include *arms transfers* (Yarhi-Milo, Lanoszka & Cooper, 2016) and *joint military exercises* (Blankenship & Kuo, n.d.). Unlike deployments, these signals do not increase the risk that a major power will *automatically* be drawn into fighting on a protégé's behalf. However, they do improve the protégé's own fighting capability (Kinsella & Tillema, 1995) and, because of the sunk costs associated with them, can help to separate the behavior of major powers that genuinely care about protégé security from those that do not. Although arms transfers provide economic benefits, they can still be costly because of the effort necessary to arrange them and because arming a state that the major power did not support could have detrimental consequences. Yarhi-Milo, Lanoszka & Cooper (2016) show how US arms sales to Taiwan and Israel have been intended as signals of support.

The signals discussed so far have all been military. However, some scholars have argued that non-military signals, such as *leader visits* and *statements of support* can also convey an interest in a protégé's security (McManus, 2018; McManus & Yarhi-Milo, 2017). Visits and statements arguably give the impression that a major power's leader cares about a protégé's well-being and thus create leader-specific reputational costs that are paid if the major power abandons the protégé. Therefore, they can function as hand-tying signals. In keeping with this argument, McManus (2018) shows that major power leader visits and statements of support deter military challenges against minor powers.

Of course, major powers occasionally use methods other than those listed above to signal support for their protégés' security. However, the list above focuses on the signals that have been identified by previous literature, and we believe that this constitutes the set of signals that major powers use most frequently and systematically.[2]

The difficulty with multiple signals

The section above established that major powers can signal support for their protégés' security in various ways. The increasing recognition of this by scholars indicates a more realistic understanding of the menu of policy options available to major powers (Most & Starr, 1989; Palmer & Morgan, 2006). However, this multiplicity of signaling options also raises questions and poses dilemmas for scholars.

One question is whether all of these gestures are truly intended as signals of support or whether they might be more highly influenced by other motives. For example, despite the argument of McManus (2018) that visits function as signals of support, Lebovic & Saunders (2016) show that US presidential travel abroad is partly influenced by routine and US domestic conditions. Additionally, leadership statements may be intended for domestic posturing, and arms sales may be influenced by

[2] To test this assertion, we also considered the potential signaling function of economic interactions. We estimated an alternate version of the measurement model including economic aid (USAID, 2015) and bilateral investment treaties (BITs) (UNCTAD, 2018) for the USA. We found that BITs are much more weakly related to overall support signaled than any variable mentioned above and that economic aid is negatively related, indicating that these variables are not strongly associated with signaling support for security.

profit motives. Given these potential alternate motives, it would be valuable to have more systematic evidence that these gestures are indeed related to the level of support that a major power wishes to signal.

Second, even if all of these gestures are signals of support, how can we determine which signals have the most informational value? Some may argue that alliances are the most meaningful signal, but the ability to form alliances can be hampered by domestic politics (McManus & Yarhi-Milo, 2017) and entrapment fears (Yarhi-Milo, Lanoszka & Cooper, 2016), even when a major power cares deeply about a protégé's security. Ranking the informational value of other signals is also difficult. A joint exercise, for example, may involve high monetary costs, but a leadership visit might create higher reputational costs. Existing theories offer little insight regarding how to weight the attributes of different signals in order to rank their informational value.

A third question is whether all major powers follow similar signaling strategies. It may be the case that the same signal is not equally informative when sent by two different major powers. If one major power deploys a particular signal widely and another deploys it selectively, then the signal might be more meaningful when sent by the latter. Previous research, however, has not systematically compared major power signaling behavior.

A final question is how we can measure the *overall* level of support that a major power signals for a protégé's security. Having a parsimonious measure of this concept is desirable for several reasons. First, it could be used to rank countries by the level of support signaled for them, enabling us to understand which countries are most important to each major power and obtain a clear view of what each major power's protégé network looks like. Additionally, such a measure would have great practical utility for statistical analysis. Currently, scholars studying major power signaling quantitatively must choose to either focus on only a few signals and risk omitted variable bias or control for many signals and risk multicollinearity. Having one parsimonious measure of the overall level of support signaled eliminates this dilemma.

A latent variable approach

We are able to address each of the theoretical questions and empirical dilemmas raised above using a Bayesian latent measurement model. The model estimates the overall level of support that a major power intends to signal for a protégé's security – a latent concept that cannot be directly measured – based on the observed individual signals. The logic is that observable signals are manifestations of the underlying latent level of support that a major power wishes to signal; therefore, the use of multiple signals indicates more support. Moreover, a latent variable approach does not require us to make our own assumptions about how much each individual signal contributes to overall support signaled. Rather, the weight of the individual signals is estimated based on the data. Generally speaking, individual signals that are more highly correlated with other signals are estimated to contribute more to overall support signaled.

In estimating the extent to which individual signals contribute to overall support signaled, our model addresses the first question posed above, regarding whether all of the gestures we consider are truly signals of support for a protégé's security. If an individual signal is estimated to be an important contributor to overall support signaled, this means that it behaves similarly to the other signals and is therefore probably driven by the same underlying intention to signal support. In contrast, if a particular gesture is found to have little relationship or a negative relationship with overall support signaled, then the gesture is probably primarily motivated by something else.

Second, the model provides new insight into which signals are most informative. As noted above, it is difficult to rank the informational value of signals because different signals are costly in different ways and because sending a less costly signal does not always mean that a major power cares less. Our approach does not directly resolve these issues, but it offers a new way of analyzing the informational value of signals which is not plagued by these difficulties. We argue that the individual signals estimated by our model to make a greater contribution to overall support signaled are also likely to carry more informational value for observers. Based on the way in which these signals are used in conjunction with other supportive signals, observers can have greater certainty about the intentionality behind them, that is, that they are indeed intended to signal support. Certainty about intentionality is not a sufficient condition for signal credibility, which is also likely to be affected by the costliness of the signal, the sender's reputation, observer biases, and other factors. However, certainty about intentionality is arguably a necessary condition, as no signal can be fully credible if observers are uncertain about how to interpret it. Therefore, our analysis fills in an important missing piece to the puzzle for understanding signal credibility.

Third, the output of our latent variable model enables us to analyze the extent to which different major powers follow different signaling strategies. We compare how much each individual signal contributes to each major power's overall level of support signaled, which provides insight into how much different major powers rely upon different signals. This analysis also helps us to understand the extent to which the same signal may have different informational value depending upon which major power sent it.

The final benefit of our model is the single parsimonious measure of overall support signaled that it yields. This measure enables us to rank minor powers by the level of support that each major power signals for them, offering a systematic method of defining exactly what a major power's network of protégés looks like. The measure also has great utility for statistical analysis, including both the applications in this article and future research.

Of course, there have been previous efforts to develop a unified measure that summarizes the state of relations between countries. Most prominent are measures of foreign policy preference similarity, such as τ_b (Bueno de Mesquita, 1975) and *S*-scores (Gartzke, 2006; Signorino & Ritter, 1999). Most recently, a spatial measure of ideal point distance has been proposed (Bailey, Strezhnev & Voeten, 2017). These measures are distinct from our latent variable in two key ways. First, our variable captures deliberate signaling rather than underlying preferences. If signals do serve a hand-tying function, then we would expect deliberate signals to matter more in international relations than general preference similarity. Second, our variable is directional and measures a major power's support signaled for a minor power, not a minor power's support for a major power or two minor powers' support for each other.

The measurement model

We now turn to a more technical discussion of the measurement model. We employ a latent variable approach developed by Quinn (2004). This approach generalizes standard normal theory factor analysis and item response theory within a Bayesian framework. This approach is advantageous in that the measurement model can accommodate both ordinal and continuous variables when calculating the underlying latent variable. The effect of the included variables, moreover, can be assessed in terms of their contribution to the calculation of the latent variable. In addition, a Bayesian approach allows us to account for measurement error and assess the uncertainty of the resulting latent variable.

We assume that observed signals of major power support are imperfect indicators of an underlying latent variable. $\mathbf{X}$ is an $N \times J$ matrix of observed variables, with $j = 1, \ldots, J$ signals and $i = 1, \ldots, N$ country-year observations composed of g countries and t years. j is either ordinal or continuous. $\mathbf{X}$ is the observed outcome of the latent variable $\mathbf{X}^*$ and, when j is ordinal, γ cut-point(s). More formally:

$$x_{ij} = \begin{cases} x_{ij}^* \text{ if variable } j \text{ is continuous} \\ c \text{ if } x_{ij}^* \in (\gamma_{j(c-1)}, \gamma_c) \text{ and variable } j \text{ is ordinal,} \end{cases}$$

where $c = 1, \ldots, C_j$ and has at least two categories.

The observed $\mathbf{X}$ of the underlying latent $\mathbf{X}^*$ is modeled via factor analysis. As stated formally in Equation 1:

$$\boldsymbol{x}_i^* = \boldsymbol{\Lambda}\boldsymbol{\phi}_i + \epsilon_i \tag{1}$$

where $\boldsymbol{x}_i^*$ is a J vector of latent indicators for i, $\boldsymbol{\Lambda}$ is a $J \times K$ matrix of item discrimination parameters, ϕ is a K vector of factor scores for each i, and $\epsilon_i \overset{iid}{\sim} N(0, \psi)$ is a J vector of error terms.[3] In other words, among the parameters of interest, λ_j represents the effect of a specific signal, ϕ_i is the latent level of major power support signaled for a minor power, and ψ_j is the error variance explained by the latent factor.[4]

If the signals are assumed to be independent across observations,[5] we can recover parameters of interest by treating $\mathbf{X}^*$ as latent data and estimating the posterior density from the model, as shown in Equation 2:

$$\begin{aligned} &p(\mathbf{X}^*, \gamma, \boldsymbol{\Lambda}, \phi, \boldsymbol{\psi}|\mathbf{X}) \propto p(\mathbf{X}|\mathbf{X}^*, \gamma)p(\mathbf{X}^*|\boldsymbol{\Lambda}, \phi, \boldsymbol{\psi})p(\gamma)p(\boldsymbol{\Lambda})p(\phi)p(\boldsymbol{\psi}) \\ &\propto \left\{ \prod_{i=1}^{N}\prod_{j=1}^{J} \{ I(x_{ij} = x_{ij}^*)I(X_j \text{ continuous}) \right. \\ &\quad \left. + \sum_{c=1}^{C_j} I(x_{ij} = c)I[x_{ij}^* \in (\gamma_{j(c-1)}, \gamma_c)]I(X_j \text{ ordinal}) \right\} \\ &\times p_N(\mathbf{X}_i^*|\boldsymbol{\Lambda}\phi_i, \boldsymbol{\psi})\}p(\boldsymbol{\Lambda})p(\boldsymbol{\Phi})p(\boldsymbol{\psi}). \end{aligned} \tag{2}$$

where $I(v)$ is an indicator function equal to 1 if v is true and 0 otherwise, and $p_N(\mathbf{z}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is a multivariate normal density distribution with mean $\boldsymbol{\mu}$ and variance-covariance $\boldsymbol{\Sigma}$ at z, and $p(\boldsymbol{\Lambda})$, $p(\boldsymbol{\Phi})$, and $p(\boldsymbol{\psi})$ are the prior densities for $\boldsymbol{\Lambda}$, ϕ, and $\boldsymbol{\psi}$. The prior densities are

[3] We follow Quinn (2004) in setting the first element of ϕ equal to 1 and constraining one element for each column of $\boldsymbol{\Lambda}$ to be positive. The latter has the effect of making higher values of the latent score indicate greater major power support signaled. For additional technical details, see Quinn (2004).

[4] Continuous variables are standardized to mean 0 and standard deviation 1 to aid in interpretation, as coefficients can then be interpreted as factor loadings, as with factor analysis.

[5] Signals are assumed to be independent conditional on the underlying latent variable. In other words, if the underlying level of support that a major power wishes to signal changes, we expect a change in the observed signals.

specified as: $\mathbf{\Lambda} \sim N(l_{0_{jk}}, L_{0_{jk}}^{-1})$,[6] the diagonal elements of $\boldsymbol{\psi}$ for ψ_{jc} are constrained to 1 (ordinal variables) and $\psi_{jj} \sim IG(\frac{a_{0_j}}{2}, \frac{b_{0_j}}{2})$ (continuous variables), all γ elements follow improper uniforms, and $\phi_{i(2:K)} \overset{iid}{\sim} N(0,1)$. Conditional distributions for the model parameters are recovered using Markov chain Monte Carlo (MCMC) simulations.

We estimate the latent degree of support signaled by major powers for all minor powers from 1950 to 2012. We identify major powers as the permanent UN Security Council members: the USA, Russia, China, UK, and France. We consider all countries in the international system to be minor powers, except the USA, Russia, and China. The UK and France are treated as both major and minor powers because they can be considered US protégés, but they act as major powers in relations with other countries. We estimate the model separately for each major power.[7]

We construct the latent measure from seven signals introduced earlier in the article: alliances, nuclear deployments, troop deployments, joint military exercises, arms transfers, leader visits, and leader statements. We operationalize *Alliances* as defense pacts, using data from Gibler (2009), which we update to account for NATO expansion. *Nuclear deployment* data were obtained from Fuhrmann & Sechser (2014) and updated through 2012 using internet searches. *Troop deployment* data were obtained from Braithwaite (2015) and updated through 2012 using the International Institute for Strategic Studies' *Military Balance* (various years).[8] Data on *Military exercises* were obtained from D'Orazio (2016), and *Arms transfer* data were obtained from SIPRI (2018). *Leader visit* data were compiled by McManus (2018) and updated through 2012 using sources listed in the Online appendix. *Leader statements* data for the USA are also from McManus (2018).[9]

The *Visit* and *Exercise* variables are coded as 1 if any number of visits or exercises took place during the year. The *Troop*, *Arms*, and *Statements* variables are logged after adding a constant.[10] Data on *Exercises* and *Troops* are unavailable prior to 1970 and 1981, respectively, while data on *Statements* and *Exercises* are unavailable after 2010. An advantage of our latent variable model is that it can incorporate these variables when they are available and omit them when unavailable.

Model results

We estimate major power support signaled for each country's security using the model described above.[11] Parameter estimates for each major power are summaries of the posterior distribution from 100,000 iterations after a burn-in of 20,000, with every 50th iteration saved.[12] Table I summarizes the effects of each variable on the latent measure of overall support signaled. λ_1, which is analogous to a slope coefficient, is the key term for interpreting how much each individual signal contributes to overall support signaled.[13] λ_0, which is only estimated for indicator variables, is analogous to a constant term. ψ_j, which is only estimated for continuous variables, is the error variance explained by the latent factor, that is, the extent to which the latent variable can explain variation in the individual signals.

All point estimates of λ_1 are positive and at least two standard deviations from 0, suggesting that all of the variables are important contributors to the overall level of support signaled. The estimated error variances are also fairly high, indicating that the latent level of support signaled can explain a large amount of the variation in the individual signals. For example, the estimated error variance of 0.949 on *Arms transfers* for France indicates that over 90% of the variability of *Arms transfers* is explained by the underlying latent factor. Substantively, these results provide validation for previous theories that proposed the gestures we consider as signals of support, as it does appear that all of these gestures reflect an underlying intention to signal support.

Looking more closely at the parameter values for λ_1, we can compare the relative influence of each signal by country. Beginning with the binary variables, for which λ_1 is interpreted like an item discrimination parameter

[6] The elements of $\mathbf{\Lambda}$ constrained to have a positive value, discussed in footnote 3, are truncated at 0.

[7] There may be preferences for specific foreign policy tools resulting in state-level, or even leader-level, variation. To account for the latter, we include year dummy variables. None of the year dummies exert any meaningful influence.

[8] Except for the updates noted above, we did not make any changes or corrections to the underlying data sources. The *Military balance* includes some hostile occupations, such as Russian troops in separatist Georgian regions. This adds noise to the data, but a benefit of our latent variable model is that it weights noisy signals less.

[9] Data on statements by other major power leaders are not available.

[10] We tried various functional forms of the continuous variables, with little effect on estimates of ψ_j.

[11] The effect of *Alliance* is constrained to be positive.

[12] All estimates of the measurement model use *MCMCpack* in R (Martin, Quinn & Park, 2011).

[13] Continuous variables are standardized, meaning λ can be interpreted in the same manner as coefficients in factor analysis.

Table I. Effect of component variables on overall support signaled

Variable	*Alliance*	*Leader visit*	*Military exercise*	*Nuclear deployment*	*Arms transfers*	*Troop deployment*	*Leader statements*
USA							
λ_1	0.720	0.739	0.796	1.048	0.652	0.519	0.577
	(0.024)	(0.033)	(0.028)	(0.046)	(0.012)	(0.012)	(0.012)
λ_0	–0.519	–2.037	–1.400	–2.450			
	(0.016)	(0.041)	(0.026)	(0.067)			
ψ					0.578	0.732	0.670
					(0.013)	(0.013)	(0.013)
Russia							
λ_1	1.544	0.625	0.687	2.651	0.509	0.323	
	(0.132)	(0.041)	(0.050)	(0.336)	(0.016)	(0.016)	
λ_0	–2.740	–2.116	–2.450	–6.982			
	(0.169)	(0.048)	(0.068)	(0.788)			
ψ					0.743	0.897	
					(0.017)	(0.015)	
China							
λ_1	1.408	0.498	0.827		0.228	0.080	
	(0.114)	(0.080)	(0.194)		(0.022)	(0.017)	
λ_0	–3.242	–2.063	–3.496				
	(0.295)	(0.072)	(0.827)				
ψ					0.948	0.994	
					(0.016)	(0.015)	
UK							
λ_1	1.408	0.763	1.501	0.499	0.277	0.177	
	(0.114)	(0.051)	(0.141)	(0.080)	(0.015)	(0.014)	
λ_0	–2.122	–2.196	–2.654	–2.925			
	(0.116)	(0.059)	(0.172)	(0.108)			
ψ					0.924	0.969	
					(0.015)	(0.014)	
France							
λ_1	0.922	0.396	4.182		0.227	0.106	
	(0.051)	(0.044)	(0.512)		(0.015)	(0.015)	
λ_0	–1.630	–2.010	–6.954				
	(0.045)	(0.040)	(0.806)				
ψ					0.949	0.989	
					(0.015)	(0.014)	

λ_1 is the factor loading/item discrimination parameter (analogous to a slope coefficient), λ_0 is the negative item difficulty parameter (analogous to an intercept), and ψ is the amount of error variance explained. Standard deviations in parentheses.

from item response theory, we find that *Nuclear deployments* contribute the most to overall support signaled by the USA and Russia, the only two countries to deploy nuclear weapons abroad on a large scale. Aside from nuclear deployments, *Alliances* contribute the most to overall support signaled by Russia and China, while *Military exercises* contribute the most to overall support signaled by the USA, UK, and France. *Leader visits* contribute less than *Alliances* or *Exercises* to the overall level of support signaled by all major powers, except the United States, for which *Visits* contribute more than *Alliances*. The contribution of *Alliances* is particularly low for the USA relative to other major powers. This probably accurately reflects that US alliances are not very informative signals, since the USA almost certainly cares more about the security of some of its non-allies, such as Israel and Saudi Arabia, than the security of many of its allies, such as Rio Pact members.

Turning to the continuous variables, for which λ_1 is interpreted as a factor loading, the signals contributing the most to the overall level of US support signaled are *Arms transfers* and *Leader statements*, with *Troop deployments* playing a strong but lesser role. Likewise for the other major powers, *Arms* contribute more to overall support signaled than *Troops*. Both *Arms* and *Troops*, however, contribute less to overall support signaled by

China, the UK, and France than by the United States and Russia. Because ψ_j is high for *Arms* and *Troops* sent by China, the UK, and France, the low λ_1 values probably simply reflect that these signals are rarely used by these countries.

Substantively, these results suggest that there are crucial differences in how major powers signal support, implying that the importance of individual signals varies when sent by different major powers. As explained earlier, the extent to which an individual signal contributes to overall support signaled has implications for how informative the signal is likely to be, but the heterogeneity among major powers makes it difficult to make blanket statements about whether certain signals are more informative than others. Indeed the most important take-away from these results is probably that we should avoid overly general theories of signal credibility and instead account for differences among signalers. Nonetheless, based on the level of intentionality they convey, we can state that alliances and joint exercises are generally likely to be among the most informative signals, while visits are likely to be among the least.

Overall support signaled

Aside from assessing the influence of specific variables, the measurement model allows us to estimate the latent level of support signaled by each major power for each individual country, ϕ_i. Our estimates of ϕ yield a cross-sectional time-series dataset, providing continuous measures of support signaled (with the degrees of uncertainty) by major powers for all minor powers' security from 1950 to 2012.

To illustrate the utility of these data, we begin by highlighting variation in the latent signaling variable that would be obscured by analyzing only one signal. Figure 1 displays US support signaled for the security of NATO allies in 2010. If we only analyzed alliance ties, we would treat the level of US support signaled for all NATO allies as equal, but Figure 1 shows there is significant variation in the degree of support signaled. This suggests that a single indicator – even a highly salient one such as *Alliances* – may miss important variation in signaled support. The latent variable, therefore, provides some context for why the Baltic states, despite being NATO allies, have requested more explicit supportive signals from the USA to deter Russia.

To provide a broader overview of these data, Figures 2 and 3 give a snapshot of the degree of US and Russian support signaled across all countries in 1982 and in

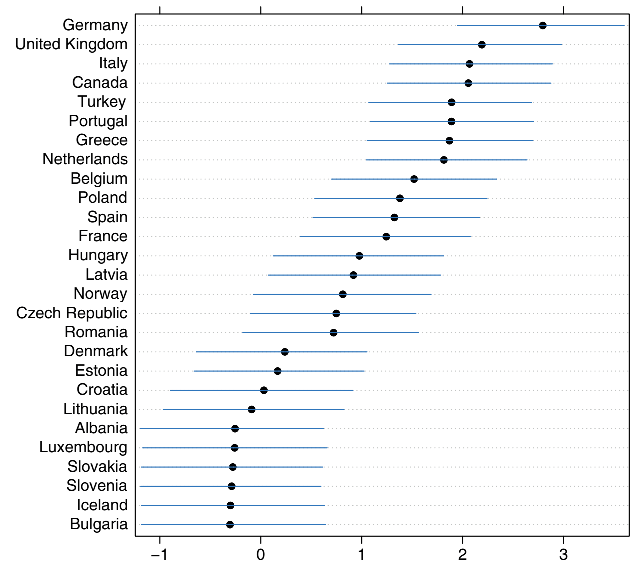

Figure 1. US support signaled for NATO allies, 2010

2008, respectively.[14] It is clear that the USA signaled a particularly high level of support for the security of Western Europe in 1982. There was an increase in US support signaled for the rest of the world from 1982 to 2008. While the USA continued to signal support for Western Europe, it also signaled support for the security of countries in both South and Southeast Asia, as well as signaling slightly more support for Latin American countries. Overall, however, the degree of stability in US signaling over time is high. The correlation in ϕ_i between 1982 and 2008 across the entire dataset is $r = 0.72$.

The degree of stability in US signaling stands in contrast to the pattern observed for Russia. Looking at Figure 3, there is a clear shift in the focus of signaling from 1982 with its emphasis on Eastern Europe and North Africa, to an emphasis on the post-Soviet region and Latin America in 2008. The correlation in the level of Russian support signaled between 1982 and 2008 across the entire dataset is $r = 0.41$, substantially lower than for the USA.

This analysis highlights the practical utility of our measure for exploring subtle variation in the level of support that major powers signal for the security of different countries and understanding a major power's foreign policy priorities and the scope of its ambition. The next section will further highlight the utility of the latent variable in two applications.

[14] We report the median value of ϕ_i. Appendix Figures 4 and 5 show the 20 countries with the most US and Russian support signaled.

(a) 1982 (b) 2008

Figure 2. US latent support signaled
Darker colors indicate more support.

(a) 1982 (b) 2008

Figure 3. Russian latent support signaled
Darker colors indicate more support.

Applications

In this section, we utilize our latent variable in two applied contexts. First, we examine which factors predict the level of support that a major power will signal for a protégé. Second, we analyze how the level of support signaled affects the probability that a major power will intervene militarily to assist a weaker power.

Predicting the level of support signaled

Analyzing which conditions affect a major power's decision to signal support is important for testing signaling theories as well as understanding how major power–protégé ties form. Previous research has explored the determinants of individual signals, including alliances (Reiter & Lai, 2000; Gibler & Wolford, 2006; Gartzke & Weisiger, 2013), nuclear deployments (Fuhrmann & Sechser, 2014), troop deployments (Martinez Machain et al., 2018), visits, and arms transfers (McManus & Yarhi-Milo, 2017). However, since these signals can be either complements or substitutes, none of this research provides a clear picture of what determines overall support signaled. Our latent variable provides the opportunity to analyze this.

We expect the level of support signaled to be a function of both the major power's underlying interest in a protégé's security – which is likely to be influenced by homophily, historical ties, and strategic value – and the level of threat that the protégé faces. Signaling is a strategic decision, and signals are costly to send. Therefore, while we generally expect major powers to signal more support for countries they care about more, major powers are likely to reserve some of their strongest signals of support for the protégés that most need support because they are under threat.

We estimate separate OLS regressions for each major power, predicting the latent measure of support signaled for each minor power. To account for homophily between major and minor powers, we include the minor power's *Polity* score (Marshall, Gurr & Jaggers, 2016)

Table II. Predicting the latent measure of support signaled

	(1) USA	(2) Russia	(3) China	(4) UK	(5) France
Polity	0.027**	–0.028**	0.004**	0.023**	0.017**
	(0.002)	(0.003)	(0.001)	(0.005)	(0.003)
GDP/capita	0.051*	–0.056**	–0.003*	0.032*	0.036*
	(0.020)	(0.015)	(0.002)	(0.013)	(0.016)
Colonial history		0.994**	–0.357**	0.091**	0.111**
		(0.172)	(0.063)	(0.024)	(0.023)
GDP	1.043**	0.263**	0.082**	0.500**	0.436**
	(0.059)	(0.039)	(0.022)	(0.081)	(0.068)
Distance	–0.169**	–0.410**	–0.101**	–0.278**	–0.164**
	(0.017)	(0.052)	(0.017)	(0.057)	(0.029)
Distance squared	0.010**	0.035**	0.006**	0.021**	0.010**
	(0.001)	(0.004)	(0.001)	(0.004)	(0.002)
Recent MIDs	0.052**	0.008**	0.009**	0.014**	0.012**
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Constant	0.32	0.451	–0.044	0.357	0.554
	(0.625)	(0.641)	(0.945)	(0.824)	(0.510)
N	7156	7156	7156	7100	7100

*$p < .05$, **$p < .01$. Robust SEs use Rubin's (1987) formula to account for uncertainty in the latent variable. *N* differs because we predict US, Russian, and Chinese signals for Britain and France, but not vice versa.

and *GDP per capita* (Gleditsch, 2002) as independent variables. To account for historical ties, we include *Colonial history* (Hensel, 2014). As proxies for the minor power's strategic value, we include its total *GDP* (Gleditsch, 2002) and the *Distance* and *Distance squared* between the major and minor power (Bennett & Stam, 2000). To account for threat level, we include the number of *Recent MIDs* in which the minor power has been involved in the last five years, excluding MIDs against the major power itself (Palmer et al., 2015). We account for the uncertainty in our estimate of the latent variable by taking five draws from the posterior distribution of the latent variable and regressing the independent variables on each draw. We then calculate point estimates and standard errors for each independent variable using Rubin's (1987) formula for multiple imputation.[15]

The results are shown in Table II. Our expectations are strongly supported. Demonstrating the importance of homophily, *Polity* is a positive and significant predictor of support signaled by democratic major powers, but a negative and significant predictor of support signaled by Russia. More surprisingly, *Polity* is also a positive and significant predictor of support signaled by China, which might reflect the fact that China became a more active signaler only in the less ideological post-Cold War era. *GDP per capita* shows a starker division among the major powers, with the USA, UK, and France signaling significantly more support for wealthier countries and Russia and China signaling significantly more support for poorer countries. *Colonial history* is a positive and significant predictor of Russian, British, and French signaling, but a negative and significant predictor of Chinese signaling.

Turning to more strategic factors, *GDP* is a positive and significant predictor of signaling by every major power, reflecting the greater strategic importance of protégés with larger economies. *Distance* also has a similar effect on each major power's signaling. The negative significance of *Distance* and the positive significance of *Distance squared* suggests a U-shaped effect, in which major powers signal the most support for countries that are very close and very far away. This might reflect a desire to protect the security of buffer states in their own backyard, but also gain leverage in rivals' areas of influence.

Finally, *Recent MIDs* is a positive and significant predictor of support signaled by each major power. This

[15] The point estimate for each parameter is the mean from the five draws, or $\frac{1}{5}\sum_k^5 \beta_k$, while the standard error is the average of the estimated variances within the datasets plus the variance in the point estimates across datasets, or $\sqrt{\frac{1}{5}\sum_k^5 s_k^2 + (1+\frac{1}{5})\sigma_\beta^2}$ where s_k^2 is the standard error for dataset k and σ_k^2 is the variance in β between datasets (see Rubin, 1987). Five draws from the posterior distribution are sufficient to incorporate uncertainty (Mislevy, 1991).

indicates that not only how much a major power cares about a protégé, but also how much threat the protégé faces, affect signaling decisions. This highlights the strategic nature of the signaling reflected in our measure. On the whole, this analysis further demonstrates the validity of the latent measure because the predictors that we find to be important are in keeping with expectations. Our analysis also confirms that a major power's decision of how much support to signal is complex and influenced by many factors.

Major power intervention

The question of when a major power will intervene to aid a weaker state under attack is important for both the theory and practice of foreign policy. By studying the relationship between signals of support and intervention, we can gain insight into the extent to which signals truly tie a major power's hands and predict its behavior. When a major power's protégé is attacked, the major power must choose between abandoning or assisting it. Theories of costly signaling suggest that a major power which has previously signaled support for the protégé's security is more likely to assist it, both because a major power that was willing to bear the cost of sending a signal is more likely to genuinely care about a protégé's security and because the signal itself creates a hand-tying effect (Fearon, 1997). This logic is widely accepted in the signaling and deterrence literature, but aside from analyses of alliance abrogation (e.g. Leeds, Long & Mitchell, 2000), it has received little empirical testing.

Analyzing major power intervention is also a critical first step to testing other aspects of deterrence theory. In its most standard and basic form, extended deterrence is modeled as a two-player, two-stage extensive form game: the attacker first decides whether or not to attack and, if it chooses to attack, the defender then decides whether to fight or capitulate. Assuming that the attacker is a rational actor, its decision is impacted by what it expects the defender to do. As with other extensive form games, equilibria are found using backwards induction. Thus, the best approach to account for this strategic process empirically is to first estimate the probability that the defender chooses to fight and then use this to calculate the attacker's expected utility from attacking, that is, statistical backwards induction (Signorino & Tarar, 2006; Bas, Signorino & Walker, 2008).[16] In other words, analyzing a major power's willingness to intervene to defend a protégé is the logical first step to obtaining a fuller understanding of the dynamics of extended deterrence.[17]

We examine major power intervention using a dataset of militarized interstate disputes (MIDs) initiated between 1950 and 2010 (Palmer et al., 2015). We estimate a separate probit model for each major power, in which the dependent variable is whether the major power became involved in the MID on the target side. Our main independent variable is the *Latent measure of support signaled* by the major power for the minor power(s) targeted in the MID. We use the highest value of this variable among all minor powers on the target side, and lag it by one year. As in the previous application, we account for uncertainty in our estimate of the latent variable using Rubin's (1987) formula for multiple imputation. We also control for other MID characteristics, including the *Total number of states* involved, the *Absolute* and *Relative capabilities* of each side (Singer, 1987),[18] and the *Distance* and *Distance squared* between the major power and the closest minor power on the target side (Bennett & Stam, 2000).

Table III reports the results. We see that the *Latent measure* is a positive and statistically significant predictor of intervention in each regression, with the exception of the China model. The insignificance for China is probably explained by the fact that China has sent relatively few signals compared to other major powers – increasing the uncertainty in the latent score estimates – and has also participated in relatively few MIDs.

Although we have seen that the latent measure is a good predictor of MID intervention, we also want to compare it to other predictors. First, we estimate alternate regressions predicting MID intervention using the individual component variables that were used to create our latent measure. All of the signaling variables are lagged by one year, and we include the same controls as before. We must omit troops and exercises because of missing values in some years,[19] which reveals the first

[16] The results of our analysis can be treated as an expectation of a future action and used to calculate an expected utility (see Bas, Signorino & Walker, 2008).

[17] Some readers may be concerned with non-random sample selection due to highly resolved actors being more likely to attack. Any selection effect from this type of process would create bias *against* finding a relationship between intervention and signaling because we would expect major powers to be *less likely* to intervene against attackers who have already demonstrated high resolve. Therefore, our test is, if anything, too conservative.

[18] We exclude the major power itself from the calculation of these controls.

[19] We also omit alliances in the China regression and nuclear deployments in most regressions due to insufficient variation.

Table III. MID intervention regressions

	(1) USA	(2) Russia	(3) China	(4) UK	(5) France
Latent measure of support signaled	0.382**	0.534**	–0.251	0.441**	0.316**
	(0.070)	(0.164)	(0.336)	(0.158)	(0.117)
Side A capabilities	0.071**	0.075**	0.063	–0.038	–0.067**
	(0.016)	(0.020)	(0.051)	(0.024)	(0.026)
Side B capabilities	–0.075	–0.013	–0.002	0.065**	0.078**
	(0.044)	(0.024)	(0.080)	(0.024)	(0.025)
Relative capabilities	–0.534	–0.810	–0.319	0.735	0.484
	(0.341)	(0.637)	(1.333)	(0.605)	(0.637)
Total states involved	0.302**	0.036	0.060	0.288**	0.154
	(0.061)	(0.032)	(0.088)	(0.079)	(0.093)
Distance from major power	–0.408**	–0.222	8.179	0.227	0.260
	(0.151)	(0.249)	(9.047)	(0.220)	(0.297)
Distance squared	0.033*	0.017	–2.504	–0.021	–0.084
	(0.013)	(0.032)	(2.475)	(0.027)	(0.056)
Constant	–1.546**	–1.913**	–8.724	–4.238**	–3.435**
	(0.511)	(0.581)	(7.777)	(0.685)	(0.649)
N	1,440	1,416	1,452	1,462	1,490

$^*p < .05$, $^{**}p < .01$. Robust SEs use Rubin's (1987) formula to account for uncertainty in the latent variable. *N* differs because we drop observations where the major power is on Side A.

downside of using multiple signaling variables compared to our latent variable. The latent measure allows a longer time span to be used, while still incorporating additional information as it becomes available.

After estimating the new models (shown in Table IV in the Online appendix), we find that they have additional disadvantages. First, none of the individual component variables significantly predicts intervention as consistently as the latent variable. Second, including multiple signaling variables individually results in a loss of efficiency without notably improving model fit. The Bayesian information criteria (BICs) (shown in Table V in the Online appendix) indicate that the model using the latent variable outperforms the model using the component variables for every major power, and the Akaike information criteria (AICs) tell a similar story.

Next, we compare the ability of our latent variable to predict MID intervention with that of the *S*-score. The *S*-score purports to measure foreign policy preference similarity rather than explicit signals of support, and it is theoretically interesting to examine whether explicit signals or underlying preference similarity tell us more about the probability of intervention. To explore this, we use two versions of the *S*-score, measured based on UN General Assembly votes (Gartzke, 2006; Voeten & Merdzanovic, 2009) and alliances (Signorino & Ritter, 1999; Bennett, Poast & Stam, 2017). Because the *S*-score is not a component of our latent variable, we compare it directly to the latent variable by including both in the same regression.[20] We estimate separate regressions for each major power and each version of the *S*-score, which is also lagged.

The results are shown in Tables VI and VII in the Online appendix. The latent measure outperforms both *S*-scores as a predictor of intervention by the USA, Russia, UK, and France. For the first three of these countries, our measure is consistently statistically significant, while neither *S*-score reaches significance. For France, the latent measure is significant in the model with the alliance *S*-score, but falls slightly below conventional significance thresholds ($p < 0.11$) in the model including the UN *S*-score. Only for China, the least active signaler, do the *S*-scores outperform the latent measure.

This exercise has shown that the latent measure of support signaled by major powers for their protégés' security is a good predictor of major power intervention, providing further evidence of the measure's validity. We also showed that using the latent measure has advantages over including multiple signal variables in regression analyses and that the latent measure is usually a better predictor than *S*-scores. Substantively, our results indicate that signals do contain meaningful information

[20] The correlation between the latent measure and the *S*-scores across major powers varies between 0.21 and 0.42 for UN votes, and –0.44 and –0.09 for alliances.

about a major power's likelihood of assisting a protégé and probably also serve a hand-tying function. Costly and deliberate signaling appears to be more informative than the relatively costless revelation of information through UN voting and similarity in alliance patterns.

Conclusion

In this article, we have introduced a new latent variable measure of the overall level of support signaled by major powers for their protégés' security. Using the latent variable itself, and information from the measurement model used to create it, we have been able to address various substantive questions about the causes and effects of major power signaling and the informational value of different signals.

First, we found evidence confirming that alliances, nuclear deployments, troop deployments, arms transfers, joint exercises, leader visits, and statements of support are all indeed driven by an underlying desire to signal support for a protégé's security. Second, our results suggest that the signals which are likely to be most informative, based on the degree of intentionality that can be inferred from them, are alliances and military exercises. A third conclusion from our analysis, however, is that there is wide variation in major power signaling strategies, meaning that the same signal can have different informational value when sent by different major powers. A key implication for future research is that we must develop signaling theories and tests that account for country differences.

In addition to the analysis of individual signals, our new measure of *overall* support signaled enabled us to address broader substantive questions. Initially, we used the latent measure to analyze patterns in major power signaling, showing nuances in the level of support that the USA signals for NATO allies and differences in how the US and Russian networks of protégés have changed over time. Next, we used the latent variable in two applications. In the first, we found that the overall level of support that a major power signals is influenced by both its general interest in the protégé's security and the threats that the protégé faces. In the second, we confirmed that a higher level of support signaled for a protégé increases the probability that a major power will intervene if the protégé is attacked.

We believe that our latent measure will also have great utility to future researchers who seek to study or control for the overall level of support signaled by major powers for protégés' security. Future research could utilize this measure as an independent variable to analyze military dispute initiation, intervention, escalation, and outcomes; trade disputes and agreements; behavior in multinational institutions; and other topics. Our measure can also be used as a dependent variable in further research on how major powers decide which protégés to signal support for. In addition, our measure can be used to identify the set of countries that constitute a major power's protégés, which may be useful in creating appropriate samples to study certain research questions.

Finally, our latent variable may also be useful for studying hierarchy or identifying spheres of influence. Unlike the explicit measures of hierarchy employed by Lake (2009) and Nieman (2016), our measure primarily seeks to capture a major power's concern for a protégé's security rather than a protégé's subordination to a major power. However, many major power–protégé interactions jointly entail a signal of support from the major power and some degree of subordination of the protégé, as this is a trade-off that protégés often make in exchange for security. In some cases, major powers may even forcibly subordinate minor powers and signal that other powers should stay out. Our latent variable has advantages over existing hierarchy measures because it covers a broader time span and a wider range of major powers, incorporates more signals, and is less reliant on weighting assumptions.

Replication data

The Online appendix, dataset, and do-files for the empirical analysis in this article can be found at http://www.prio.org/jpr/datasets.

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References

Allen, Michael A; Sam R Bell & K Chad Clay (2018) Deadly triangles: The implications of regional competition on interactions in asymmetric dyads. *Foreign Policy Analysis* 14(2): 169–190.

Bailey, Michael A; Anton Strezhnev & Erik Voeten (2017) Estimating dynamic state preferences from United Nations voting data. *Journal of Conflict Resolution* 61(2): 430–456.

Bas, Muhammet Ali; Curtis S Signorino & Robert W Walker (2008) Statistical backwards induction: A simple method for estimating recursive strategic models. *Political Analysis* 16(1): 21–40.

Bennett, D Scott & Allan Stam (2000) EUGene: A conceptual manual. *International Interactions* 26(2): 179–204.

Bennett, D Scott; Paul Poast & Allan Stam (2017) NewGene: A conceptual manual. SSRN (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2596297).

Blankenship, Brian & Raymond Kuo (n.d.) Excising threats or exhibiting resolve? The causes and consequences of joint military exercises. Manuscript.

Braithwaite, Alex (2015) Transnational terrorism as an unintended consequence of a military footprint. *Security Studies* 24(2): 349–375.

Bueno de Mesquita, Bruce (1975) Measuring systemic polarity. *Journal of Conflict Resolution* 19(2): 187–216.

D'Orazio, Vito (2016) Joint military exercises: 1970–2010 (http://vitodorazio.weebly.com/data.html).

Fearon, James D (1997) Signaling foreign policy interests: Tying hands versus sinking costs. *Journal of Conflict Resolution* 41(1): 68–90.

Fuhrmann, Matthew & Todd S Sechser (2014) Signaling alliance commitments: Hand-tying and sunk costs in extended nuclear deterrence. *American Journal of Political Science* 58(4): 919–935.

Gartzke, Erik (2006) The affinity of nations index, 1946–2002, Version 4 (http://dss.ucsd.edu/egartzke/datasets.htm).

Gartzke, Erik & Alex Weisiger (2013) Fading friendships: Alliances, affinities and the activation of international identities. *British Journal of Political Science* 43(1): 25–52.

Gibler, Douglas M (2008) The costs of reneging: Reputation and alliance formation. *Journal of Conflict Resolution* 52(3): 426–454.

Gibler, Douglas M (2009) *International military alliances, 1648–2008*. Washington, DC: CQ.

Gibler, Douglas M & Scott Wolford (2006) Alliances, then democracy: An examination of the relationship between regime type and alliance formation. *Journal of Conflict Resolution* 50(1): 129–153.

Gleditsch, Kristian Skrede (2002) Expanded trade and GDP data. Version 6.0 beta. *Journal of Conflict Resolution* 46(5): 712–724.

Hensel, Paul R (2014) ICOW colonial history data set, version 1.0 (http://www.paulhensel.org/icowcol.html).

International Institute for Strategic Studies (various years) *The Military Balance*. New York: Routledge.

Johnson, Jesse C & Brett Ashley Leeds (2011) Defense pacts: A prescription for peace? *Foreign Policy Analysis* 7(1): 45–65.

Kenwick, Michael R; John A Vasquez & Matthew A Powers (2015) Do alliances really deter? *Journal of Politics* 77(4): 943–954.

Kinsella, David & Herbert K Tillema (1995) Arms and aggression in the Middle East overt military interventions, 1948–1991. *Journal of Conflict Resolution* 39(2): 306–329.

Lake, David A (2009) *Hierarchy in International Relations*. Ithaca, NY: Cornell University Press.

Lebovic, James H & Elizabeth N Saunders (2016) The diplomatic core: The determinants of high-level US diplomatic visits, 1946–2010. *International Studies Quarterly* 60(1): 107–123.

Leeds, Brett Ashley; Andrew G Long & Sara McLaughlin Mitchell (2000) Reevaluating alliance reliability: Specific threats, specific promises. *Journal of Conflict Resolution* 44(5): 686–699.

Marshall, Monty G; Ted Robert Gurr & Keith Jaggers (2016) Polity IV project: Political regime characteristics and transitions, 1800–2015 (http://www.systemicpeace.org/inscrdata.html).

Martin, Andrew D; Kevin M Quinn & Jong Hee Park (2011) MCMCpack: Markov chain Monte Carlo in R. *Journal of Statistical Software* 42(9): 1–21.

Martinez Machain, Carla & T Clifton Morgan (2013) The effect of US troop deployment on host states' foreign policy. *Armed Forces & Society* 39(1): 102–123.

Martinez Machain, Carla; Mark David Nieman, Olga Chyzh & Sam R Bell (2018) An international game of risk: Troop placement and major power competition. Manuscript (http://www.marknieman.net/research/).

McDonald, Patrick J (2015) Great powers, hierarchy, and endogenous regimes: Rethinking the domestic causes of peace. *International Organization* 69(3): 557–588.

McManus, Roseanne W (2018) Making it personal: The role of leader-specific signals in extended deterrence. *Journal of Politics* 80(3): 982–995.

McManus, Roseanne W & Keren Yarhi-Milo (2017) The logic of 'offstage' signaling: Domestic politics, regime type, and major power–protégé relations. *International Organization* 71(4): 701–733.

Mislevy, Robert (1991) Randomization-based inference about latent variables from complex samples. *Psychometrika* 56(2): 177–196.

Morrow, James D (2000) Alliances: Why write them down? *Annual Review of Political Science* 3: 63–83.

Most, Benjamin A & Harvey Starr (1989) *Inquiry, Logic and International Politics*. Columbia, SC: University of South Carolina Press.

Nieman, Mark David (2016) The return on social bonds: Social contracts and international conflict. *Journal of Peace Research* 53(3): 665–679.

Palmer, Glenn & T Clifton Morgan (2006) *A Theory of Foreign Policy*. Princeton, NJ: Princeton University Press.

Palmer, Glenn; Vito D'Orazio, Michael Kenwick & Matthew Lane (2015) The MID4 dataset, 2002–2010: Procedures, coding rules and description. *Conflict Management and Peace Science* 32(2): 222–242.

Quinn, Kevin M (2004) Bayesian factor analysis for mixed ordinal and continuous responses. *Political Analysis* 12(4): 338–353.

Reiter, Dan & Brian Lai (2000) Democracy, political similarity, and international alliances, 1816–1992. *Journal of Conflict Resolution* 44(2): 203–227.

Rubin, Donald B (1987) *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley & Sons.

Schelling, Thomas C (1966) *Arms and Influence*. Hartford, CT: Yale University Press.

Signorino, Curtis S & Jeffrey M Ritter (1999) Tau-b or not tau-b: Measuring the similarity of foreign policy positions. *International Studies Quarterly* 43(1): 115–144.

Signorino, Curtis S & Ahmer Tarar (2006) A unified theory and test of extended immediate deterrence. *American Journal of Political Science* 50(3): 585–605.

Singer, J David (1987) Reconstructing the Correlates of War dataset on material capabilities of states, 1816–1985. *International Interactions* 14(2): 115–132.

SIPRI (2018) Arms transfers database. Stockholm International Peace Research Institute (http://www.sipri.org/databases/armstransfers, accessed 19 February 2018).

UNCTAD (2018) International investment agreements navigator. Investment Policy Hub, United Nations Conference on Trade and Development (http://investmentpolicyhub.unctad.org/IIA/IiasByCountry#iiaInnerMenu, accessed 19 February 2018).

USAID (2015) Foreign assistance, 1946–2012. Prepared Foreign Assistance Data Files (https://www.usaid.gov/results-and-data/data-resources, accessed 24 June 2016).

Voeten, Erik & Adis Merdzanovic (2009) United Nations General Assembly Voting Data (https://dataverse.harvard.edu/dataset.xhtml;jsessionid=650f2355441b81b5f162a8e625ed?persistentId=hdl%3A1902.1/12379&version=2.0, accessed 6 June 2016).

Waltz, Kenneth N (1979) *Theory of International Politics*. New York: McGraw-Hill.

Yarhi-Milo, Keren; Alexander Lanoszka & Zack Cooper (2016) To arm or to ally? The patron's dilemma and the strategic logic of arms transfers and alliances. *International Security* 41(2): 90–139.

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