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The Logics of Systemic Theory

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Summary and Keywords

The history of systemic theory in international relations is a tragedy of bad timing: Interest in systemic theory and awareness of its importance preceded widespread understanding of the methodologies needed to formulate and test it. In the intervening decades, dyadic studies dominated empirical studies of international relations to such an extent that the influences of the international system on actors' behavior and vice versa were all but forgotten. This need not be the case. Through the lenses of four methodologies, systemic theory can be surveyed to capture their logics in order to highlight the value and feasibility of systemic theorizing.

Keywords: empirical international relations theory, system theories, logic, equation-based methods, game theory

Introduction

Systemic theories occupy a curious position in international relations theory. No international relations field seminar syllabus is complete without a week on systemic theories—typically the first week. Because they are complex, difficult to specify, and notoriously difficult to test, there are relatively few of them. Their logic consistently fails to inform empirical analyses of international relations. At the same time, the short list of systemic international relations theories includes some of the most widely read and widely cited books in the discipline (for example, Gilpin, 1981; Organski & Kugler, 1980; Waltz, 1979).

This curious disconnect between interest in systemic theory and applications of it occurs in part, we suspect, because of timing. The heyday of systemic theorizing in international relations, as the above citations suggest, was the late 1970s and early 1980s—a time in which the methodologies appropriate to systemic theorizing were little known in political science. Systemic theories of that generation were often dismissed as being vague and unfalsifiable, and not without reason. Scholars’ focus soon turned toward more concrete analyses that could be readily accomplished using dyadic Correlates of War data. Increasingly, the impact of the system was assumed away, except in a very superficial sense: While the balance of power could arguably be measured and included in a dyadic analysis of international conflict, for example, the logic of balance-of-power politics did not inform the analysis (e.g., Bueno de Mesquita & Lalman, 1988, 1992; Huth, 1993).

This needs no longer to be the case. While systemic theory by its nature will always be more complex than dyad-level theory, the methodological tools necessary both to formulate and to test systemic theories are well established and are increasingly being brought to bear to help understand the complex interdependencies of the international system.

In the following chapter we describe four of these methodologies—systems of differential equations, network theory, agent-based modeling, and game theory—and highlight some ways in which each has been used to capture the systemic logic of international relations. We focus mostly on the first two, partly because they are the methodologies that we ourselves know best and partly because applications of those methods to systemic phenomena in the social sciences are relatively more widespread. Systemic theorizing in international relations is a very worthwhile endeavor, if only because the international system is a system and should be treated as one. We hope to show that it is straightforward as well—and that different methodologies can be used to capture different theoretical emphases on the relationship between structures and agents.

Equation-Based Models

A *difference equation* is an equation that explains the rate of change of some quantity of interest. A standard econometric equation of the form

$$y_t = X_t\beta + \epsilon,$$

which predicts the level of y at time t based on some set of covariates, can be rendered as a difference equation by subtracting y_{t-1} from both sides:

$$y_t - y_{t-1} = X_t\beta - y_{t-1} + \epsilon,$$

or, equivalently,

$$\dot{y} = X_t\beta - y_{t-1} + \epsilon,$$

where the rate of change in y is denoted by $\dot{y}$. As this simple example suggests, difference equations are not very different from the statistical equations that quantitative international relations scholars have been using for decades. If more than one difference equation is required, as will generally be the case when modeling systems, they are typically referred to as a *system of difference equations*. Estimating a system of equations takes a little more work than estimating a single equation, but libraries like system fit in R and commands like reg3 in Stata make it very straightforward to accomplish.

Difference equations—and their continuous-time cousins, *differential equations*—are most closely associated with physics. Newton’s Second Law of Motion; Maxwell’s equations governing the interrelationship of electric and magnetic fields; and Einstein’s field equations, which explain gravitation as a function of the curvature of space-time by matter and energy, are all captured by systems of differential equations. Nevertheless, difference and differential equations have also found diverse applications in the social and biological sciences—most notably for our purposes in the area of macroeconomic modeling (Hickman, 1991). An intuitive motivating example from the field of ecology is the Lotka-Volterra Equations, which describe predator-prey dynamics. In the canonical case, the interaction between rabbits (*r*) and foxes (*f*) takes the form

$$\dot{r} = \alpha r - \beta f r$$

$$\dot{f} = \delta f r - \gamma f$$

In plain English, the model tells us that every rabbit will produce α new rabbits; every possible rabbit-fox interaction will result in the death of β rabbits and the birth of δ new foxes; and the foxes die off or leave the area at a constant rate of γ deaths per fox.

The outer curve in Figure 1 illustrates the dynamics that result from one version of this model with parameters: $\alpha = 4, \beta = 0.5, \delta = 0.01, \gamma = 0.5, r_0 = 200, f_0 = 10$. The initial population of 200 rabbits and 10 foxes represents a food-rich environment for foxes: Before long, the fox population has population has increased by about 50% and the rabbit population has dropped by more than 75%. At that point, the success of the foxes is their undoing, and the fox population can no longer find enough food to sustain itself. The fox population plummets precipitously, at which point the rabbits begin to breed more quickly than the foxes can kill them off. The size of the rabbit population skyrockets but is soon brought to a standstill by the rapidly increasing fox population. At this point the simulation ends, but if we were to allow it to continue indefinitely the rabbit and fox populations would continue to cycle in the same pattern—the fox population surging when there are many rabbits, the rabbit population surging when there are few foxes.

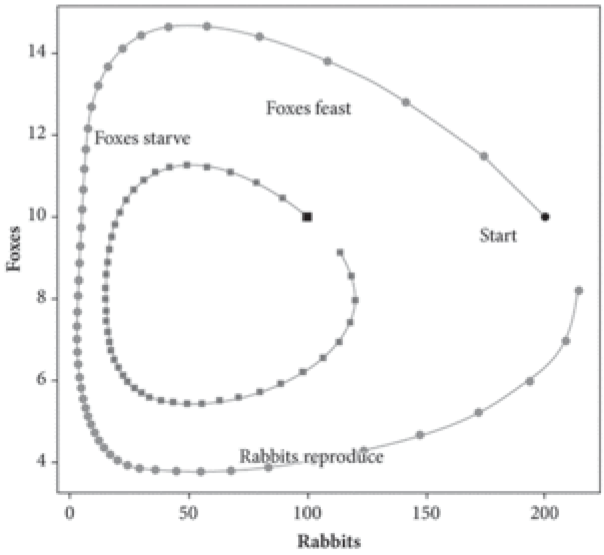

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Figure 1. The dynamic relationship between a fox population and a rabbit population over time, starting with either 20 foxes and 200 rabbits (circles) or 20 foxes and 100 rabbits (squares). Rabbits reproduce exponentially, fueling growth in the fox population. The foxes reduce the rabbit population until it can no longer sustain them. When the rabbit population begins to skyrocket in the absence of predation, the cycle begins anew.

The behavior of this simplified predator-prey system is governed, most obviously, by the parameters. Less obviously, the behavior of the system is also governed by the starting point. If we start with 10 foxes and only 100 rabbits, the rabbit and fox populations would still have oscillated in the same way, but the spikes and crashes would have been less severe, as the inner curve of Figure 1 demonstrates.

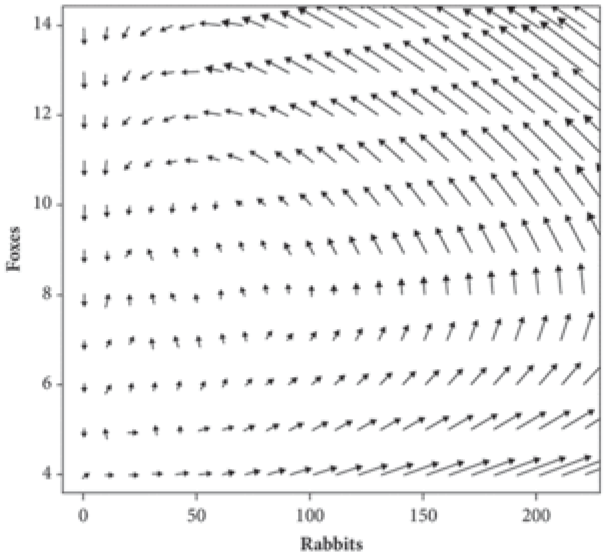

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Figure 2. A vector field illustrating the dynamic relationship between a fox population and a rabbit population over time. Model parameters are set to $\alpha = 4, \beta = 0.5, \delta = 0.01, \gamma = 0.5$.

We can see how these dynamics work more generally by creating a *vector field*. A vector field is a handy way to illustrate the dynamics of a system: It illustrates what happens when the system starts at a given point and moves forward by a fixed unit of time. The direction in which the arrow points tells you the direction in which the system moves, and the length of the arrow reflects the rate of change.

The plot in Figure 2 depicts a vector field for the system in Figure 1 ($\alpha = 4, \beta = 0.5, \delta = 0.01, \gamma = 0.5$). It’s reasonable to think of this vector field as an illustration of how the system “pushes” the populations of the two groups up and down. The foxes do not intend to produce population cycles, nor do the rabbits; those cycles arise naturally out of the logic of their interaction.

As the long arrows on the right-hand side of the vector field suggest, the system is most dynamic when there are plenty of rabbits. The Figure also shows an area, roughly between 30–60 rabbits and 6–10 foxes, in which very little action takes place. That suggests that there might be an *equilibrium point*—a state of the system that does not change over time. In fact, there is one, and we can find it by setting the first derivatives in the above equations equal to zero and solving

$$0 = -f(\gamma - \delta r)$$

which gives an equilibrium point at

$$f = \frac{\alpha}{\beta}$$

$$r = \frac{\gamma}{\delta}$$

So, in the original example, if we start with a population of 8 foxes and 50 rabbits, fox predation and rabbit reproduction will perfectly balance out and both populations will remain stable over time.[1] We can see this in the left-hand vector field in Figure 2 by looking for an arrow with a length of zero; we can find it precisely at (50, 8).

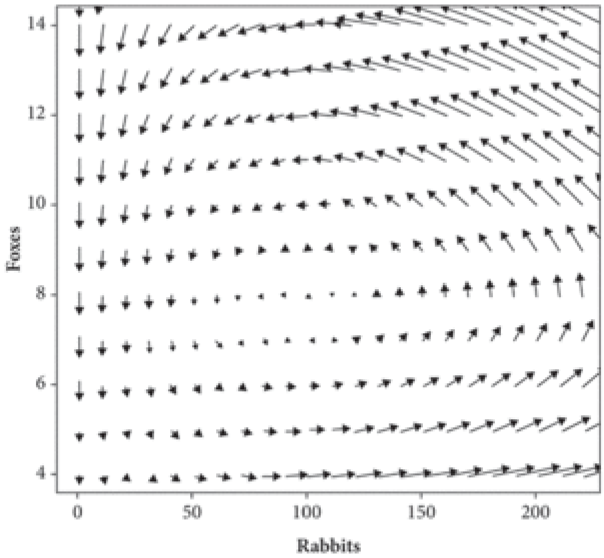

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Figure 3. A vector field illustrating the dynamic relationship between a fox population and a rabbit population over time. The model parameters $\alpha = 4, \beta = 0.5, \delta = 0.01, \gamma = 1$.

Even in this incredibly simple system, though, it turns out that the implications of a change in one of the parameters produce complex and nonobvious results. To illustrate this point, let’s modify the world in Figure 2 by allowing some people from a nearby village to hunt the foxes, increasing their mortality rate γ. What would happen to the dynamics of the rabbit- fox system? Most obviously, the population of foxes would decrease more rapidly. Most people would probably anticipate that the equilibrium path would simply shift downward—that there would be fewer foxes at every point in the cycle than there had been previously, thanks to the activity of the hunters. They’d be mistaken.

Figure 3 shows what happens when we double γ, the fox mortality rate. As predicted, the fox population experiences less dramatic booms and more pronounced downward swings. That, in turn, allows the rabbits to proliferate to an even greater degree, which increases the food supply for the foxes. In fact, the increase in the foxes’ available food supply perfectly counterbalances their losses from hunting. In the end, the equilibrium fox population doesn’t change at all—but the equilibrium *rabbit* population doubles.

Advantages for Systemic IR Theory

Systemic international relations theories typically involve change and/or equilibrium. Gulick (1955), for example, sees the balance of power as an equilibrium state, while Gilpin (1981) and Organski and Kugler (1980) focus on the dynamics that produce the rise and decline of systemic hegemons. Waltz (1979) argues both that equilibration occurs and that states, sooner or later, reach an equilibrium in the form of an equal distribution of power:

> From the theory, one predicts that states will engage in balancing behavior, whether or not balanced power is the end of their acts. From the theory, one predicts a strong tendency toward balance in the system. The expectation is not

> that a balance, once achieved, will be maintained, but that a balance, once disrupted, will be restored in one way or another. Balances of power recurrently form (p. 128).[2]

These are precisely the sorts of expectations that can readily be formulated in equation-based models. The equations themselves capture the phenomena that produce change in the international system—the rise and fall of hegemons, for example, or the equilibrating behavior of major powers—while the equilibrium point can capture the idea of a balance toward which systems of major powers tend to gravitate. The dynamics of the system can be readily represented with a vector field.

More generally, equation-based models allow the theorist both to evaluate the logic of a systemic theory (do the conclusions follow from the premises?) and assess how well or poorly the theory describes the behavior of actual international systems (do the data fit the theory?). The ability to do both is rare: Game theory is designed to evaluate the logic of an argument but not to test it empirically, while network theory does the converse.

While the use of equation-based models to capture systemic behavior has a robust tradition in economics (see, e.g., Markowich, Burger, & Caffarelli, 2014), applications in international relations are less common. Zinnes and Muncaster (1988) is an early theoretical example from two pioneers in the discipline; Kadera (1998) uses differential equations to model the spread of war in the international system, while Kadera, Crescenzi, and Shannon (2003) focus on the complex relationship between one aspect of the international system—the size and strength of the democratic community—and systemic levels of international conflict. These isolated examples stand out as evidence of an even larger potential that has yet to be realized.

To illustrate the advantages of using equation-based models in the context of international relations, we now turn to a discussion of a book that one of us knows intimately: Bear Braumoeller’s *The Great Powers and the International System*.

Example: Braumoeller, The Great Powers, and the International System

The goal of Braumoeller’s book is to explain how the actions of states have an impact on the structure of the international system and how that structure, in turn, has an impact on the actions of states. Braumoeller, drawing inspiration from Wendt (1999), conceives of the structure of the international system as “distributions . . . of any characteristic deemed important by the main actors” (p. 6). The main actors, in turn, are the major powers in the international system (pp. 79–82). Within each of these countries, constituencies have preferences about the ideal state of the structure of the system (the balance of power, for example) and exert pressure on leaders to use the power of the state to bring the structure of the system more closely into line with their preferred vision of it. The pushing and pulling of various major-state leaders attempting to do just that is what drives change in the structure of the international system.

To represent this theory as a system of differential equations,[3] Braumoeller first defines the distribution of ideal points of the constituency of state *i* as c_i and the function that aggregates those preferences into a single, collective ideal point as $\nu()$. In the simplest case, if the leaders of a state take the preferences of the average, or mean, voter to represent the state’s collective preference, $v(c_i) = mean(c_i)$.

He then denotes the present state of the system along a given dimension *d* as s_d. s_d generally represents the balance, or present distribution, of something deemed important by the major powers—typically political ideology or power, in Braumoeller’s case studies. That allows him to measure the distance between state i’s ideal state of the world and the actual state of the world (or, more succinctly, state *i*’s *dissatisfaction*) along dimension *d* as

$$\left[v_i\left(c_{id}\right) - s_d\right]^2$$

(The distance is squared for the sake of mathematical convenience.)

What we don’t yet know is how much state i’s constituents actually care about the discrepancy about their ideal state of the world and the actual state of the world. Some people might believe, for example, that the ideal state of the world involves global democracy or American military hegemony, but if they don’t care much about foreign policy in general, they won’t take part in demonstrations, sign petitions, or factor those preferences into their voting decisions. What is needed, for each dimension, is a weight, ω, that captures the salience of that dimension to the constituents of the state.

Weighting each distance by the salience accorded to it by the population involves simple multiplication:

$$\omega_{id}\left[v_i\left(c_{id}\right) - s_d\right]^2$$

Next, state *i*’s level of activity at any given time, a_i, is driven by its dissatisfaction with the state of the world across all dimensions that are relevant to it, multiplied by the salience of those dimensions:

$$a_i = \sum_d \omega_{id}\left[v_i\left(c_{id}\right) - s_d\right]^2 - a_i$$

In other words, states that are perfectly satisfied with the status quo and states that are indifferent to the status quo will not seek to change it, but states that are neither satisfied nor indifferent will do so. The effort that the latter group will expend to change the status quo will be proportional to the product of their dissatisfaction and salience.

Finally, the actions of the various states change the structure of the international system along dimension d in direct proportion to each actor's level of activity (a), material capabilities (π), the salience of the issue area in question (ω), and the extent of the state's dissatisfaction with the status quo ($\nu(c) - s$):

$$\dot{s}_d = \sum_i a_n \pi_n \omega_{nd} [v_n(c_{nd}) - s_d]$$

These changes take place along all dimensions of the international system (for example, the balances of power and political ideology) deemed relevant by the major actors. Because the result of the states' actions may make the constituents of some states more satisfied and those of other states less satisfied than they had been previously, a change in the structure of the international system has an impact on the desires of each state's constituency—and the cycle begins anew.

These differential equations translate readily into statistical equations, which Braumoeller estimates using a combination of historical data and data derived from a survey of historical experts (see Braumoeller, 2012, ch. 3, for details). Having done so and concluding that the data fit the model reasonably well, he is then able to describe the pressures exerted on the Great Powers by the international system in terms of vector fields similar to those displayed above.

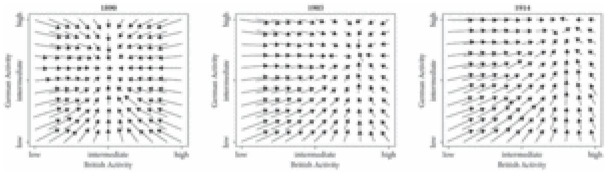

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Figure 4. Systemic pressures and German and British activity prior to World War I.

Two quick examples suffice to illustrate this technique. In Figure 4, we can see systemic pressures exerted on British and German activity from the fall of Bismarck in 1890 to the onset of the First World War in 1914. The axes represent levels of security-related activity (arms buildups, alliance activity, etc.) on the part of the actors, and the vector fields chart the systemic pressures on state activity that result from the shift in German preferences away from Bismarck's maintenance of the status quo and toward Wilhelm's *Weltpolitik*: Germany's desire for a "place in the sun" created pressure for increased German activity, and the success of that policy created pressure for increased British activity. The result was a security spiral (Jervis, 1978) that led to the outbreak of war.

Figure 5 illustrates the markedly different process that played out prior to the Second World War. Following the settlement at Versailles, neither Germany nor the United States had a compelling reason to attempt to challenge the status quo. Following the rise of Hitler and the accompanying dramatic change in Germany's worldview, which again underscored the importance of Germany's weakness relative to the other major powers, systemic pressures pushed Germany toward higher and higher levels of activity.

The systemic incentives for the United States, however, were very different. Throughout the “isolationist” 1920s and 1930s, the United States faced very little by way of systemic pressure to act. Even as late as 1939, the increase in German military power was not sufficient to warrant concern across the Atlantic. Only after the abrupt shock of the fall of France in 1940 did the United States face compelling systemic incentives to act, and they did: Defense appropriations jumped from $1.12 billion in 1939 to $10.5 billion in 1940. The model highlights a fact that has often been missed by subsequent commentators and even some historians: Isolationism, to the extent that it ever existed in the 1930s, died in July 1940, following the fall of France, rather than in December 1941 (Braumoeller, 2010).

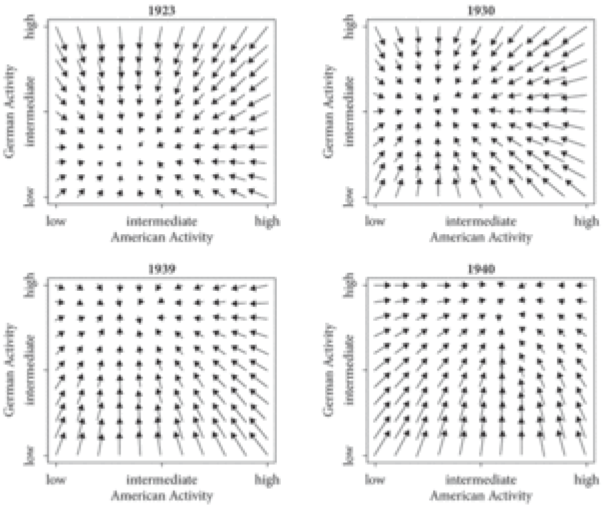

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Figure 5. Systemic pressures and German and American activity prior to World War II.

In each case, the outcomes reflect a fully systemic logic in which the behavior of the actors has an impact on the international system and the international system creates pressure for the actors to act. The impact of the system neatly reflects the fact that, as Waltz (1986, p. 343) puts it,

> structures shape and shove. They do not determine behaviors and outcomes, not only because unit-level and structural causes interact, but also because the shaping and shoving of structures may be successfully resisted.

The relatively abstract, unstructured nature of equation-based modes is essential to the modeling endeavor: It permits the theorist to model dynamic relationships among states or between states and the structure of the international system.

Networks

A network is a collection of nodes or vertices (entities or actors) bound together through ties or edges (measurements of interaction or relations between actors). Social interactions within a network are often governed by a set of principles or the broader system structure. Consider a cohort of 30 middle school students (nodes) and their friendships (ties). Many middle school students live their lives in pursuit of popularity, a network-defined property, which may inform a student’s choice of friends. Arguing that students form friendships with those who would make them the most popular, or choose to be friends with their friends' friends, would be forms of network theorizing. These theories may be considered in terms of the probability of student *i* forming a friendship with student *j*

$$\Pr(i \rightarrow j) = logit^{-1}\left(\alpha + \beta\pi_j + \delta\mu_{ij}\right)$$

with the logistic transformation of a numerical constant α, an effect β associated with forming a potential tie with a popular or unpopular π student j, and an effect δ associated with the number of mutual friends μ between students *i* and *j*. In other words, the probability of two students becoming friends is a function of the pattern of social relations among other students and their placement within the broader friendship network.

Network theorizing is an emerging and powerful approach to systemic theorizing. At its core, network theory emphasizes the influence of social structure in explaining a variety of phenomena (Wasserman & Faust, 1994). Patterns of social relations among actors within a system may not only influence the formation of new social relationships or ties, but a variety of actor, group, and system-level outcomes. Beyond this emphasis on patterns of social relations, network theorists typically work from four first-principles:

- Contrary to the assumptions of independence made by many theoretical and empirical models, network theorists emphasize the interdependence of actors and their behaviors. In the middle school example, the existence of other social actors, mutual friends, informs the likelihood that two students become friends.[4]
- Social relations between actors provide vectors or avenues for the diffusion of material or nonmaterial resources. In the world of our example, let us assume that a popular new band emerges. Awareness of this band may become diffused through the student friendship network as word of the band spreads from one student to another through friendships.[5]
- The embeddedness of actors in broader social structures provides opportunities or constraints on their behavior. If a student is at the core of the friendship network, they may have more opportunities to form friends as they are popular, but face potential reputational costs for becoming friends with too many students.[6]
- There exists a fundamental problem of network inference, such that it is often difficult to tease out if certain phenomena are the result of actors selecting into a network with entities similar to themselves (homophily), or if there is spread of certain phenomena through the network (diffusion or contagion). For instance, if we observe two students listening to the same band, is it because one turned the other onto it, or that their friendship was informed due to similar music preferences?[7]

Examples of network theorizing are far reaching. In 1929, Frigyes Karinthy argued that the world has become smaller, and that advances in communication and travel had led to the possibility of relatively close social connections regardless of distance. He hypothesized that due to these changes, any individual in the world could be connected to any other individual through no more than five social relationships (Karinthy, 1929). This proposition has inspired many (Barabasi, 2002; Gurevitch, 1961; Milgram, 1967; de Sola Pool & Kochen, 1978; Newman, Barabasi, & Watts, 2011), including the Small World Project at Columbia.

This idea was further developed and formalized by Watts and Strogatz (1998) who developed a model of small-world random networks. They showed that the average distance between any two nodes in a network is computed as

$$d_{ij} = \frac{ln(N)}{\ln(K)}$$

where d_{ij} the average distance between any two nodes i and j in a network of size N with K average number of ties of each node in the network. As of 2016, approximately 7.5 billion individuals live in the world. Figure 6 shows the average number of relationships each person in the world must have such that everyone is connected by, at most, six degrees of separation. Watts and Strogatz (1998) would say that Karinthy's proposition would be true now assuming each individual in the world had 44 social relationships.

It is worth noting that this relatively parsimonious model may overestimate just how many degrees of separation exist between people as it neglects the presence of certain hubs or highly influential people. Nevertheless, this allows one to consider how the broader social structure may influence individuals. Networks can be exceptionally complex, and this example allows one to consider the possibility that the structure of a network or one's placement in the network influences a variety of social phenomena (Christakis & Fowler, 2009).

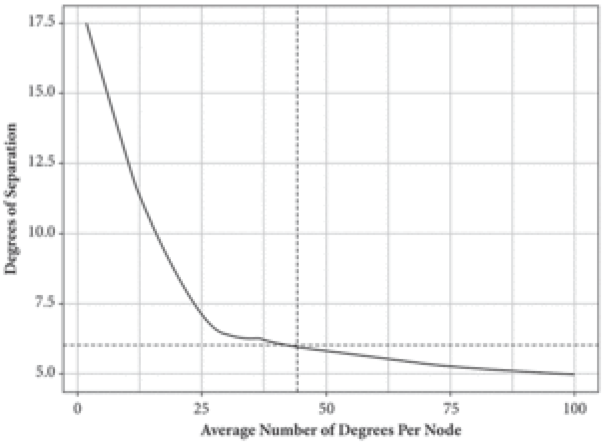

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Figure 6. Six Degrees of Separation. The degrees of separation between any two people and its relationship with the average number of relationships per person.

Advantages for Systemic IR Theory

Many systemic international relations theories involve the role of social structure and emergent phenomena on conditioning state behavior. A fundamental theory of international politics holds that states are influenced by systemic norms, and through socialization, behave in predictable ways. Within certain epistemic communities, which are examples of interstate networks, Haas (1992) argues that foreign policy making elites are informed through socialization and peer emulation according to norms emerging from state interaction. While rarely considered explicitly as a network theory, this is representative of a systemic network theory.

Applications of network theorizing run the gamut of disciplines, with actualized potential in political research (Victor, Montgomery, & Lubell, 2016). Within the context of international relations theorizing, network analysis offers a well-developed theoretical toolkit to assist scholars in developing systemic theory (Dorussen, Gartzke, & Westerwinter, 2016; Hafner-Burton, Kahler, & Montgomery, 2009; Patty & Penn, 2016). Within IR, scholars have typically used three of these tools when deriving and testing theory. The first tool, centrality, attempts to describe and measure properties of a node’s location within the network. There are many centrality measurements, including but not limited to degree centrality (the number of edges a node has), betweenness centrality (the extent to which the node is a “bridge” in the network), and eigenvector centrality (the relatedness of a node based upon its connection to other central nodes). Kinne (2012) uses closeness centrality, a measure of the average distance between a node and any other node in the network, to measure openness within the trade network, while Maoz (2010) uses centrality to measure prestige and status. The second measure, polarization, refers to how fractionalized a particular network is and has been used by Maoz (2006) and Cranmer, Menninga, and Mucha (2015) to predict international conflict. The final measure, clustering, refers to a tendency within the network to form cliques. Cranmer, Desmarais, and Kirkland (2012) find that within the defensive alliance network, there are strategic efficiencies associated with triadic closure, that the ally of my ally is my ally.

It is important to emphasize the fact that not all network theories are systemic theories, and that not all systemic theories are network theories. While either proposition could be logically deducted (Emirbayer, 1997), such a conclusion would be analytically and pedagogically problematic (not to mention frustrating to non-networks scholars).

For example, one might consider direct or indirect diffusion of a phenomenon of interest, such as regime type, as a systemic dynamic (Hafner-Burton, Kahler, & Montgomery, 2009). However, such dynamics cannot truly be considered systemic as such behaviors can play out in purely dyadic ways, irrespective of the broader social structure of the network, and as such, may not always be considered systemic. Alternatively, while one might consider the socializing effects of international norms as a network-level dynamic (Hafner-Burton et al., 2009), the effects of international norms may exist independent of the social structure of a particular network. As such, it is worthwhile to articulate the logic of systemic network theorizing clearly.

The networks approach to systemic theorizing uses the organization of actors within a network (topology) in conjuncture with network-level properties (attributes) to explain outcomes of interest, including the formation, maintenance, or termination of social relationships, actor-level outcomes, or broader network-level dynamics. In other words, theorizing just about the effects of topology produces theory that is agnostic toward broader system-structure dynamics, and as such, would just be a network theory. Alternatively, focusing just upon the role of network-level properties would be akin to traditional systemic theories that are agnostic to how these properties interact with network structure to produce outcomes of interest.

Allow us to unpack this logic through the previous example, as socialization can certainly be understood as, but not inherently is, a systemic network phenomenon. In the previous example of the diffusion of state behavior, the diffusion of democracy could be considered a function of contact through shared borders (Gleditsch & Ward, 2006) or common institutional memberships (Cranmer, Campbell, & Desmarais, 2017; Pevehouse, 2002). Simply considering the probability of diffusion as a function of contact or emulation would not be an example of a network-systemic theory as it does not incorporate information about broader system-level dynamics such as norms favoring democracy. However, should one consider this contact, or indirect contact, as operating in conjuncture with broader network-level features like the normative superiority of democracy, then one might consider such a theory as a network-systemic theory (Cranmer, Campbell, & Desmarais, 2017). Alternatively, simply considering the socializing effect of a network-emergent norm might not be an example of a network theory, but a self-organizing theory. It is when those norms are actualized through social relationships that the systemic theory becomes network systemic. Interestingly, network analysis offers an opportunity to also understand norms as an emergent property. Wendt (1999) and Carpenter (2007), among others, view norms as an emergent property of network interactions, and as such, the result of systemic-network dynamics.

Network-systemic theory offers scholars an opportunity to develop hypotheses and explanations related to a wide variety of interdependent phenomena. Over the last 20 years, the ability to test these hypotheses rigorously has emerged. While a review of these techniques is beyond the scope of this chapter, it is worth providing some direction as to the methods that exist. There exist models to test network-informed individual outcomes (Leifeld & Cranmer, 2016), the coevolution of actors and networks (Franzese, Hays, & Kachi, 2012; Minhas, Hoff, & Ward, 2016), tie formation (Desmarais & Cranmer, 2012), among many others (Cranmer, Leifeld, McClurg, & Rolfe, 2016; Desmarais & Cranmer, 2016).

A network-systemic approach is best suited for theories that consider the broader system structure as the causal factor on an outcome of interest, a top-down relationship. This stands in contrast to agent-based modeling or game-theoretic approaches that consider the micro-incentives of actors in producing bottom-up system-level outcomes, or differential equations-based modeling that examines the cyclical relationship between actors and structure in producing outcomes.

Example: Cranmer, Menninga, and Mucha: Kantian Fractionalization Predicts the Conflict Propensity of the International System

While there are a litany of network theories of interstate politics beyond those previously discussed,[8] few can truly be considered systemic theories.[9] This is a shame, as such approaches show great promise. A well-known and emblematic example of network-systemic theory is Cranmer, Menninga, and Mucha's (2015) study of the Kantian tripod and its collective effect on systemic conflict. The Kantian tripod, initially introduced by Kant (1795) refers to the collective influence of democracy, economic interdependence, and international institutions in mediating disagreements between states. This literature is the foundation for much of the quantitative study of conflict, and while ripe for systemic applications, has largely played out in dyadic research designs that treat militarized disputes as distinct phenomena. However, such decisions are problematic and often neglect the systemic network-level dynamics that may inform conflict processes. Cranmer et al. (2015) develop a systemic theory of the Kantian tripod and its effects on conflict, developing a measure called "Kantian fractionalization," which is a unified system-level measure of the degree of division in the trade, joint democracy, and IGO networks.

Cranmer and colleagues (2015) expect that as the Kantian fractionalization of a system increases, the system-wide incidence of conflict should increase. Whenever two states become involved within a dispute, the broader system exercises influence over the dyad. As the system becomes less fractionalized, disagreements would be less likely to escalate as the costs of conflict increase and alternative opportunities for resolution increase. In particular, this theory can be broken down into the actors involved, the broader social structure, the actors' decision spaces, the factors that influence decision outcomes, and what is treated as endogenous or exogenous:

- Actors or Nodes: States.
- Decision-Space: Refrain from fighting, or initiate a militarized interstate dispute (MID).
- Structure or Network: The broader "Kantian" multilayer network composed of states and overlapping relationships with respect to joint democracy, trade, and IGO membership.
- Factors Influencing Decision Making: The costs associated with initiating armed conflict vary according to the overall fractionalization of the multilayer "Kantian" network. This translates to observable implications on the systemic prevalence of conflict:

  - ○ Low levels of fractionalization decrease conflict: The costs associated with conflict increase as the system is less fractionalized and pressure is more likely to be exerted directly or indirectly. As the system becomes increasingly interconnected and less fractionalized, the material and nonmaterial consequences of conflict escalation (economic, normative, etc.) are felt throughout the system. In other words, low levels of fractionalization mean that there are more extensive connections between states and more avenues for recourse or dispute resolution when a conflict arises.
  - ○ High levels of fractionalization increase conflict: The costs of armed conflict decrease as the system becomes more fractionalized and as the trade or normative costs of conflict are less salient. Greater divisions within the international system undermine the effectiveness of trade, democracy, and institutions in mitigating conflict likelihood while also decreasing the appeal of nonviolent solutions to interstate disputes.

- Endogenous and Exogenous Dynamics: Regime type, IGO membership, and trade are treated as exogenous of conflict. While some might argue that this is an unfair assumption, it does not seem relevant to the theory of interest, which considers this as a top-down theoretical dynamic.

They find robust support for this proposition that as Kantian fractionalization increases, the system-level prevalence of conflict increases. This relationship is robust to the inclusion of relevant controls, out-of-sample prediction, and forecasting 10 years into the future (Cranmer et al., 2015, p. 11815). Network-systemic theorizing offers the opportunity to develop, and test, insightful international relations theory. While the number of network approaches to studying international phenomena has proliferated over the last 10 years, few have attempted to devise systemic-level theories. As such, it remains an open and promising literature.

Other Models

While systems of differential equations and network models are probably the methods that are used most often to capture the dynamics of systemic interaction, other methods have been used as well, especially when the goal is to highlight different aspects of systemic politics. However, many methods beyond those presented here possess great, often unexplored potential in developing and testing systemic theory. In this section, we briefly explore two—agent-based models and game theory—which have actualized this potential, and outline the circumstances under which they are most useful. However, it is worth noting that a variety of methods and techniques beyond those presented in this chapter show great promise in the study of systemic theory, including multilevel models (Gelman & Hill, 2006), time series analysis (Box-Steffensmeier, Freeman, Hitt, &

Pevehouse, 2014), survival analysis (Box-Steffensmeier & Jones, 2004), process tracing (Collier, 2011), and qualitative comparative analysis (Braumoeller, 2015).

Agent-Based Models

An *agent-based model* is a computer simulation in which individual actors (the agents, which can represent individual people, organizations, countries, and so on) interact with one another and undergo changes as a result of their interaction. The point of the model is to explore how the “micromotives” of the actors have an impact on the “macrobehavior” of the system as a whole (Schelling, 1978; for a recent review in political science, see de Marchi & Page, 2014).

The great strength of agent-based models is their ability to capture nuanced behavior on the part of agents. The agents in the two systemic models described have fairly straightforward decisions to make—more or less activity; initiate a militarized dispute or don’t—based on the outcome(s) of interest. As those examples suggest, the natural tendency in such models is to build a model with a particular outcome in mind and to focus on the circumstances under which agents do or don’t produce that outcome. By contrast, the logic of agent-based models is more bottom-up: The focus is on the actions of the agents, which produce *emergent properties* at the level of the system—meaning simply that systemic outcomes emerge, often unpredictably, from the interactions of the agents.

As a result, inputs and actions in agent-based models tend to be more open ended than those in other sorts of models. Agents can be thought of as tiny automata that carry out sets of actions conditional on their environment, or on the actions of other agents, or on the amount of time that has passed in the simulation, or at random. If a quantity somewhere in the model can be measured, it can be used as an input that influences an agent’s behavior. In the same way, agents can take a wide range of actions (ally, merge, fight, surrender) rather than just a single action.

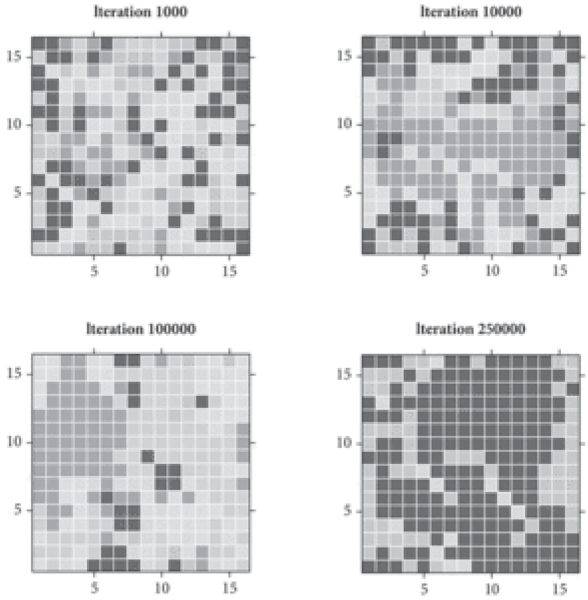
The bottom-up, actor-centered focus of agent-based models does come at a cost: They tend not to focus on the impact of the system on the behavior of agents as much as other models do. Like the generalizations in the previous paragraph, this is a tendency rather than an iron law. Nothing inherent in the nature of agent-based models precludes agentic actions based on systemic structure. But the academic culture of agent-based models is such that the tendency is to focus only on the actor’s immediate environment (a state’s immediate neighbors, for example) rather than on the global environment.

Axelrod (1997) provides an excellent example of how the logic of agents’ behavior—their micromotives—can have a counterintuitive impact on the macrobehavior of the system as a whole. Axelrod explores an artificial system in which actors are differentiated by their values along some number of cultural traits or characteristics. In concrete terms, we can think of these traits as being things like belt color, whether or not they wear hats, and so forth. In each iteration of the model, one actor attempts to interact with an immediate neighbor, selected at random. The probability that the actor will succeed is a function of how similar the two actors are: Very similar agents have a higher probability of communicating with one another. If the agent succeeds, it becomes more like its neighbor along one dimension (changes belt color, starts wearing a hat, or what have you).

The interesting and counterintuitive outcome of this model is the fact that, although the only process is one of cultural convergence, the outcome at the level of the system is divergence. We tend to assume that polarization, whether among nationalities or into Facebook "bubbles," must be the result of hostility among the relevant groups driving them into separate camps. But as Figure 7 demonstrates, a highly heterogeneous initial system in which actors can *only* become more similar to one another gradually becomes more polarized over time.

Applications of agent-based models to the international system, while rare, are generally very interesting. In a shockingly early attempt at modeling balance of power dynamics, Bremer and Mihalka (1977) (see also Bremer, 1977) set up an artificial international system in which actors imperfectly calculate the capabilities of their neighbors and threaten their weakest neighbor if they believe that they can prevail in a fight. Threatened neighbors attempt to form defensive coalitions, and depending on their degree of success the initial actor either attacks or does not. If there is an attack, the loser is absorbed by the winner. Their surprising conclusion is that, while all of their assumptions are derived from existing theories of the balance of power, the result of the model is invariably universal empire—precisely the outcome that the balance of power is meant to prevent.

Starting with a logic that is similar to that of Bremer and Mihalka, Cederman (1997) explores the implications of changes in the degree of aggressiveness of the actors in the system and of changes in the balance between offense and defense on the outcome at the system level. Cederman finds that varying these dimensions allows for outcomes other than universal empire and has a significant impact on the emergent property of systemic polarity.



Click to view larger

Figure 7. A system with local convergence and global divergence (3 traits).

Because the results of an agent-based model are typically *path dependent*, or conditional on intervening states of the world, it can be very difficult to infer much of anything from a single run of the model. Cederman's solution to this problem is to run the model many, many times and compare the percentage of outcomes of a given type (stable balance of power, say, or empire) under one set of circumstances to the percentage of outcomes of that type under different circumstances. It is then possible to conclude, for example, that the percentage of balance-of-power cases increases when the defense becomes more dominant.

More generally, comparing the results of multiple runs of an agent-based model, either to one another or to the actual state of the world, can be a very powerful technique for drawing inferences either about the influence of varying model parameters or about the most likely parameters given the state of the world. For instance, Kinne and Bunt (2017; see also Kinne, 2013) use a stochastic-actor oriented model of network evolution developed by Snijders (2005) that they describe as "an agent- based model that achieves statistical inference by comparing simulated networks to real-world networks, with the goal of selecting model parameters that generate simulated networks that resemble as closely as possible the observed networks" (p. 20). These approaches, which compare results of simulations to observed phenomena, offer a powerful means of appraising self-organizing theories.

Because agent-based models focus on emergent properties, they are also well suited to capturing constructivist arguments about identity formation. At present, much of this potential remains underexplored (though see Lustick, 2000; and Rousseau & van der Veen, 2005, for exceptions).

Game Theory

Game theory is a method of theorizing that emphasizes situations of *interdependence*. At its foundation are a set of *players*, or decision making agents, which act in *strategic situations* where each player's behavior affects the other's well-being, and as a result, players come to decisions conditioned on the expected behavior of other players (Myerson, 1991; Watson, 2002). Often, game theory is performed using formal mathematical models, or models in which actors, their interests, exogenous rules, and the strategic setting are written in mathematical language as to allow for the derivation of certain theoretical expectations (Watson, 2002, p. 5). Typically, scholars envision strategic settings where actors either attempt to cooperate, or to compete (Watson, 2002).

Consider the canonical Prisoner's Dilemma, which tells the story of two alleged criminals taken into custody. The two accused (players) are interrogated separately, where each has the ability to *cooperate* with the other criminal and remain silent, or *defect* and admit to the crime while selling out their partner. Each player has the goal of maximizing their payoff through minimizing the amount of time they serve in jail.

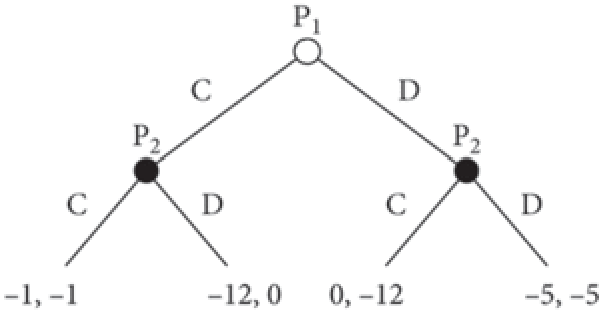


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Figure 8. Payoffs in the Prisoner's Dilemma game. Payoffs are in years of freedom, with payoff to Player 1 listed first.

The Prisoner's Dilemma's strategic setting is constituted by a set of rules, including the inability of players to coordinate, incentives for actors to defect, and the rules of the game that influence each player's payoff schedule. Each player's payoff is determined by the interaction between their decision and the decision of their partner. This schedule of different outcomes is presented in Figure 8. For each player, defection while the other cooperates leads to the optimal outcome: The player who defects turns state's witness and spends no time in prison, while the player who cooperates pays the full price for the crime and spends 12 years behind bars. If both players try to defect, they share the blame for the crime and each spends 5 years in prison. If both cooperate, there is enough circumstantial evidence to send each to prison for a year, but no longer.

The logic of the game is fairly straightforward to follow. Regardless of what Player 1 does, Player 2's best option is to defect: S/he can walk free rather than spend a year in jail if Player 1 cooperates and can spend 5 years in jail rather than 12 if Player 1 defects. Knowing that Player 2 will defect, Player 1's best option is to defect as well in order to avoid spending 12 years behind bars. (D,D) is therefore the sole equilibrium outcome in pure strategies when the game is played once.

The Prisoner's Dilemma provides a useful simplification of a common strategic logic of state interaction under anarchy: The best collective outcome can be achieved by cooperation, but cooperation is undermined by individual states' self-interest. As Waltz (1979, p. 109), citing the logic of the Prisoners' Dilemma, wrote,

> How can [states] resolve the tension between pursuing their own interest and acting for the sake of the system? No one has shown how that can be done, although many wring their hands and plead for rational behavior. The very problem, however, is that rational behavior, given structural constraints, does not lead to the wanted results. With each country constrained to take care of itself, no one can take care of the system.

Fortunately, a response to Waltz's grim depiction of the international system was not long in coming: Axelrod (1981, 1984) underscored the importance of the "shadow of the future," or the prospects of future interaction, in promoting cooperation. To return to Figure 8, when players play the game multiple times and have the option of punishing one another for defection, the advantages of defection dwindle: The fact that no one would willingly suffer the "sucker's payoff" of 12 years in jail more than once permits a cooperative equilibrium in iterated play. When realist scholars questioned these conclusions on the grounds that the logic of competition under anarchy forced states to emphasize relative rather than absolute gains, Snidal (1991) demonstrated that cooperation could be sustained under nearly any admixture of relative and absolute gains calculations.

While this and other rational-choice models[10] usefully capture the impact of anarchy on the behavior of states, however, models that actually capture the behavior of entire systems of states are very rare, largely due to the complexity of figuring out how every state's optimal strategy interacts with every other state's. The main exception to this generalization is Niou, Ordeshook, and Rose (1989), which utilizes *cooperative game theory*, a branch of game theory in which outcomes are assumed to be enforceable (via contracts, for example),[11] to model coalition formation among major powers and help us to understand the logic of balance-of-power politics.

The effort is a remarkably illuminating one. It portrays balance-of-power dynamics as a contest over the distribution of resources. States prefer to maximize resources, although their first priority is survival. Given that relatively spare set of eminently reasonable assumptions, the authors derive some surprising conclusions. First, system stability (the continued existence of all of the major states) occurs only when each state can contribute to a dominant coalition, thereby nullifying a threat to its own existence. Moreover, resource stability (an unchanging distribution of resources) never happens unless one state possesses exactly half of the system's resources—no more, no less. Its most compelling feature, however, is the manner in which it manages to capture the logic of balance-of-power politics in a world in which states focus on survival and resources, in that order.

Conclusion

We hope that our article has illustrated some noteworthy similarities and differences across the different methods used to capture systemic theories of international relations. All of the methods that we have described are useful for capturing emergent properties—system-level outcomes that cannot be inferred from the behavior of the individual actors. Each places emphasis on different aspects of systemic theorizing, from the variety of actor-actor, actor-structure, and structure-actor relationships that comprise a system (equation-based modeling) to the embeddedness of actors in broader social structures (network theory) to the macrostructural implications of agents' activity (agent-based modeling) to strategic interdependence (rational choice). Each lends itself to different depictions of agent-structure relationships: While network theory emphasizes the structure of the network itself and its impact on state behavior, agent-based models focus on distributions of outcomes across agents or across different runs of the model, and systems of differential equations can be used to illustrate the ways in which systemic forces “shape and shove” the behavior of actors.

We also hope that the diversity of the methods that we have described will help to avoid, or at least alleviate, the common pathology of “methods-first theorizing.” There is no doubt that methods can powerfully shape theory: Students who learn regression have a remarkable tendency to think about their chosen y as a function of $X\beta$, One solution to the problem of hammer owners perceiving everything as a nail is to give them a more diverse toolbox. Another, of course, is to urge them to revisit the qualitative literature on systemic theory, which was conceived in the absence of the sorts of intellectual constraints that a narrow training in methods can impose.

Despite their differences, these approaches are unified in one important sense: They reject the theoretical proposition that the international system can usefully be understood as the simple sum of the actions, characteristics, and preferences of the actors that comprise it. Just as the utility of game theory surpasses that of decision theory when the number of actors goes from one to two, the utility of systemic theory surpasses that of monadic or dyadic theory when the number of actors goes from two to many. In short, as Braumoeller (2012, pp. 10–11) puts it, “no amount of sophistry, deft wielding of assumptions, or outright hand-waving can provide an adequate substitute for actually including the entire system in the analysis.”

Fortunately, as the discussions and examples demonstrate, systemic theorizing and testing systemic theories are more straightforward now than they’ve ever been before.

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Notes:

(1.) There is another equilibrium at $f = 0$ and $r = 0$, of course, but it’s less interesting.

(2.) It is worth noting that Waltz, confusingly, uses the word “balance” to connote both equilibration (“balancing behavior”) and the condition of equal power across the major powers (“balance in the system”). Although he theorizes that the former will produce the latter, that need not be the case, as Braumoeller (2012, ch. 2) demonstrates.

(3.) For full details and derivation, see Braumoeller (2012, Appendix A).

(4.) Cranmer and Desmarais (2016) provide an exceptional treatment of this principle and the theoretical and empirical problem of independence in the context of IR research.

(5.) For additional reading on this principle, we direct readers to Wejnert (2002) and Lazer (2005).

(6.) Hanneman and Riddle (2005) discuss this principle within the context of an entity’s individual ego network in Chapter 9.

(7.) For a good discussion on this problem, we refer the reader to Fowler, Heaney, Nickerson, Padgett, and Sinclair (2011), Franzese, Hays, and Kachi (2012), Rogowski and Sinclair (2012), and Sinclair and Rogowski (2016).

(8.) For further reading, we would direct the reader to Chyzh (2016), Cranmer, Campbell, and Desmarais (2017), Cranmer, Desmarais, and Kirkland (2012), Cranmer, Desmarais, and Menninga (2012), Cranmer, Heinrich, and Desmarais (2014), Dorussen, Gartzke, and Westerwinter (2016), Gallop (2016), Gartzke and Westerwinter (2016), Haim (2016), Metternich, Dorff, Gallop, Weschle, and Ward (2013), and Ward and Dorussen (2016). For a more complete treatment, see Victor, Montgomery, and Lubell (2016).

(9.) Among these systemic theories, one might consider Cranmer, Menninga, and Mucha (2015), Dorussen and Ward (2008), Maoz (2009). and Maoz and Joyce (2016) as proper examples.

(10.) See, e.g., Fearon (1995) and Jervis (1978).

(11.) The Prisoner’s Dilemma, by contrast, is an example of noncooperative game theory, in which outcomes are self-enforcing.

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