POWER IN POLITICALLY CHARGED NETWORKS

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Abstract

We offer a theory and measure for determining powerful nodal positions based on potential inter-actor control in "politically charged" networks, which contain both allies and adversaries. Power is derived from actors that are dependent on the focal actor and sociometrically weak, either due to a lack of alternative allies or from being threatened by others. We create a new Political Independence Index (PII), compare it to other established measures, and illustrate its use in the setting of an international network of alliances and military conflicts from 1946-2000. Results show that politically independent nations as measured by PII have smaller increases in military personnel than others over time.

Keywords: Power; politics; control; social networks; political independence; conflict.

ACKNOWLEDGEMENTS: The authors are grateful to Patrick Doreian, David Lazer, Scott McClurg, members of the LINKS Center for Social Network Analysis at the University of Kentucky, as well as the three anonymous reviewers for their helpful suggestions and criticisms. This work was funded in part by grant HDTRA1-08-1-0002-P00002 from the Defense Threat Reduction Agency.

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1. Introduction

A central issue in understanding any type of network – whether comprised of individuals, groups, organizations, or even nations – is recognizing which actor in the network has power. The ability of an actor to influence other actors into doing what they might not otherwise do, or to avoid being influenced in such a manner, affects many aspects of the actors' behaviors and outcomes. Researchers attempting to identify powerful actors often focus on the actor's attributes – the actor's characteristics or the actor's formal roles in the organization or network that can create power differentials between actors (French and Raven, 1968) – or on behavioral power strategies and tactics that actors use to gain influence (Kipnis and Schmidt, 1980; Ferris, et al., 2007). However, power is inherently a structural phenomenon where one actor's influence over another needs to be considered within a wider network of relationships (Pfeffer, 1981; McClurg and Young, 2011). "Being in the right place" in the network is strongly related to power because certain network positions allow the actors to have more *access* to resources flowing through the network, or more *control* over these flows based on how dependent other actors are on the focal actor (Brass, 1984).

Most of the research conducted from this structural perspective on power has focused on networks where the flows are assumed to be either positive or neutral. For example, researchers at the interpersonal level have studied how positions in positive networks determine which actors have access to diverse, useful and trusted information that can lead to power in organizations (e.g., Brass, 1984; Burkhardt and Brass, 1990; Sparrowe and Liden, 2005) or that can enhance their performance or creativity (e.g., Burt, 2004; Burt, 2010). Similarly, researchers of international networks have examined how dependence in terms of international trade or mutual alliance ties, or being structurally equivalent in these positive-tie networks, can affect whether two countries end up in conflict (e.g., Maoz, 2006; Maoz, Kuperman, Terris, and Talmud, 2006). However, little attention has been devoted to actors and flows that might constitute active threats to other network actors (e.g., Maoz, 2004; Tita and Radil, 2011).

We contribute to the literature on political networks (Lazer, 2011) by presenting a theory and a measure for determining powerful positions based on control in "politically charged" networks where actors can have *both* allies and adversaries. This theory's boundary conditions are that the actors are attempting to achieve some goals and are embedded in networks with both potential allies and adversaries. These politically charged networks include actors actively vying for preeminence by both enhancing their own position while also potentially subverting another's outcomes (e.g., Siegel, 2007). We argue that allies and adversaries are inextricably linked – soliciting an ally is done for the specific purpose of countering the potential threats created by adversaries. Thus these relationships should be studied as part of a greater network whole as opposed to separate relational networks. Many real-world networks have these types of negative, adversarial, or threatening ties that seek to undermine the flows or interactions within the network, and also contain coalitions and counter-coalitions of allies (Labianca, Brass and Gray, 1998; Labianca and Brass, 2006; Murnighan and Brass, 1991; Maoz et al., 2007). suggesting a need to alter existing theory and methods to identify powerful positions.

Our approach considers an actor's position within the entire network of allies and adversaries and relies on the following general principle: being allied with actors who are themselves under threat increases the focal actor's potential power because those allies become dependent on the focal actor for resources and support. Our goal is to lay out a theory of actor positional power based on inter-actor control in networks of allies and adversaries that can act as a complement to the power-as-access approach that is often used in studying these networks. We introduce a new network power measure – the Political Independence Index (PII) – which we compare to existing measures on an international network of military alliances and conflicts (drawn from the Correlates of War project; Ghosn, et al., 2004; Ghosn, and Barker, 2003). We argue that researchers interested in understanding positional power in politically charged networks at a particular point in time should include measures whose underlying mechanisms are theorized to capture power-as-access (e.g., Bonacich power centrality with a positive beta) along with the PII, which captures power-as-control (see Section 7 of this paper for more on using PII).

2. Underlying sources of network positional power

In attempting to understand which positions in a network are more powerful than others, theorists have focused on the actor's potential to do two things: a. *access* resources through networks flows; or b. *control* those same resources by having other actors remain dependent on the focal actor (Brass, 1984). Our goal is to focus on the latter control-driven sources within a politically charged network setting while recognizing that access-driven sources of network positional power are important as well and must be accounted for empirically. We describe both mechanisms below.

2.1 Power-as-access approach

The power-as-access approach focuses on the actor's potential to access other actors' resources through the actor's position in the network. The sheer volume of other actors to which the focal actor is tied is often considered indicative of that actor's potential to access and assemble those resources in a manner that makes them valuable to others, and hence makes the actor powerful (Brass and Burkhardt, 1993). This is often measured through degree centrality, the number of other actors the focal actor is tied to directly (Freeman, 1979) – for example, a nation's number of international alliances. Other centrality measures consider indirect ties and illustrate how the actor has the potential to indirectly reach others and "catch" network flows. Actors high in closeness centrality are more powerful because they have a low average number of steps or ties to access other actors in the network (Brass, 1984). Actors high in eigenvector centrality or Bonacich power centrality (when applying a positive beta) are tied to others who have high degree centrality and thus can also have access to network flows through their indirect connections without the need to directly maintain those ties (Bonacich, 1987; Bonacich and Lloyd, 2004; see Hafner-Burton, Kahler, and Montgomery, 2009, for applications in political networks).

The power-as-access perspective typically assumes that all ties are positive (or at least neutral), and actors allow for the flow of resources, such as vital information, to continue unimpeded through the network. But the essence of politically charged networks is the recognition that some actors in the network might be adversaries who actively attempt to undermine others or inject harmful flows into the network. We use the terms "threats," "adversaries," and "negative ties" interchangeably to refer to relationships where at least one actor has adopted a relatively stable pattern of negative evaluations (e.g., dislike, negative judgments or feelings) for the other and possibly an intention to disrupt or thwart that party's outcomes. Power-as-access ideas might also apply to injurious flows and disinformation flowing through negative ties. Consider how this might apply to international political networks: As Iran attempts to build its domestic nuclear industry with an alleged eye toward developing a nuclear weapon, the United States and Israel, its adversaries, are alleged to be introducing faulty software into their program's equipment supplier network in an attempt to forestall Iran's ambitions (Broad et al., 2011). This, in turn, motivates Iran to find many like-minded allies to oppose the U.S. and Israel. Thus, it becomes important to understand both allies, which are a source of positive, useful flows (e.g., Maoz et al., 2004), as well as adversaries, which can be a source of negative, detrimental flows (e.g., Read, 1954). This intuitive understanding of power is reflected in how politicians decide whether to run for office by examining not only how many probable voters would cast a vote in favor of them, but how their candidacy might mobilize voters to organize to vote *against* them (e.g., Stonecash, 2008). Thus, we believe that researchers of politically charged networks need to account for an actor's degree centrality among both allies and adversaries, as well as consider indirect ties using measures such as Bonacich power centrality with a positive beta, eigenvector centrality, or a localized decomposition of eigenvector centrality termed derived centrality (see Appendix A for more on these measures). Without understanding both the positive and negative entries in this social ledger (Labianca and Brass, 2006), we get an incomplete picture of an actor's potential power.

2.2 Power-as-control approach

While the power-as-access approach is important, the control or dependence approach is also critical for understanding actor power, especially in politically charged networks. This approach recognizes that when a focal actor is dependent on another actor for resources, that other actor has potential power over the focal actor (Emerson, 1962, 1972). Conversely, the focal actor can become more powerful by decreasing his dependence on the other through developing alternative sources for acquiring the needed resources (e.g., forming ties with other actors in the network). Thus, the focal actor's political independence or security is enhanced by having alternatives (Willer et al., 2002; Cook and Yamagishi, 1992) and minimized by others' ability to control the flows that ultimately reach the actor.

The ability of an actor to control the flows reaching other actors is one of the underlying mechanisms cited for the power of the broker's position in a structural hole. The broker, by virtue of being the intermediary between two otherwise disconnected actors, has control over the flows between them. Burt's (1992) measure of constraint is most typically used to measure this concept, and it considers, in part, the extent to which an actor is dependent on a single other actor for access to otherwise disconnected alters. The measure considers an actor's local egocentric network – that is, only the focal actor, the actors to which it is tied directly, and whether those actors are themselves tied. As it has been used traditionally, the measure does not reach beyond the local network level to consider the actor's position within the entire network (Burt, 2007).[2]

Betweenness centrality considers the whole network to determine how often a particular actor lies on the shortest path between any other two actors in the network. If we imagine various flows and exchanges traveling through a network, betweenness captures the extent to which an actor is likely to be involved in various exchanges. We might also consider betweenness as a measure of the potential control an actor has in flows between clusters in a network. If we view a network as a collection of clusters that are held together by cross-cluster ties, the actors high in betweenness are the ones holding together the clusters and controlling flows across the clusters. This control is considered a source of power for those actors (Actor A in Figure 1a has the highest betweenness centrality and sits between four clusters).

Insert Figure 1 about here

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[2] The UCINET network analysis program allows researchers to consider more of the network when calculating constraint, though this option is rarely used in practice.

However, measures such as betweenness are difficult to interpret with negative ties. While Actor A in Figure 1a might have the highest betweenness centrality, A's power can be undermined if Actors B and C are intentionally undermining the flows to A. The introduction of negative ties, as would be the case in a politically charged network (Figure 1b), renders the interpretation of such measures problematic.

Closely tied to the power-as-control approach is Emerson's social exchange theory (1962, 1972), which proposes that the more dependent A is on B (due to a lack of alternative partners), the greater B's power over A. For example, Brass (1984) found that an actor's transaction alternatives in a workflow network were related to power in an organization. The graph theoretic power index (GPI) designates a monopoly position as a strong positive for the focal node (Markovsky et al., 1988; Markovsky et al., 1993). A focal node's power is weakened to the extent that his alters have alternatives. The GPI predicts power in experimental research on exchange networks (Cook and Yamagishi, 1992; see Cook, et al., 2006a, for a review). For example, it finds that Actors B, C, D, and E in Figure 1a are all in a more powerful position than Actor A because each of those nodes has alternative exchange partners who are completely dependent on them (Actors F, G, H, and I). Actor A has no exchange partner that is completely dependent on it, and has less control than do its partners. However, the GPI does not take account of adversarial ties – again, an assumption is made that exchanges in the network are at least neutral, and that being in a position where others are highly dependent on the focal actor will not engender threatening ties to that actor in an attempt to subvert that actor's position. Our power-as-control-based theory and PII measure are designed to remove this assumption. Readers should refer to Figure 1 for a comparison of scores from various common measures used to evaluate nodal power.

3. Power-as-control in politically charged networks

It is within this context of power-as-control that we introduce our measure of network positional power. We argue that actors in politically charged networks seek to be free to act in their best interests – to have autonomy and act as they please. In pursuit of autonomy, the focal actor might be impeded by adversaries who attempt to exert power over him. To counterbalance adversarial "negative ties," the focal actor might form alliances in an attempt to outmaneuver the adversaries (Murnighan and Brass, 1991; Labianca and Brass, 2006).

We theorize that the process of attracting allies is not without cost and might involve a loss of resources in a *quid pro quo* manner. For example, another actor might agree to join the focal actor's coalition in exchange for some valued resource. Consider how politicians will extract promises of future office positions in exchange for their public support of a campaigning politician during election season. Even if the ally comes willingly and without any need for recompense, the focal actor might reward that ally for joining the coalition. While the substance of those rewards might differ depending on whether the actors are people (e.g., the grateful actor might spread positive gossip about the ally in appreciation of that ally's assistance) or nations (e.g., the grateful nation might lower trade barriers with the ally out of a sense of gratitude for joining their coalition), the result is similar – the focal actor is willing to give up some resource in exchange for an ally with which to counter the threat inherent in negative, adversarial ties (Watkins and Rosegrant, 1996).

Finally, we argue that the extent to which the focal actor will sacrifice resources to a potential ally is driven by the extent to which the focal actor has a need for allies and is dependent on the specific potential ally for help. When the focal actor has numerous adversaries attempting to undermine its goals, the focal actor will feel a sense of increased urgency to gain allies to counter these threats and be willing to give up more resources to secure those allies. These resources then flow to the allies, which benefits the allies' outcomes. To the extent that there are limited potential allies, we further expect that the potential allies will be able to extract a maximum amount of these resources in attempts to increase their power. As an example, a nation (A) at war with another nation (B) has a negative, adversarial tie. If a third nation (C) joins the war on nation B's side, it puts added pressure on the focal nation (A) to find allies (see Figure 2).

Insert Figure 2 about here

Even if a potential ally (D) doesn't get drawn in directly to the conflict, the ally can provide nation A with help (e.g., guns, political support in international bodies, training, trade). The focal nation (A) will, thus, have an incentive to offer resources to potential allies to join a formal alliance (e.g., by offering to eliminate all trade barriers to their goods). If, however, there is only one possible ally (D), that ally has a great deal of power to extract resources from the focal nation (A) in exchange for alliance. Thus, as the threats to the focal nation grow and the number of potential allies shrink, the focal nation's network positional power decreases. We theorize that this logic extends beyond the focal nation's direct ties. If the focal nation's (A) only potential ally (D) already has a great many allies (E, F, and G), we argue that the focal nation will likely need to offer more resources in return for nation D's assistance than a potential ally who has no allies or who is itself under direct threat. This is irrespective of whether the other actor intentionally or overtly asks for more in return – the actor requesting the help will recognize the situation and will be more inclined to offer a more attractive package in return for an alliance. The extent to which the focal actor is dependent on potential allies that are themselves in powerful network positions – either because they have a lot of allies or are free of threats – decreases the focal actor's positional power and should result in poorer outcomes for the focal actor.

4. Political Independence Index

We introduce the Political Independence Index (PII) to better capture power from a control perspective in a politically charged network. Based on the previously noted theoretical considerations the measure should: 1) capture both alliance and adversarial ties simultaneously; 2) capture beyond ego-network direct tie-links to consider position within the entire network; 3) capture the notion that being allied with actors who are themselves under threat increases the focal actor's potential power because those threatened allies become dependent on the focal actor for resources and support, particularly when they have few other alternatives. PII combines insights from the graph-theoretic power index (Markovsky et al., 1993) and Bonacich power centrality (Bonacich and Lloyd, 2004), but is specifically designed to compare the potential power in nodal positions at a particular point in time in politically charged networks.[3]

We begin by defining the concept of the distance of a node to a line in a network, which is the distance from node u to an edge (v,w) as $\mathrm{MIN}(\mathrm{d}(u,v),\mathrm{d}(u,w))$, where d is the ordinary geodesic distance between pairs of nodes. Since the geodesic distance from a node to itself is zero, the distance of any edge (u,w) from u is the $\mathrm{MIN}(\mathrm{d}(u,u),\mathrm{d}(u,w))$, which is the minimum of 0 and 1. Hence, a node's direct ties are distance 0 from itself and ties between a focal node's alters out to third parties are distance 1 from itself, and so on. Given a node whose PII score is being

[3] The PII is an evaluation of nodal position favorability where each actor obtains a score based on their particular portfolio of direct and indirect ties. Those scores can then be used to rank actors from the most powerful in terms of political independence (being free of other actors' control) to the least powerful actor in that particular network at that time. Comparing PII scores across networks or even time points is not intended.

calculated, let P(*i*) be the number of positive edges at distance *i* from the node, and N(*i*) be the number of negative edges at distance *i* from the node. Then we have the PII[4] as follows:

$$\sum_{i=0}^{K} \beta^{i} \left[P(i)^{x} - N(i)^{x}\right]$$

where β is an attenuation factor that discounts the importance of edges far away from the node (and is assumed to be negative), K is the maximum distance from a node to a line that we are willing to consider, and *x* is defined as

$$x \leq \frac{\ln(2) - \ln(|\beta|)}{\ln(M)}$$

where M is the maximum number of ties incident on any node in the network. Note that

$$\beta M^{x} \leq 2$$

The Political Independence Index has the following properties:

1. The focal node (*i*) scores higher the greater the number of positive ties it has and the fewer the number of negative ties it has.
2. Signed ties at odd-numbered distances from node *i* have inverse valence for the node. For example, if node *i* has a positive tie with *j* who, in turn, has a negative tie with a node *k* not connected to *i*, ally *j* will be under threat from *k* and be more dependent on node *i* for assistance, thereby increasing node *i*'s ability to extract resources in exchange for assisting *j*. Note that node *k* is two links from *i*, but the tie from node *j* to node *k* is distance 1 from *i*.

[4] The PII can be calculated in UCINET VI (Borgatti, Everett and Freeman, 2002), versions 6.439 or later. The program includes a help guide describing the measure, input values, and outputs.

3. The lower the absolute value of the attenuation factor (β), the less that ties farther away from *i* affect *i*'s score.
4. A negative value for beta implements the dependency logic that says that a focal actor's power is reduced if its allies have other allies they can rely on instead of the focal actor. That is, a focal actor is powerful to the extent it has ties to weak others. A positive value of beta implements the power-as-access logic where a node is powerful to the extent it is connected to powerful others.
5. The *x* exponent resolves the particular concern that a given node be subjected to extreme influence from indirect ties. For example, if node *i* has two adversaries, *j* and *k*, and each of those adversaries has allies who, in turn, have a great many allies (that is, there are a great number of positive ties at distance 3 from the focal node), the raw model would suggest that node *i* is in a very powerful position. The *x* exponent ensures that node *i*'s direct ties have a stronger impact on nodal power than the large number of indirect ties.[5]

Insert Figure 3

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[5] Arriving at the *x* exponent involves a number of steps. The minimal situation in which to use PII involves having one direct tie and one indirect tie. If the beta attenuation is set at 1.0, then the maximum PII score in that situation would be 2.0. Using that minimal situation as a basis, we reduce the influence of the indirect connections to be less than the score the node would receive from two direct connections. First, since the attenuation factor lessens the impact of the indirect ties, we take that maximum PII score in the minimal situation and scale up the value of 2.0 by the attenuation factor (that is, we divide 2.0 by the attenuation factor). Second, we apply a discount to ensure that the largest egocentric network size is less than this scaled up value. *x* is the "discount" and is found by simply solving for the value that guarantees βM^x is less than or equal to two. *x* then guarantees that two direct ties provide more benefit or harm than any amount of indirect ties. It has the added helpful property of being network dependent – the value depends on the maximum number of direct ties at any given node in the network being studied. This explicitly rules out scenarios in which positive or negative ties at a great distance from *i* overwhelm direct ties. For example, with *x* and $|\beta|$ equal to 1 (as in the raw model), node *i* might have an adversarial tie with node *j* at a distance of 6 from *i*. If *j* has three direct alliance ties and *i* has only two direct alliance ties, the simple PII value would be -1. With *x* equal to our normalization by the largest ego network size, *i*'s PII value is 0.470.

We illustrate how this measure is calculated on the graph in Figure 3 for node A, which has four positive ties to allies who each have one additional ally, using an attenuation factor of -0.8. Since M (the largest ego network size) is 4, the value of *x* is (ln(2)-ln(0.8))/ln(4), or 0.66096. There are four direct ties (distance 0) and four indirect ties (distance 1). Thus, the value of PII is given by $(-0.8)^0 * 4^{0.66096} + (-0.8)^1 * 4^{0.66096} = 0.5$. If we now introduce two negative ties into A's personal network (to nodes B and C), A's PII score changes. Node A now has two direct positive ties and two direct negative ties, yielding a first-order score of $(-0.8)^0(2^{0.66096} - 2^{0.66096}) = 0$. In addition, A has four distance 1 positive ties, yielding a second-order score of $(-0.8)^1(4^{0.66096}) = -2$. The final PII score is 0 + (-2) = -2. Figure 3 lists the final PII scores for each node.

The results in the all-positive network suggest that the nodes in position B (B, C, D, E) are the most powerful from this power-as-control perspective because, despite the fact that A has the most allies, all of its allies have other allies (F, G, H, I) that are entirely dependent on them, while none of the nodes in the B position are entirely dependent on A. This is generally consistent with the type of results found in experimental exchange network research (Cook and Yamagishi 1992; Cook et al., 2006a; Cook et al., 2006b). This contrasts with measures whose underlying mechanisms are derived mainly from a power-as-access perspective such as closeness, eigenvector, and Bonacich power with a positive beta.

By introducing the AB and AC negative ties, we see that node A is now the least powerful actor in the network from a control perspective. Node A has the most direct threats (from B and C), and while it has two allies (D and E), neither is entirely dependent on A. In this network, nodes D and E are in the most powerful position because each has another actor that is completely dependent on them (H and I respectively), and each is allied with the weakest actor that is under the most threat – node A. We can also contrast nodes I and F, each which has only one direct positive tie. In I's case, that direct tie makes them entirely dependent on the most powerful node in the network (E), while in F's case, they are dependent on an actor (node B) who is under direct threat from A and has no other allies, placing F in a superior position.

5. Comparison to Other Measures

We illustrate how the Political Independence Index (PII) assesses nodal power in comparison to existing measures of dependence and power in a number of datasets. We include two well-known datasets – Read's (1954) Highland Tribes GAMA and the Sampson (1968) monastery dataset. The Highland Tribes' GAMA data (Read 1954) is a signed graph of a network of alliances and antagonistic relations among 16 tribes in the Eastern Central Highlands of New Guinea. The Sampson monastery dataset includes multiple relations linking 18 men preparing to join a monastic order. For our comparison, we focus on the signed network capturing "esteem" and "disesteem" relationships. We then compare measures in a larger 75 node interpersonal signed network dataset collected in a contemporary life sciences organization (Grosser et al., 2010), capturing interpersonal "liking" and "disliking" amongst the employees. Finally, we compare the measures in an international dataset of 180 nations' alliances and military conflicts (the Correlates of War dataset).

We used these datasets to compare PII to a number of measures that are typically computed on the network of positive-only ties, including degree centrality and a number of measures that rely on underlying mechanisms of power-as-access, including closeness centrality, eigenvector centrality, and two-step eigenvector centrality. We also compare it to measures relying on underlying mechanisms of power-as-control, including effective size, constraint, and betweenness centrality.

We then compare PII with degree centrality (*Negative Degree*) and two-step eigenvector centrality[6] computed only on the network of negative-only ties. We might view this as a reversing of the power-as-access mechanism – these nodes might have greater access to injurious flows, including disinformation and attempts to thwart their goals.

Finally, we compare PII with measures that are computed on signed graphs containing both positive and negative ties, including Bonacich power, utilizing either a positive beta (*Bonacich Power on Signed Network with Positive Beta*) or negative beta (*Bonacich Power on Signed Network with Negative Beta*). Using Bonacich power with a positive beta suggests that a node has greater status to the extent to which it is has many direct ties and is connected to other nodes with many ties. Using Bonacich power with a negative beta, however, suggests that being connected to other nodes with many ties would be detrimental, which is most in keeping with our notion of power-as-control, and thus should be somewhat analogous to PII. We also compare PII to a ratio of the node's positive tie count to its total number of ties (*Ratio of Positive to Total Ties*).

Tables 1, 2, 3, and 4 present the correlational similarities of these measures when using the Highland Tribes GAMA dataset, Sampson dataset, the interpersonal Life Sciences dataset and the Correlates of War dataset. As evident in all examples, the PII measure captures a unique form of power not necessarily captured by any existing measure. Generalizing across all datasets, the PII measure is most closely related to the ratio of positive ties to total ties. Although, these correlations are not excessively high, in practice we suggest controlling for the node's number of direct positive and negative ties, as we do in our analyses (see appendix C for a comparison of these measures across multiple datasets and appendix D for a comparison of the

[6] Going beyond two steps in a purely negative tie network was meaningless and prevented us from using eigenvector centrality or closeness centrality.

ratio of positive to total ties measure and PII within the Correlates of War dataset). Among the measures that take into account indirect ties, PII correlates most highly with Bonacich power centrality with a negative beta, as expected. However, the correlations are not excessive (ranging from a low of 0.39 in the Life Sciences dataset to a high of 0.70 in the Sampson and COW datasets), suggesting that there is a good deal of distinction between PII and Bonacich power centrality.

Insert Tables 1, 2, 3, and 4 about here

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6. Using the Political Independence Index on an International Politically Charged Network as a Predictive Measure

We illustrate the application of PII in the empirical setting of a politically charged international network following the end of World War II (1946-2000). Figure 4 displays a global conflict and alliance network created from data collected as part of the Correlates of War (COW) Project. Nation-states have positive ties representing defense pacts, non-aggression treaties, and entente agreements (Gibler, 2009; Gibler and Sarkees, 2004; Singer and Small, 1966; Small and Singer, 1969), and negative ties representing dyadic military disputes in which each of two states were directly involved in militarized incidents against the other (Ghosn et al., 2004; Ghosn and Bennett, 2003).

We expect that an actor's network positional power influences future behaviors and outcomes. When the focal actor's network positional power is low or decreasing, we expect that the actor will undertake actions to increase their power and autonomy. We argue that different sources of power are at least somewhat fungible (Hafner-Burton et al., 2009) and, thus, the focal actor might seek to increase some aspect of its attribute power – power that is not dependent on other actors in the network -- in order to compensate for its lack of network positional power. For example, by developing a nuclear weapon, which increases a nation's power but is not a source of power derived relationally, a nation like North Korea or Iran can compensate for a lack of network positional power by reducing the likelihood that another nation will attack it. Thus, we argue that actors seek independence and, when under threat, will attempt to counteract the threat through increasing their attribute power. [7] Thus, actors lacking in power-as-control as captured in PII will be more motivated to increase their attribute power in a future time period in order to compensate for their lack of relational power.

> *Hypothesis: Nodal power in a politically charged network (as indicated by the Political Independence Index) will be negatively related to future increases in attribute power.*

We use variables capturing inherent national resources (i.e., attribute-based sources of power), as well as the number of direct allies and threats a nation-state has in its network, as controls in our investigation on the outcomes related to a nation's PII. We use PII to predict changes to the nation's military in a future time period. Note that most research using the COW data attempt to predict future military conflicts (e.g., Maoz, et al., 2006), but that we are instead attempting to predict future changes to the nation's military forces – in particular, the number of military personnel.

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[7] The focal actor might also attempt to alter its network position by attracting more allies, reducing the number of threats it faces, or dragging its allies directly into the conflict. Thus, we might reasonably expect that as network positional power decreases, network actors will attempt to engage in network-altering tactics to restore their autonomy. These types of network dynamics are studied from a number of perspectives, including balance theory perspectives (e.g., Doreian, 2004; Doreian & Krackhardt, 2001; Hummon & Doreian, 2003) and status theory perspectives (e.g., Leskovec, Huttenlocher, & Kleinberg, 2010), but are outside the purview of the current manuscript. Instead, we are focusing on nodal position power at a point in time within the network.

Insert Figure 4 here

Dependent Variable: Change in Number of Military Personnel. We used the Correlates of War dataset to identify the change in number of military personnel between t and t+1. For example, Cuba expanded the number of military personnel from 46,000 in 1959 to 260,000 soldiers in 1960, so its 1960 score would be +214,000. This variable captures a nation's attempt to use its national power (an attribute variable) to protect against international threats.

Independent Variable: Political Independence Index in Inter-National Relations. We calculated each nation's PII measure using rolling four year windows in the politically charged international network. To create these rolling windows, we first identified all dyadic disputes and formal alliances in each year between 1946 and 2000 for 180 nation-states using the Military Dispute dataset v3.10 and pre-1993 military dispute dataset (Ghosn et al., 2004; Ghosn and Bennett 2003), and the Formal Alliance dataset version 3.03 (Singer and Small, 1966; Small and Singer, 1969; Gibler and Sarkees, 2004; Gibler 2009). We created a series of 180x180 politically charged network matrices for each year, and aggregated and dichotomized them into rolling four year windows (e.g., 1946-1949, 1947-1950, 1948-1951).[8] Each resulting matrix was coded such that x_{ij}= 1 if nations i and j had a formal alliance during that four year period, and x_{ij} = -1 if nations i and j had a military dispute during that period. We coded instances in which nations had both a formal alliance and a military dispute in the period as -1. We then calculated the PII for each network using a beta attenuation of -0.8.[9]

[8] We also conducted robustness checks on other windows. The same relationships were found in the same directions, though the significance of the PII coefficient was highest at 4 years, with other windows producing marginally significant results ($p < 0.06$).
[9] We conducted a series of simulations to determine which beta attenuation rates to use. Our simulations suggest that PII stabilizes at beta weights with absolute values above 0.5. Therefore, we recalculated PII with a beta attenuation

Control Variables. To separate the nation's political independence in the international network from inherent attribute power, we controlled for each nation-state's total population, iron and steel production, primary energy consumption, and annual military expenditures over time. Each nation's attribute data came from the National Material Capabilities dataset version 4.0 (Singer et al., 1972). To further separate political independence's effects from network power-as-access, we controlled for each nation's number of formal allies with shared borders (*Contiguous Allies*) as well as number of allies without shared borders (*Non-Contiguous Allies*) over time. This allows us to control for the possibility that increasing the number of contiguous allies grants you greater access to resource flows than non-contiguous allies, which might allow for greater military expansion. Similarly, we controlled for each nation's direct level of network threat by controlling for the number of bordering and non-bordering countries that each nation had military disputes with in that time period (*Contiguous Threats*, *Non-Contiguous Threats*). This allows us to control for the possibility that contiguous threats might lead to a more dramatic reaction in terms of expanding the military than non-contiguous threats. In addition we controlled for Bonacich power centrality using a positive beta on the politically charged networks for each 4 year window to better highlight the unique properties of PII. Like PII, calculating Bonacich power involves the user selecting a beta attenuation rate. The norm is to adopt a beta weight which approaches to within 99.5% of the inverse of the largest eigenvalue, and this has been institutionalized with a "get beta" facility in UCINET 6 (Borgatti, et al., 2002). In the COW dataset, the beta for Bonacich power averaged 0.03, meaning that the measure was nearly entirely dependent on the node's degree centrality since each additional link away from

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of 0.5 in the COW data, and the results were nearly identical, with the significance level falling to marginal significance.

ego was weighted only 0.03 of the previous link. This accounted for its Pearson correlation of 0.92 with degree centrality in the positive tie network, and 0.88 with degree centrality in the negative tie network (see Rodan, 2011, for an extended discussion on beta in Bonacich power centrality). We also controlled for nations that lacked any formal alliances or threats during the selected time windows (*Isolate*).

Analysis and Results

We used a fixed effects cross-sectional time series analysis in Stata 10. All network statistics were calculated using UCINET 6. Table 5 shows the descriptive statistics. We find that after controlling for each nation's attribute power (population, iron and steel production, primary energy consumption, and military expenditures), network power-as-access (number of continuous and non-contiguous allies, and Bonacich power centrality), and level of threat (number of contiguous and non-contiguous threats), nations with greater PII had significantly less of an increase in military personnel than nations with lower PII (β = -2.02*). These findings (see Table 6) suggest that nations occupying higher power-as-control positions in the international network of formal alliances and disputes might have less need to expand their military than nations lacking such network positional independence. For example, Mauritania managed to have a high level of PII in the early 1980's through their strategic alliances with numerous African, European, and Middle Eastern nations and did not develop its military despite contiguous threats from more powerful neighbors. Cuba, in contrast, had a very low PII in the late 1950's and thus might have had more need to develop their military, which might have been one proximal cause for their military expansion during that time period.

Insert Tables 5 and 6 about here

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7. Suggestions For Using the Political Independence Index

There are a number of assumptions and suggestions for using the Political Independence Index that need to be made explicit to ease its research use. First, PII is a nodal level measure. As such, it aggregates the direct and indirect ties in the node's network to provide a description of that focal node's power-as-control relative to other nodes at a particular point in time. Since power-as-control is only one form of power derived from network relationships, we suggest using PII alongside degree centrality and power-as-access measures such as the node's eigenvector centrality. We also recommend the inclusion of traditional attribute measures of power. In our COW example, we included attribute measures of power (e.g., military expenditures), power-as-access measures (e.g., degree centrality of both allies and threats), in addition to our power-as-control measure (PII). This allows researchers to consider the differences in situations where one type of power might be more important to consider than others, or how the various forms of power complement each other.

Using PII instead of other measures is most useful when the network has a number of characteristics. First, the network should have some path lengths of at least two (i.e., neither a collection of isolated dyads nor a complete network in which everyone is directly connected to every other); otherwise simple degree centrality is sufficient. The network should have a combination of positive and negative ties, because, in the absence of negative ties PII becomes similar to the graph power theoretic index (although far easier to compute on large graphs – see Appendix A). Additional research needs to be conducted to understand which network characteristics affect the appropriateness and utility of using PII.

8. Conclusion

There has been growing interest in using social network theory and analysis for the study of power and politics, particularly within the field of political science (Hafner-Burton and Montgomery, 2006; Lazer, 2011; McClurg and Lloyd, 2011; Maoz, 2007; Ward et al., 2011). With this interest has come the dilemma of whether to adopt existing theories and methods, or modify or create new theories and methods. Some political scientists have argued that there is such a rich tradition of research in social networks that there is no need to "reinvent the wheel." For example, Hafner-Burton et al. (2009) suggest that Maoz's recent work (2006, 2007) in which he created new theories and methods for capturing interdependence and polarization among nations in order to predict military conflicts between nations might not be the best strategy for political scientists moving forward. Hafner-Burton, et al. (2009: 578) argue that "the need for new system-wide measures at this stage of development [of the field of political science] is unclear…existing measures that can be applied to networks (such as centralization) may perform the same task." While we agree that those looking to apply a network perspective to power and politics should consider existing methods, we feel that it is more important for researchers to understand the underlying theoretical mechanisms that are embedded within those methods and measures (Borgatti et al., 2009). We advocate a middle way, with researchers adopting existing network approaches as much as possible, but maintaining a flexibility and willingness to introduce new approaches when appropriate.

Politically charged networks provide an instructive example for this. Much of the existing network theorizing, methodology, and measurement assumes that ties between parties are either positive or at least neutral. Yet much of what interests political scientists involve relationships where parties are actively attempting to undermine other parties' goals, as evidenced by studies on terrorist networks, political legislatures, online political blogging, and international alliances and wars. Many of these studies inherently adopt a power-as-control perspective in their theorizing, and it will be necessary to develop or modify theories and measures to be more closely adapted to these politically charged networks. Applying theoretical mechanisms and measures developed for use in positive or neutral tie networks appears to inadequately capture the task at hand.

Our theory and results suggest that researchers need to consider that threats in some networks are more complex than simple dyadic relationships (e.g., Maoz, 2007). While our PII approach to integrating alliance ties with adversarial ties must be viewed as preliminary, it speaks to a greater need to consider these politically charged networks through a new lens. We argue that the concept of an alliance in the political arena only makes sense when considered in the context of a perceived threat to the node – alliance ties are formed as a reaction to threats in politically charged networks. Network theories and measures need to consider that a threatening tie is qualitatively different than the lack of a positive tie, and that understanding phenomena such as nodal positional power in the political arena relies on understanding the simultaneous interplay between both positive and negative ties.

Our results also suggest that power sources might be at least somewhat fungible, a point that Hafner-Burton et al. (2009) anticipated and urged as important for future study. In our examination of international alliances and military disputes, we found that as nations' PII scores dropped, they tended to increase their number of military personnel. In other words as a nation's network positional power dropped, it responded by increasing an attribute source of power. While our results are preliminary and mainly intended to illustrate how one would use the Political Independence Index in a research study, they suggest that examining power fungibility between network and non-network sources of power might be a fruitful area of research to pursue in the future. This might be a starting point for further research on such issues as whether a drop in network positional power leads, for example, to nations adopting weapons of mass destruction programs.

Future work on network sources of power can also address varying levels of threat based on actor attributes. Currently, the PII measure treats actors of equal distance to the focal actor equally. For example, every actor who is perceived as a threat is perceived to supply the same level of threat, without regard to any attributes of the threatening actor. However, a focal actor will likely experience a greater degree of threat from an actor with high levels of attribute-based power (e.g., the United States with its very capable military) than from an actor with low levels of attribute-based power (e.g., Poland). Thus, incorporating these nodal characteristics into future research might enhance our understanding of the power-as-control response underlying the PII.

Future research is also needed to develop a more detailed understanding of PII. We need to study the network circumstances in which PII outperforms other metrics, and the circumstances when it does not (e.g., through Monte Carlo simulations). It will also be necessary to develop a better understanding of how to choose the beta coefficient, as well as how stable the results are at varying levels of beta in different types of networks.

In conclusion, there are a great many situations that involve politically charged networks of allies and adversaries, from intra-organizational settings to inter-organizational settings to legislatures to international settings. While our work is not intended to negate the power-as-access perspective, we feel that a more accurate understanding of nodes' power in these networks needs to also reflect a power-as-control approach. The two approaches are complementary, and would work best in unison when conducting empirical research on networks. We hope that this work is viewed as a step forward in understanding nodal power from a control perspective, and that further research is conducted to refine the theorizing and measures necessary to pursue this perspective in politically charged networks.

Figure Captions

Figure 1: A Comparison of Nodal Power Position Scores

1.a: All the ties between the nodes are positive or neutral

1.b: The A-B and A-C ties are negative, making this a politically charged network

Figure 2: Nation A is an adversary (dotted lines) of B and C (who are allies), and is therefore dependent on nation D, its only ally. Nation D has many other alternative allies.

Figure 3: Illustrating the Political Independence Index on Two Networks

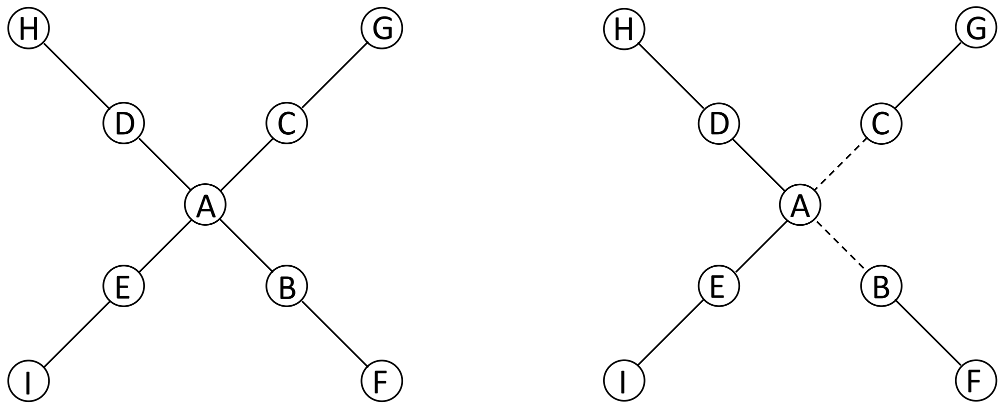
3.a: All Positive Tie Network

3.b: A Politically Charged Network

Figure 4: Main Component of Politically Charged Network 1996-2000. Dotted lines indicate military dispute. Solid lines indicate formal alliance

Figure 1

1a **1b**



Note: Solid lines denote allies, dashed lines denote threats

Common Measures of Nodal Position Favorability in an All-Ally Network (Figure 1a)

Node(s)	Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Bonacich Power (+β)*	Bonacich Power (-β)*	Constraint
A	4	24	12	0.632	757.87	44.13	0.25
B C D E	2	7	17	0.354	423.54	-22.54	0.50
F G H I	1	0	24	0.158	189.47	11.03	1.00

Note: * The β used was 0.4449775.

Common Measures of Nodal Position Favorability in a Politically Charged Network (Figure 1b)

Node(s)	Positive Degree Centrality	Negative Degree Centrality	Positive Tie Ratio	Eigenvector Centrality	Bonacich Power (+β)*	Bonacich Power (-β)*
A	2	2	0.50	0.632	178.43	-178.43
B C	1	1	0.50	-0.354	-98.45	-99.56
D E	2	0	1.00	0.354	102.05	100.94
F G	1	0	1.00	-0.158	-42.41	45.30
H I	1	0	1.00	0.158	46.41	-43.92

Note: * The β used was 0.4449775.

Figure 2

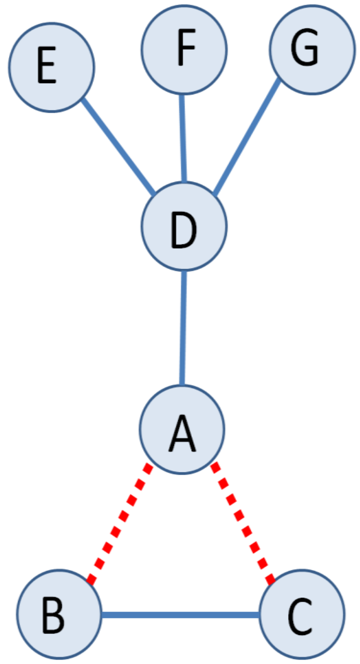
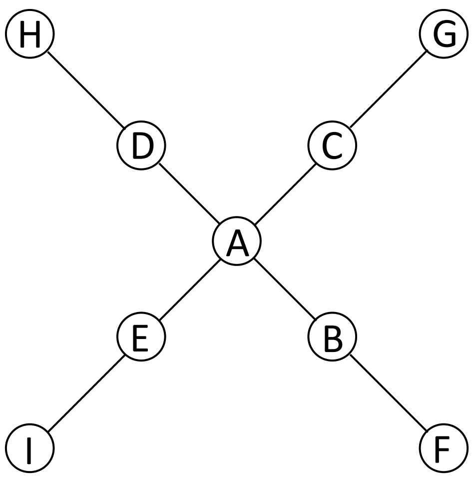
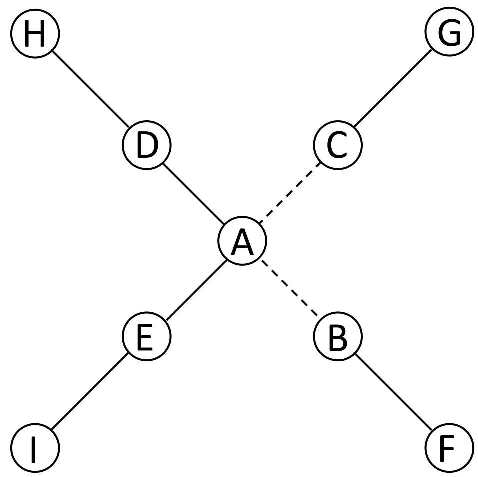


Figure 3

3a



3b



Note: Solid lines denote allies, dashed lines denote threats

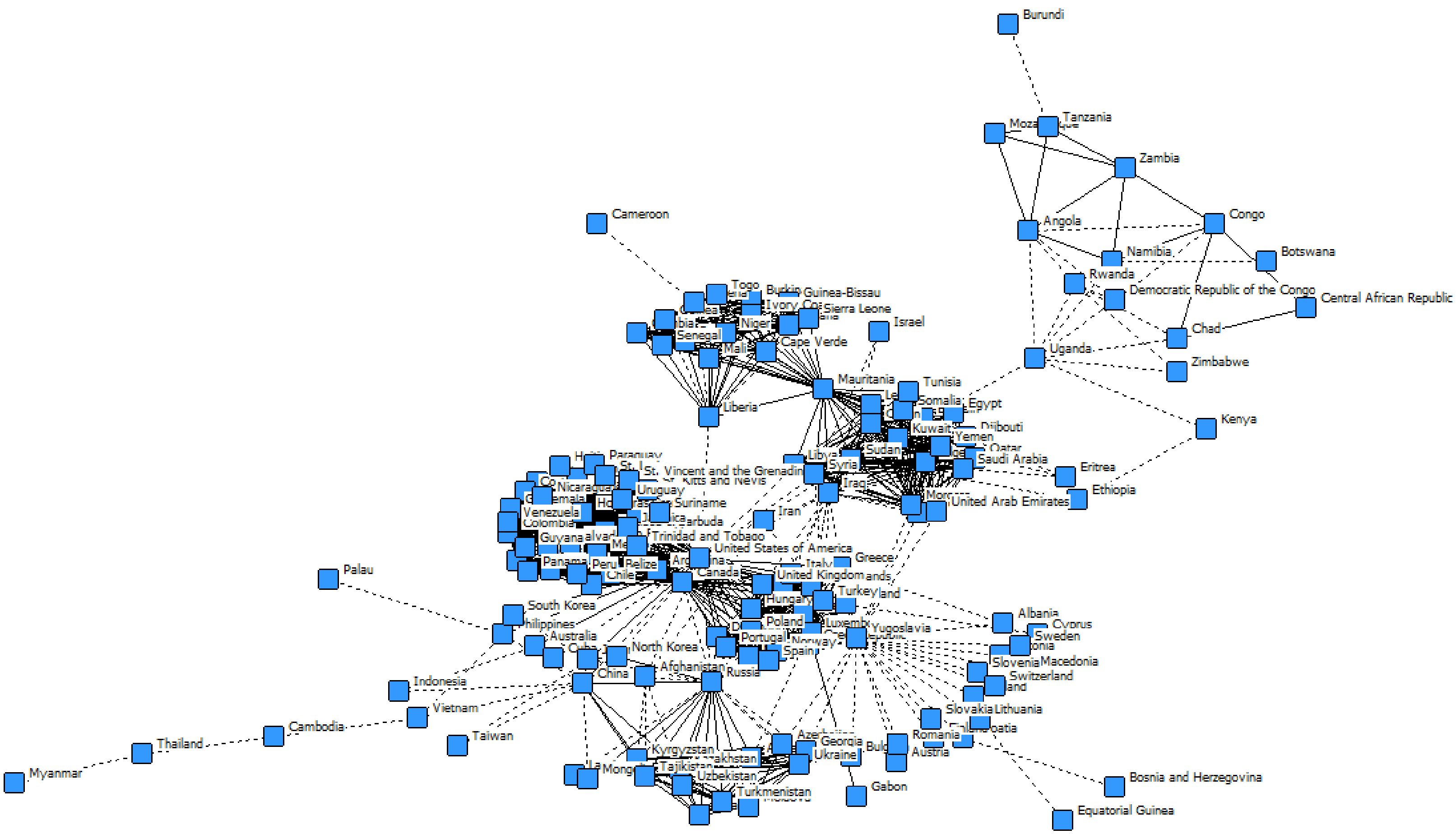
PII scores for the all-ally network (3a)

Node(s)	PII
A	0.500
B C D E	1.250
F G H I	0.465

PII scores for the signed network (3b)

Node(s)	PII
A	-2.000
B C	0.858
D E	3.369
F G	1.114
H I	-1.230

Figure 4



Burundi
Tanzania
Zambia
Congo
Angola
Namibia
Botswana
Rwanda
Democratic Republic of the Congo
Central African Republic
Chad
Uganda
Zimbabwe
Kenya
Cameroon
Togo
Guinea-Bissau
Sierra Leone
Israel
Niger
Senegal
Mali
Cape Verde
Liberia
Mauritania
Tunisia
Somalia
Egypt
Kuwait
Djibouti
Yemen
Qatar
Sudan
Saudi Arabia
Eritrea
Ethiopia
Libya
Syria
Iraq
United Arab Emirates
Iran
Paraguay
St. Vincent and the Grenadines
Nicaragua
Uruguay
Suriname
Venezuela
Colombia
Guyana
Trinidad and Tobago
United States of America
Panama
Peru
Belize
Chile
Canada
Greece
Italy
United Kingdom
Turkey
Hungary
Poland
Portugal
Norway
Spain
Yugoslavia
Albania
Cyprus
Sweden
Slovenia
Macedonia
Switzerland
Slovakia
Lithuania
Romania
Austria
Georgia
Ukraine
Gabon
Bosnia and Herzegovina
Equatorial Guinea
Palau
South Korea
Australia
North Korea
Afghanistan
China
Russia
Indonesia
Vietnam
Taiwan
Cambodia
Thailand
Myanmar
Kyrgyzstan
Tajikistan
Uzbekistan
Turkmenistan

Table 1: Correlational similarities of measures using Gama network of alliances (positive) and conflicts (negative) among 16 tribes. The signed graph is comprised of -1s (conflict), 0s (no relationship), and 1s (alliance).

	1	2	3	4	5	6	7	8	9	10	11	12
1-PII	1											
2-Bonacich Power on Signed Network with Positive Beta	-0.02	1										
3-Bonacich Power on Signed Network with Negative Beta	0.57	0.32	1									
4-Positive Degree	0.66	0.48	0.64	1								
5-Negative Degree	-0.23	-0.56	-0.86	-0.40	1							
6-Ratio of Positive to Total Ties	0.47	0.58	0.89	0.76	-0.88	1						
7-Eigenvector (Positive ties)	0.26	0.82	0.52	0.82	-0.52	0.76	1					
8-Betweenness (Positive ties)	0.69	0.33	0.67	0.69	-0.55	0.70	0.42	1				
9- Closeness (Positive ties)	-0.05	0.96	0.37	0.40	-0.62	0.57	0.7	0.40	1			
10- Effective Size (Positive ties)	0.59	0.45	0.64	0.66	-0.57	0.67	0.44	0.90	0.56	1		
11-Constraint (Positive ties)	-0.40	-0.50	-0.35	-0.57	0.27	-0.4	-0.44	-0.64	-0.56	-0.86	1	
12-Two-step Eigenvector (Positive ties)	0.46	0.67	0.55	0.94	-0.43	0.76	0.96	0.55	0.55	0.53	-0.5	1
13-Two-step Eigenvector (Negative ties)	-0.27	-0.35	-0.91	-0.38	0.95	-0.85	-0.43	-0.48	-0.4	-0.46	0.16	-0.37

Table 2: Correlational similarities of measures using Sampson network of esteem (positive) and disesteem (negative) relationships. The signed graph is comprised of -1s (disesteem), 0s (no relationship), and 1s (esteem).

	1	2	3	4	5	6	7	8	9	10	11	12
1-PII	1											
2-Bonacich Power on Signed Network with Positive Beta	0.52	1										
3-Bonacich Power on Signed Network with Negative Beta	0.70	0.33	1									
4-Positive Degree	0.32	0.31	0.57	1								
5-Negative Degree	-0.73	-0.58	-0.65	-0.04	1							
6-Ratio of Positive to Total Ties	0.77	0.51	0.80	0.48	-0.82	1						
7-Eigenvector (Positive ties)	0.4	0.44	0.54	0.95	-0.21	0.58	1					
8-Betweenness (Positive ties)	0.29	0.25	0.59	0.90	-0.04	0.36	0.79	1				
9- Closeness (Positive ties)	0.28	0.21	0.50	0.93	-0.05	0.44	0.92	0.83	1			
10- Effective Size (Positive ties)	0.25	0.10	0.63	0.93	0.02	0.37	0.8	0.94	0.87	1		
11-Constraint (Positive ties)	-0.11	-0.15	-0.48	-0.9	-0.09	-0.38	-0.8	-0.79	-0.87	-0.89	1	
12-Two-step Eigenvector (Positive ties)	0.38	0.41	0.53	0.96	-0.17	0.56	0.99	0.82	0.95	0.83	-0.83	1
13-Two-step Eigenvector (Negative ties)	-0.66	-0.31	-0.66	0.05	0.94	-0.79	-0.07	0.02	0.01	0.06	-0.15	-0.05

Table 3: Correlational similarities of measures using the Life Sciences dataset (Grosser, et al., 2010) of liking (positive) and disliking (negative) relationships. The signed graph is comprised of -1s (liking), 0s (no relationship), and 1s (disliking).

	1	2	3	4	5	6	7	8	9	10	11	12
1-PII	1											
2-Bonacich Power on Signed Network with Positive Beta	0.23	1										
3-Bonacich Power on Signed Network with Negative Beta	0.39	0.85	1									
4-Positive Degree	0.11	0.92	0.88	1								
5-Negative Degree	-0.56	0.12	0.00	0.39	1							
6-Ratio of Positive to Total Ties	0.71	0.42	0.56	0.30	-0.55	1						
7-Eigenvector (Positive ties)	0.07	0.92	0.75	0.93	0.41	0.24	1					
8-Betweenness (Positive ties)	0.12	0.59	0.69	0.67	0.18	0.16	0.52	1				
9- Closeness (Positive ties)	0.09	0.54	0.47	0.53	0.10	0.42	0.53	0.26	1			
10- Effective Size (Positive ties)	0.08	0.83	0.86	0.95	0.42	0.21	0.86	0.77	0.44	1		
11-Constraint (Positive ties)	-0.27	-0.77	-0.79	-0.83	-0.22	-0.57	-0.77	-0.44	-0.74	-0.74	1	
12-Two-step Eigenvector (Positive ties)	0.08	0.95	0.83	0.98	0.39	0.29	0.97	0.59	0.58	0.91	-0.83	1
13-Two-step Eigenvector (Negative ties)	-0.49	0.22	0.08	0.46	0.94	-0.44	0.51	0.20	0.14	0.48	-0.28	0.47

Table 4: Correlational similarities of measures using one time slice of the Correlates of War dataset (1991-1994) indicating formal alliances (positive) and military conflicts (negative). The signed graph is comprised of -1s (military conflict), 0s (no relationship), and 1s (formal alliance).

	1	2	3	4	5	6	7	8	9	10	11	12
1-PII	1											
2-Bonacich Power on Signed Network with Positive Beta	0.52	1										
3-Bonacich Power on Signed Network with Negative Beta	0.70	0.33	1									
4-Positive Degree	0.32	0.31	0.57	1								
5-Negative Degree	-0.73	-0.58	-0.65	-0.04	1							
6-Ratio of Positive to Total Ties	0.77	0.51	0.80	0.48	-0.82	1						
7-Eigenvector (Positive ties)	0.4	0.44	0.54	0.95	-0.21	0.58	1					
8-Betweenness (Positive ties)	0.29	0.25	0.59	0.90	-0.04	0.36	0.79	1				
9- Closeness (Positive ties)	0.28	0.21	0.50	0.93	-0.05	0.44	0.92	0.83	1			
10- Effective Size (Positive ties)	0.25	0.10	0.63	0.93	0.02	0.37	0.80	0.94	0.87	1		
11-Constraint (Positive ties)	-0.11	-0.15	-0.48	-0.90	-0.09	-0.38	-0.80	-0.79	-0.87	-0.89	1	
12-Two-step Eigenvector (Positive ties)	0.38	0.41	0.53	0.96	-0.17	0.56	0.99	0.82	0.95	0.83	-0.83	1
13-Two-step Eigenvector (Negative ties)	-0.66	-0.31	-0.66	0.05	0.94	-0.79	-0.07	0.02	0.01	0.06	-0.15	-0.05

Table 5: Descriptive statistics and correlations for Correlates of War analysis

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1-Change in Military Personnel (thousands)	-0.04	59.76	1										
2-Military expenditures (thousands)	3646038	21000000	-0.07*	1									
3-Total population (thousands)	29456.21	103578.5	-0.04*	0.28*	1								
4-Iron and Steel production (thousands of tons)	4191.09	16826.43	-0.07*	0.63*	0.51*	1							
5-Primary Energy consumption (thousands of coal-ton equivalents)	86445.45	344263.2	-0.09*	0.89*	0.47*	0.82*	1						
6-Contiguous Allies	1.26	1.83	-0.02	0.17*	0.07*	0.20*	0.17*	1					
7-Non-Contiguous Allies	6.98	9.79	-0.03*	0.22*	-0.06*	0.13*	0.23*	0.43*	1				
8-Contiguous Threats	0.53	1.01	-0.02	0.13*	0.25*	0.12*	0.12*	0.25*	0.03*	1			
9-Non-Contiguous Threats	0.59	1.67	-0.02*	0.4*	0.29*	0.42*	0.42*	0.14*	0.16*	0.34*	1		
10-Isolate	7782=no 3294=y	0.46	0.00	-0.05*	-0.07*	-0.07*	-0.07*	-0.51*	-0.53*	-0.39*	-0.26*	1	
11-Bonacich Power	5.58	12.2	0.00	0.07*	-0.05*	0.04*	0.08*	0.29*	0.75*	-0.06*	0.04*	-0.34*	1
12-Political Independence Index	0.12	0.69	-0.02	-0.02	-0.10*	0.02	-0.01	0.28*	0.30*	-0.37*	-0.20*	-0.12*	0.15*

Table 6: Cross-sectional time series analysis with fixed effects predicting change in military personnel, 1946-2000.

	Model 1	Model 2
Node Attributes		
Military Expenditures	6.21** (0.001)	6.19** (0.001)
Total Population	-0.04 (0.001)	-0.02 (0.001)
Iron and Steel Production	1.81^{t} (0.001)	1.74^{t} (0.001)
Primary Energy Consumption	-10.35** (0.001)	-10.36*(0.001)
Contiguous Allies	1.25 (1.05)	1.71^{t} (1.08)
Non-Contiguous Allies	-1.86^{t} (0.20)	-1.72^{t} (0.20)
Contiguous Threats	-0.13 (1.05)	-0.83 (1.11)
Non-Contiguous Threats	-2.07* (0.61)	-2.41* (0.61)
Political Independence Index		-2.02* (1.31)
Controls		
Bonacich Power	0.46 (0.25)	0.63 (0.25)
Isolate (dummy)	-0.63 (3.41)	-0.57 (3.41)
Constant	2.47* (3.07)	2.40* (3.07)
Between R squared	0.0998	0.1046
Within R squared	0.0299	0.0306
Overall R squared	0.0121	0.0124

^{t} $p < 0.10$, * $p < 0.05$, ** $p < 0.01$ N = 6558 Standardized coefficients reported. Standard errors are in parentheses.

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APPENDIX A: Existing Measures of Nodal Power in Politically Charged Networks

There are a number of existing measures that can be used to assess nodal favorability in signed graphs, including eigenvector centrality, Bonacich power (beta centrality) and the Markovsky, et al. (1988) graph theoretic power index (GPI). In this appendix, we discuss some of the strengths and weaknesses of these measures for the analysis of politically charged networks.

1. Eigenvector Centrality

Bonacich (1972) suggested using the principal eigenvector of the adjacency matrix representing a network as a way to capture node centrality. An eigenvector is defined as any vector satisfying $\lambda \boldsymbol{v} = \boldsymbol{A}\boldsymbol{v}$, where $\boldsymbol{A}$ is the adjacency matrix of the graph, λ is a constant (the eigenvalue), and $\boldsymbol{v}$ is the eigenvector. The principal eigenvector is the eigenvector associated with the largest eigenvalue. The essential property of an eigenvector is that a node's score is proportional to the sum of the scores of the nodes it is adjacent to, weighted by the strength and valence of the tie. Eigenvectors can be computed on any symmetric matrix A, including ones with positive and negative values.

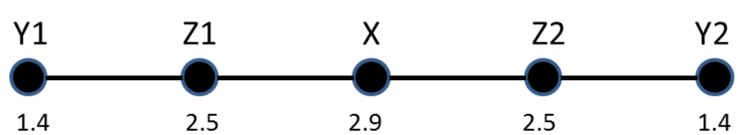

Figure A1. A Five Node Chain Network, with eigenvector scores.

For example, in Figure A1, node X has the highest eigenvector centrality score (2.9), followed by nodes in the Z position (2.5), and nodes in the Y position (1.4). This is because X has ties to two nodes (the Zs) who, in turn, have multiple ties (to a Y and back to X). All else being equal, having more ties to others increases eigenvector scores, often leading to a strong correlation with simple degree (Rodan, 2011). For example, in Figure A2, all nodes have the same eigenvector score, three direct ties, and despite a structure that suggests that nodes A and B might hold a special role in the structure, the Bonacich power centrality scores for all of the nodes are identical. In our real-world COW data, this is also the case – the Bonacich power measure is correlated 0.92 with degree centrality.

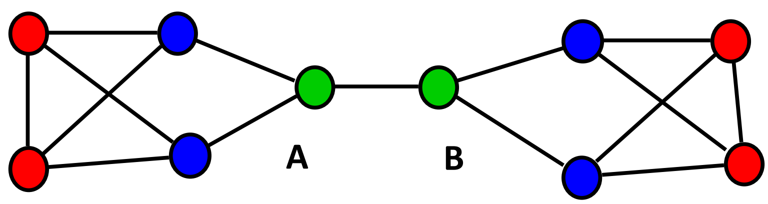

Figure A2. A ten node network where each node has the identical degree and power centrality

Mizruchi, et al. (1986), recognized that an actor's eigenvector centrality is partly determined by their own degree centrality, which determines the number of alters that reflect back their centrality to the actor (which they termed "reflected" centrality), and partly by the centrality of their alters (which they termed "derived" centrality). Actors affiliated with alters high in sociometric status would thus have higher derived centrality. Mizruchi et al. showed that eigenvector centrality could be decomposed into derived and reflected portions for each node.

Although rare in practice, eigenvector centrality (along with its decompositions) can in principle be applied to data with a mix of positive and negative values. However, the results are not always easy to understand. In general, adding positive ties increases a node's score while adding negative ties reduces a node's score. Depending on the balance of positive and negative ties, a node's net score could be strongly positive, close to zero, or strongly negative. However, this is a much more subtle process than it might at first appear. Figure1 (in the main body of this article) provides an interesting example where changing two positive ties to negative makes no difference in the centrality of A, the most central point. What's happening is that the negative ties to B and C cause B and C to have negative centrality scores. The product of a negative tie with a node that has negative centrality is a positive, resulting in a positive gain for node A. Essentially, with positive and negative ties, eigenvector centrality becomes a measure of node's location along a continuum defined by positive and negative poles. If, for convenience of exposition, we identify the positive pole with "good" and the negative pole with "evil", we can see that having positive ties to good nodes increases one's goodness score (i.e., strong positive score), as does having negative ties to evil nodes. Conversely, having either positive ties to evil nodes or negative ties to good nodes increases one's evilness score (strong negative score). Thus, the addition of negatives subtly changes the nature of eigenvector centrality to measure each node's allegiance to the positive or negative pole. If instead one had in mind using negative ties in a social ledger kind of way in which a negative tie was even more of a drag on a node than the absence of a positive tie, one would have to take the signed adjacency matrix and add a large enough constant to eliminate the negatives. Unfortunately, different constants yield different eigenvector scores, and there are no established criteria for selecting the constant.

2. Bonacich Power

Bonacich power, also known as alpha centrality or beta centrality (1987), can be seen as a generalization of the eigenvector concept. Beta centrality is defined as:

$$c = (I - \beta R)^{-1} R1$$

where I is an identity matrix, β is a user-selected constant known as the attenuation parameter, 1 is a vector of ones, and R is the network adjacency matrix. When |β| is less than 1/λ, the measure can be rewritten more meaningfully as

$$c = (b^0 R^1 + b^1 R^2 + b^2 R^3 + b^3 R^4 + ...)1$$

In other words, the values of beta centrality are the row sums of an infinite sum of powers of the adjacency matrix, each weighted by a corresponding power of β. For a 1/0 matrix R, it is well known that the i,jth entry of R^k gives the number of walks of length *k* from *i* to *j*. This means that beta centrality can be viewed as the total number of walks from a given node to all other nodes, weighted by the attenuation parameter beta. We can see that when beta is fractional, the effect is to weight walks inversely by their length. When beta is zero, only walks of length 1 are counted, making beta centrality precisely equal to degree centrality. As the absolute value of beta gets larger, longer walks are given increasing weight. As the beta approaches 1/λ, beta centrality becomes indistinguishable from eigenvector centrality. In this way, beta centrality is a parameterized family of centrality measures that includes both degree centrality and eigenvector centrality as extreme special cases. Like degree and eigenvector centrality, beta centrality can be applied to valued ties, and the values can be both positive and negative.

Of special interest to this paper is the valence of the beta parameter. When beta is positive, being positively connected to nodes with high positive scores increases a node’s score. In contrast, when beta is negative, being positively connected to nodes with high positive scores reduces a node’s score. A positive beta corresponds to the case where nodes acquire power through association with powerful others, as when power is a function of access to resources (the power-as-access perspective). A negative beta matches situations where being surrounded by weak others makes a node more powerful, as when power is a function of dependence (the power-as-control perspective). This makes beta centrality a flexible generalization of simple eigenvector centrality. However, as Rodan (2011) notes, this does not mean that beta centrality is always easy to understand. For example, Node A in the Figure 2 illustration has the highest beta centrality without regard to whether we employ a positive or negative beta despite having only one positive ally and two negative adversaries. Similarly, in our COW data, the beta centrality measure with a positive beta is correlated 0.72 with the same measure with a negative beta. This is not a flaw in the measure – it just means that certain positions in a network have power under a variety of social regimes. The inclusion of negatively charged ties also complicates the interpretation of the measure as beta centrality handles negative ties the same way as eigenvector centrality. This is not a problem when beta is small. For example, when beta is 0, beta centrality reduces to a sum of positive ties minus negative ties. However, as the absolute value of beta is increased to take account of indirect connections, what is summed by the measure is a product of tie strengths and valences such that strong negative values of beta centrality do not imply lack of power but rather power with respect to a different set of nodes (Indeed, when Hubbell (1965) introduced a forerunner of beta centrality, he saw it as a means of clique identification).

3. Graph Theoretic Power Index

The graph theoretic power index (GPI) is a measure that subtracts the number of "disadvantageous paths" from the number of "advantageous paths" emanating from a given node (Markovsky, et al., 1988; Markovsky et al., 1993). An advantageous path is defined as one with an odd number of links, while a disadvantageous path is one with an even number of links. Paths of all lengths are considered, but only node-independent paths are counted. In other words, if there are multiple paths emanating from a node that share any nodes besides the origin, they are counted as just one. The formula for GPI is

$$p_i = \sum_k (-1)^{k-1} m_{ik}$$

where m_{ik} is the number of node-independent paths of length k emanating from node i.

This measure effectively matches experimental results from exchange networks and can be a useful power-as-dependence measure. However, the GPI has yet to be extended to include both positive and negative ties. In addition the measure doesn't include an attenuation rate and is prohibitively expensive to compute due to the need to identify node-independent paths. These limitations make it less useful for studying real-world, larger-scale politically charged networks such as the COW dataset or the South Korean legislature (Siegel, 2007).

APPENDIX B: Comparing PII results when using β = -0.50 in the Correlates of War dataset

In simulations we conducted on a number of different networks, PII scores tended to stabilize once the β became higher than 0.50. Therefore, we recalculated PII with a β = 0.50 and reran our Correlates of War analysis. The results reported below are similar to those presented in Table 6.

	Model 1	Model 2
Nodal Attributes		
Military Expenditures	6.21** (0.001)	6.20** (0.001)
Total Population	-0.04 (0.001)	-0.05 (0.001)
Iron and Steel Production	1.81[t] (0.001)	1.75[t] (0.001)
Primary Energy Consumption	-10.35** (0.001)	-10.36** (0.001)
Contiguous Allies	1.25 (1.05)	1.77[t] (1.10)
Non-Contiguous Allies	-1.86[t] (0.20)	-1.69[t] (0.20)
Contiguous Threats	-0.13 (1.05)	-0.98 (1.19)
Non-Contiguous Threats	-2.07* (0.61)	-2.55* (0.63)
PII		1.83[t] (1.31)
Control Variables		
Bonacich Power on Signed Network	0.46 (0.25)	0.74 (0.25)
Isolate dummy	-0.63 (3.41)	-0.55 (3.41)
Constant	-2.47* (3.07)	-2.47* (3.07)
Between R squared	0.0998	0.1057
Within R squared	0.0299	0.0304
Overall R squared	0.0121	0.0123

t p<0.10, *p< .05, ** p <.01 N= 6558 Standardized coefficients reported.
Standard errors are in parentheses.

APPENDIX C: Comparison of PII with a β = -0.80 and ratio of positive to total ties across multiple datasets.

Gama Dataset

Tribe	PII	Positive Ties	Negative Ties	Proportion Positive
Masil	2.552976	7	0	1
Ukudz	1.244853	6	1	0.857143
Ove	-0.27555	4	2	0.666667
Alika	-1.13494	2	1	0.666667
Gahuk	-0.23535	5	5	0.5
Asaro	0.141358	4	4	0.5
Uheto	-0.1316	4	4	0.5
Geham	-0.49395	4	5	0.444444
Nagam	**0.78781**	**3**	**4**	**0.428571**
Notoh	**-0.10489**	**3**	**4**	**0.428571**
Kohik	0.053231	2	3	0.4
Sueve	-0.59982	2	3	0.4
Gavev	0.098063	3	5	0.375
Kotun	0.370631	3	5	0.375
Nagad	0.498928	3	6	0.333333
Gama	0.940842	3	6	0.333333

PII acts differently than the ratio of positive to total ties because it incorporates both direct and indirect ties, taking into account the structure of those ties in terms of their distance from the focal actor. In the Gama dataset, for example, there are two tribes with the exact same number of positive ties and negative ties (and thus the same ratio) who have dramatically different PII scores. While the Nagam and Notoh tribes are identical in terms of their direct ties, their PII scores are radically different – Nagam's PII is +0.79, while Notoh's is -0.10.

Sampson Dataset

ID	PII	Positive Ties	Negative Ties	Proportion Positive
Winfrid	1.735646	5	0	1
Bonaventure	1.333554	7	3	0.7
Greg	1.331843	10	5	0.666667
Ambrose	0.847476	5	3	0.625
John Bosco	0.312358	8	5	0.615385
Victor	-0.03287	6	5	0.545455
Romuald	**0.47149**	**1**	**1**	**0.5**
Boniface	**0.338017**	**5**	**5**	**0.5**
Amand	**-0.10872**	**5**	**5**	**0.5**
Louis	-0.37516	5	6	0.454545
Mark	-0.2401	5	6	0.454545
Albert	0.303256	4	5	0.444444
Peter	-0.2248	6	9	0.4
Hugh	-0.51454	4	6	0.4
Berthold	**1.082802**	**3**	**6**	**0.333333**
Elias	-0.48781	4	9	0.307692
Basil	-0.45045	4	10	0.285714
Simplicius	-0.40331	3	9	0.25

In the Sampson dataset, we have three actors with the same positive to total tie ratio of 0.5 (Romuald, Boniface, and Amand). While Boniface and Amand have the identical direct tie network (5 positive ties and 5 negative ties), Boniface's PII score is +0.34 while Amand's is -0.11. Notice also that the ratio does not distinguish between their personal networks and those of Romuald's, who has only 2 direct ties (1 positive, 1 negative). There is even a case where an actor (Berthold) has twice as many direct negative ties than positive ties (6 vs. 3), and yet has a relatively high PII score (+1.08).

Life Sciences Dataset

ID	PII	Positive Ties	Negative Ties	Proportion Positive
100	1.14553	7	0	1
129	1.56263	18	0	1
147	1.18693	16	0	1
16	0.90343	8	0	1
180	1.39965	8	0	1
192	1.57754	15	0	1
238	1.23196	9	0	1
245	**2.34395**	**5**	**0**	**1**
246	1.07078	9	0	1
273	0.74254	4	0	1
291	1.07501	5	0	1
30	0.79612	13	0	1
304	0.81871	4	0	1
306	1.51429	16	0	1
329	1.43002	9	0	1
332	1.1708	9	0	1
341	1.67114	13	0	1
344	**0.99246**	**5**	**0**	**1**
41	0.98193	14	0	1
50	1.57082	13	0	1
70	-0.0417	3	0	1
75	1.13273	10	0	1
80	0.88801	9	0	1
87	1.28341	6	0	1
267	0.66789	27	1	0.96
84	0.84501	23	1	0.96
20	-0.022	18	1	0.95
276	0.58393	18	1	0.95
298	0.86837	18	1	0.95
21	0.88889	16	1	0.94
24	0.53785	16	1	0.94
349	0.55421	16	1	0.94
109	0.29049	15	1	0.94
257	0.9331	13	1	0.93
37	0.11387	13	1	0.93
145	0.69846	24	2	0.92
183	-0.3339	12	1	0.92
90	0.13375	12	1	0.92
220	0.35071	22	2	0.92

60	0.26804	10	1	0.91
312	0.77324	19	2	0.9
209	0.29746	9	1	0.9
59	0.06478	9	1	0.9
82	-0.5646	9	1	0.9
319	0.41977	17	2	0.89
130	0.14813	8	1	0.89
77	0.19235	8	1	0.89
83	0.21935	8	1	0.89
56	-0.3086	18	3	0.86
302	0.30483	17	3	0.85
52	0.09704	22	4	0.85
78	0.34976	11	2	0.85
194	-0.0949	21	4	0.84
114	0.0509	5	1	0.83
171	1.01616	19	4	0.83
40	0.02515	22	5	0.81
163	-0.3621	13	3	0.81
182	-0.5227	17	4	0.81
300	-0.1675	8	2	0.8
211	0.05795	22	6	0.79
350	-0.0972	7	2	0.78
275	-0.8526	10	3	0.77
111	0.02949	12	4	0.75
134	-0.1506	6	2	0.75
197	0.91201	3	1	0.75
116	**-0.0404**	**20**	**7**	**0.74**
173	**-0.6536**	**14**	**5**	**0.74**
200	0.05525	6	3	0.67
256	0.08611	8	4	0.67
10	-0.8933	2	2	0.5
196	-0.7031	1	1	0.5
222	-0.7031	1	1	0.5
9	-0.7183	1	1	0.5
229	0.10995	2	3	0.4

In a larger dataset such as the Life Sciences dataset, we see that nearly one-third of the actors did not have a direct negative tie, rendering their ratio score identical (1.0). PII distinguishes them based on their indirect ties (e.g., while actors 245 and 344 both have only 5 direct positive ties, their PII scores are dramatically different, with 245's score as 2.34 and 344's as 0.99). Notice also that actor 116 has 20 direct positive ties, nearly the highest total in the dataset, but also has 7 negative ties, which is the highest in the dataset. This actor has a PII score of -0.04. Actor 173 has fewer positive ties, but also fewer negative ties, the identical ratio (0.74), but a much lower PII score (-0.65).

Appendix D: Cross-sectional time series analysis with fixed effects predicting change in military personnel, 1946-2000 : A comparison of PII and the ratio of positive to total ties.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Nodal Attributes							
Military Expenditures	4.83** (0.001)	4.83** (0.001)	4.83** (0.001)	4.80** (0.001)	6.19** (0.001)	6.19** (0.001)	6.17** (0.001)
Total Population	0.31 (0.001)	2.54 (0.001)	2.62** (0.001)	2.61** (0.001)	0.27 (0.001)	0.31 (0.001)	0.28 (0.001)
Iron and Steel Production	2.05* (0.001)	2.06* (0.001)	-0.13* (0.001)	2.05 * (0.001)	2.01* (0.001)	2.01* (0.001)	2.01* (0.001)
Primary Energy Consumption	-7.34** (0.001)	-7.34** (0.001)	-7.37** (0.001)	-7.32* (0.001)	-10.62** (0.001)	-10.63** (0.001)	-10.63** (0.001)
Ratio of Total Positive Ties to Total Ties		-0.29 (0.001)		0.52 (2.53)	-0.15 (3.73)		0.58 (4.65)
Political Independence Index			-1.50 (1.08)	-1.56 (1.24)		-1.03 (1.14)	-1.17 (1.42)
Controls							
Bonacich Power on signed network					-0.03 (0.24)	0.08 (0.94)	-0.05 (0.24)
Isolate dummy	-0.15 (2.90)	-0.22 (3.00)	-0.13 (2.90)	0.04 (3.05)	-0.30 (3.55)	-0.22 (3.15)	0.15 (3.81)
Constant	1.03 (1.02)	0.88 (1.60)	1.22 (1.03)	0.32 (1.69)	2.05* (2.99)	2.63* (2.19)	1.24 (3.40)
Between R squared	0.1294	0.1281	0.1246	0.1263	0.1125	0.1171	0.1155
Within R squared	0.0089	0.0089	0.0092	0.0092	0.0285	0.0287	0.0287
Overall R squared	0.0064	0.0063	0.0063	0.0064	0.0131	0.0134	0.0133

t p<0.10, *p< .05, ** p <.01 N= 6558 Standardized coefficients reported. Standard errors are in parentheses.