A Behavioral View of Core-Periphery Dynamics in Social Networks

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Abstract

We model the dynamics associated with evolution of the core and the periphery of a social-network. The model is based on an existing behavioral theory of the inter-firm (Baum and Ingram 2002). The formalization allows us to refine this existing theory through the introduction of a target setting process. Allied analysis documents the efficacy of exploration and exploitation policies within the core and across the periphery of a social network. Our results show that the competitive advantage accrued through exploration and exploitation is crucially affected by the behavioral biases, imitation and the target setting associated with the evolution of key constructs such as core and periphery embeddedness.

(Behavioral Theory, Core-Periphery Dynamics, Exploration, Exploitation, Social Networks)

1. Introduction

The interest in studying social networks has been rising in diverse organizational settings (Borgatti and Foster 2003). Within this context, core and peripheral embeddedness have been shown to be key constructs that govern network evolution (Gulati and Gargiulo 1999). The term core refers to the topography at the center of a network, whereas periphery refers to the edges of such a network. Embeddedness is defined as a stock of social relations or organizational ties that shapes economic action in ways that some economic schemes overlook (Granovetter 1985). For example, Powell et al. (2005) observe embeddedness in terms of formal *and* informal exchanges of R&D know-how across an emerging network of firms in the biotech industry. Scientists in this industry trade information with like-minded scientists and experts outside their firms, even in the absence of formal economic ties.

Managing trade-offs underlying the core-periphery evolution is a central theme in social network research. We view this theme through the lens of behavioral theory (Cyert and March 1963). An example of such trade-off is the behavioral choice: exploration of the network, instead of exploitation, is the preferred approach for organizational learning (March 1991) -- exploration builds more embeddedness into the periphery than into the core. Exploitation reverses this bias. Linkages of these choices into the network evolution process are complex. For instance, some organizational scientists have argued that social networks evolve in a nonlinear manner owing to a paradox of embeddedness (Uzzi 1997), i.e. the marginal gains from increasing embeddedness are positive up to a threshold. Increasing embeddedness beyond this threshold provides diminishing returns. Others have argued that there is a saturation level associated with the evolution of embeddedness (Baum and Ingram 2002). These arguments raise many managerially relevant questions: what might be the antecedents and consequences of embeddedness thresholds and the saturation phenomena? Is exploration a desirable strategy for network growth, as opposed to exploitation, when embeddedness lies below the above-mentioned threshold? And if so, should a firm explore the core or the periphery of a social network?

While network studies have been using a variety of methodologies, ranging from ethnography (Uzzi 1997) to system dynamics modeling (Rahmandad and Sterman 2004), much of recent social network research has relied on empirical studies. Most of these empirical approaches have not been able to explore above-mentioned questions due to data limitations. It is difficult to find datasets that address scenarios where the network evolution spans the embeddedness threshold or where embeddedness approaches a saturation level. Hence, most studies cannot take on systematic exploration of allied behavioral choices (e.g. institutional and firm decision rules associated with social network emergence, target setting processes and cognition delays). On the other hand, this literature offers rich descriptions, careful statistical analysis, and theory driven insights for selected phases of the social network evolution.

Modeling can stitch together a theory that spans all the phases of evolution and overcome some of the limitations of empirical research. We formalize a qualitative description of a network evolution theory put forth by Baum and Ingram (2002). System dynamics modeling is our method of choice because of its ties to the behavioral research tradition (Sterman 1989, Sastry 1997, Reppening 2002), and because non-linearity (Uzzi 1996) and feedback effects are inherent within descriptions of social network emergence (Gulati and Gargiulo 1999). This formalization allows us to connect March's view of exploration/exploitation and the competition for primacy (1991) with theories about the evolution of networks: the paradox of embeddedness (Uzzi 1997), process evolution hypotheses (Baum and Ingram 2002) and Powell et al's view of co-evolution (2005) between a focal firm and an institution. The term institution refers to an environment within which the social network can evolve. We explore, and in some instances refine, previously postulated relationships among constructs such as embeddedness, interdependence and positional advantage. These constructs are defined in §2 and §3.

Along with theory refinements, our model offers opportunities for policy analysis. The model structure and outputs are seen to be consistent with Uzzi's (1996) empirical findings on the paradox of embeddedness and Baum and Ingram's (2002) process evolution hypotheses. This has built confidence in our belief about the validity of the underlying model structure. The second half of this paper demonstrates how the model can be applied for policy analyses in order to verify and extend existing empirical findings. We simulate a variety of exploration and exploitation policies for growing the network core or the periphery, or both. These simulations provide insights for accruing positional advantage (defined in §3.3) under a wide range of behavioral conditions: when the institution values core more than periphery, when the firm has a bias for growing its dyadic relations in the core instead of the periphery, when the institution is seen to set up embeddedness targets in an endogenous manner and so on. Our results show that the competitive advantage accrued through exploration and exploitation is crucially affected by the behavioral biases, imitation and the target setting associated with the evolution of constructs such as core and periphery embeddedness.

The rest of the paper is organized as follows. In §2, we discuss the behavioral theory of the inter-firm and identify dynamic hypotheses. §3 and §4 cover model specification and validation respectively. We lay out policy analysis results in §5 and conclude in §6.

2. Behavioral Theory for Network Evolution

Goal setting, expectations and choice are central tenets of the behavioral theory of the firm (Simon 1959, Cyert and March 1963). This theory addresses decision-making processes. The unit of analysis of the theory is a firm or a node within a social network. Firm's behavioral choices involve picking a goal and getting close to this goal in a satisfying manner. Cyert and March have argued that, "we can analyze the process of decision making in a modern firm in terms of the variables that affect organizational goals, the variables that affect organizational expectations and the variables that affect organizational choice." In this theory, choices and search are closely intertwined: search mechanisms (e.g. exploration or exploitation) are often motivated, simple minded and biased by behavioral choices.

Translating the concepts underlying a nodal theory of the firm into an inter-firm or network-based theory is not a trivial exercise. Recent advances in organizational science have explored many underlying concepts with "links" or "dyads of firms" as their unit of analysis (see

Borgatti and Foster 2003 for a review). Key constructs and their interrelations are described in the next section.

2.1 Key Constructs and Interrelations

Organization science literature has identified core and peripheral embeddedness as key dyadic constructs that govern the emergence of networks. Numerous studies have added to our understanding of how these constructs might be measured and what their antecedent and consequences might be. Some researchers have observed core embeddedness in structural terms by measuring the extent to which dyads shared common partners. Peripheral embeddedness has been viewed in terms of structural differentiation by measuring the standard deviation of the normalized prominence (Gulati and Gargiulo 1999). Others have added cognitive dimensions such as shared beliefs and mental models to these measurements (Baum et al. 2003).

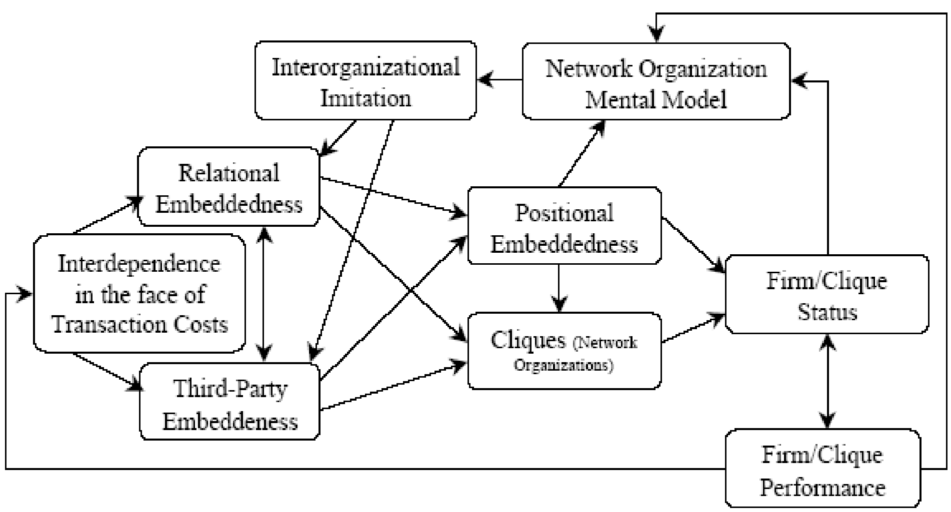

Figure 1: Postulated Relationships between Constructs (Baum and Ingram 2002)

Several other constructs have been observed to be significantly associated with the evolution of embeddedness. These constructs are often related to network performance such as growth in network size (Gulati and Gargiulo 1999) and status (Baum and Ingram, 2002). Interdependence is a construct that measures formal information exchanges across a dyad. Raising embeddedness can lower interdependence in the face of transaction costs (Williamson 1975). Interdependence has also been shown to rise as a consequence of increased coordination requirement when the network size grows.

Based on a review of social network theory and empirical findings, Baum and Ingram (2002) postulate that these key constructs relate to one another in the manner shown in Figure 1. Their approach is a conceptual – it does not focus on whether some of these relationships are causal or correlated and a goal setting process has not been captured explicitly in their argument. We will draw upon their work while specifying the constitutive relationships in §3.

2.2 Dynamic Hypotheses

The term dynamic hypothesis refers to the nature of changes in the strengths of key constructs, as these constructs evolve based on their interplay with other constructs. Baum and Ingram use the structure in Figure 1 to postulate the modes of evolution for embeddedness, interdependence and network performance as shown in Figure 2. They separate structural and cognitive elements of embeddedness in their figure. We have eliminated some details from their hypotheses for ease of presentation.

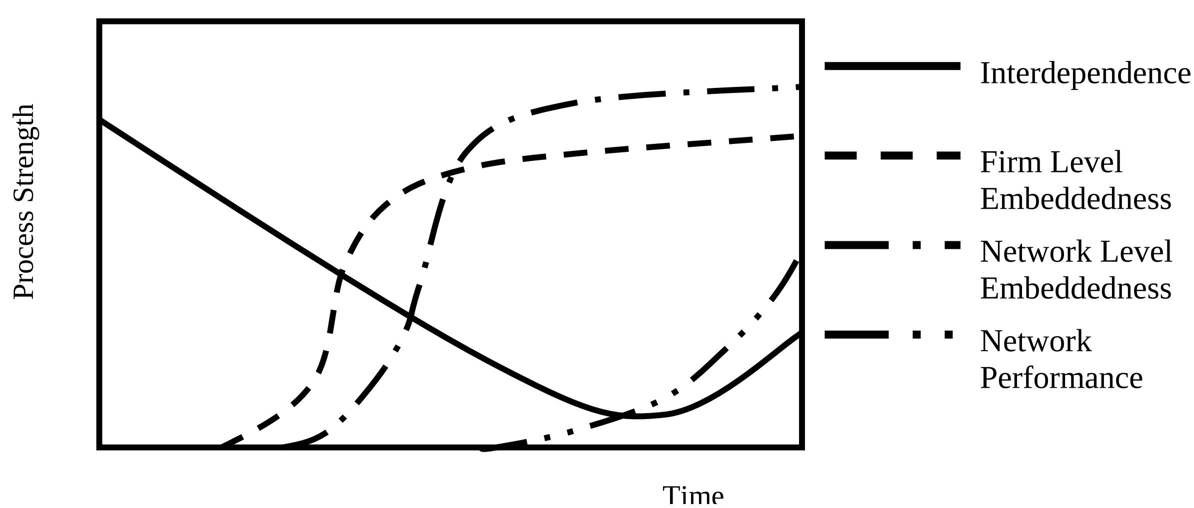

Figure 2: Postulated Evolution of Process Strength (Based on Baum and Ingram 2002)

These modes of evolution suggest that while embeddedness exhibits growth and saturation, the network size continues to rise. The rise in embeddedness is accompanied by a reduction in the interdependence. Subsequent increase in the network size raises interdependence. Baum and Ingram also suggest that for search processes to be effective, a focal firm within a network ought to organize their search policies in the manner shown in Table 1. They have tested their hypotheses for exploration and exploitation by conducting empirical studies in the Canadian banking industry (Baum et al. 2003).

Table 1: A Satisfycing Organizational Search Policy

		Behavior Mode	
		Exploration	**Exploitation**
Embeddedness	**Firm Level**	Weak ties	Strong ties
	Network Level	Structural holes	Closure

The policy in Table 1 does not account for the institution's bias (e.g. core versus periphery) for assessing competitive advantage. We introduce the idea of positional advantage in §3 and later discuss the efficacy of a family of policies, based on Table 1, in accruing such an advantage.

2.3 Refinements

The process of building a formal model has allowed us to verify, and in some instances refine, the relationships between key constructs.

The most important refinement offered by our approach is the introduction of a target embeddedness construct explicitly into the theory. While Uzzi (1997) has pointed to a paradox of embeddedness, explicit attention to goal setting has been lacking in the theory of inter-firm literature. Drawing upon the basic tenets of the behavioral theory, we add **embeddedness target** to the list of key constructs. This allows us to explain the S-shaped growth of embeddedness shown in Figure 2 with a parsimonious formulation (Sterman 2000). We set up our model sequentially: we begin with exogenous target embeddedness and later make it endogenous. The empirical evidence on how embeddedness targets evolve is scant. We *assume* that one mechanism that will contribute to the target setting process is interdependence in the face of transaction costs. This assumption is motivated by a boundedly rational view of transaction costs.[1] We exclude other constructs, e.g. trust, that could contribute to target setting to keep the formulation parsimonious.

Another refinement involves the segregation of causal versus correlated relations between constructs. Existing theories do not specify whether connections between various embeddedness constructs are have causal links. Based on evidence of co-evolution of firms and institutions (Powell et al 2005), we treat all the embeddedness stocks as correlated, although there may be time delays between their evolution due to imitation and/or formation of expectations. A side benefit of this effort is the construction of a system dynamic structure for co-evolution of networks and a focal firm's links within an institution.

We also make explicit causation assumptions about other constructs (e.g. status and network size). These assumptions are discussed in §3. Recall that the goal of our policy analysis effort is to assess the efficacy of the policies for exploitation (and exploration) of the network core and periphery. We have made modeling choices that allow us to set up policy analysis in a structured manner. For instance, decision rules for assignment of embeddedness are set up as exogenous variables, so that they can be varied systematically during policy analysis.

3. Model Specification

For ease of description, our model specification has been divided into three sectors that address the diffusion of overall embeddedness, the assignment of individual embeddedness stocks, and

[1] The parameters used for the endogenous specification have been selected arbitrarily. We have tested our model for all possible values of these parameters and the results of our subsequent analyses are robust over the entire range. We call for empirical measurements of such a specification in future research.

the computation of positional advantage based on these individual stocks, respectively. We begin by specifying constituent relations in each sector. We then identify feedback relations that integrate these sectors to set up the base case model. We end this description by specifying additional relationships, that make certain control constructs endogenous, and extend the boundaries of the base case model.

3.1 Embeddedness Diffusion

In the base case, we assume that there exists a level of embeddedness, termed as embeddedness target (ET), which is set to be the goal for each firm within an institutional context. We also assume that initial embeddedness is set at a level below the target. The diffusion of embeddedness from the initial condition to the target level is governed by two mechanisms. Embeddedness attracts embeddedness. And, the growth in embeddedness is also driven by the gap between ET and the existing embeddedness stock. These mechanisms are shown as feedback loops in Figure 3. The interplay between these mechanisms yields a S-shaped diffusion curve (Sterman, 2000).

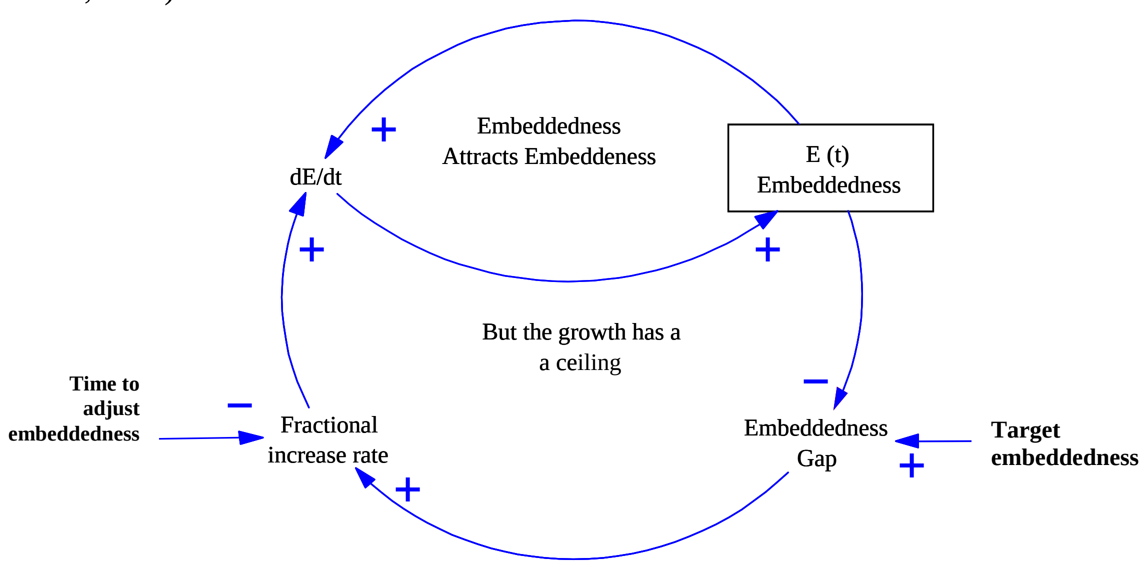

Figure 3: Embeddedness Diffusion Mechanisms

The speed of diffusion is controlled by the Time to Adjust Embeddedness (T_{AE}). If E(t) is the overall embeddedness at a firm within the institution, then:

$$dE/dt = (E / T_{AE}) * (ET-E)/E \qquad \ldots\ldots (1)$$

3.2 Decision Rules for Assigning Embeddedness

The growth rate (dE/dt) for overall embeddedness for any one firm within an institution is derived in §3.1. We assign this growth rate to two pairs of stocks. Each pair features core embeddedness and peripheral embeddedness. While making this assignment, we draw upon the work of Powell *et al* (2005) to posit that these two pairs of embeddedness stocks co-evolve over the time duration of interest.

The first pair consists of the firm core embeddedness (F_{CE}) and firm peripheral embeddedness (F_{PE}). The firm is identified as an agent within an institution that can make assignment decisions in self-interest. These decisions may either be identical be different from the decisions made by another firm in the surrounding institution.

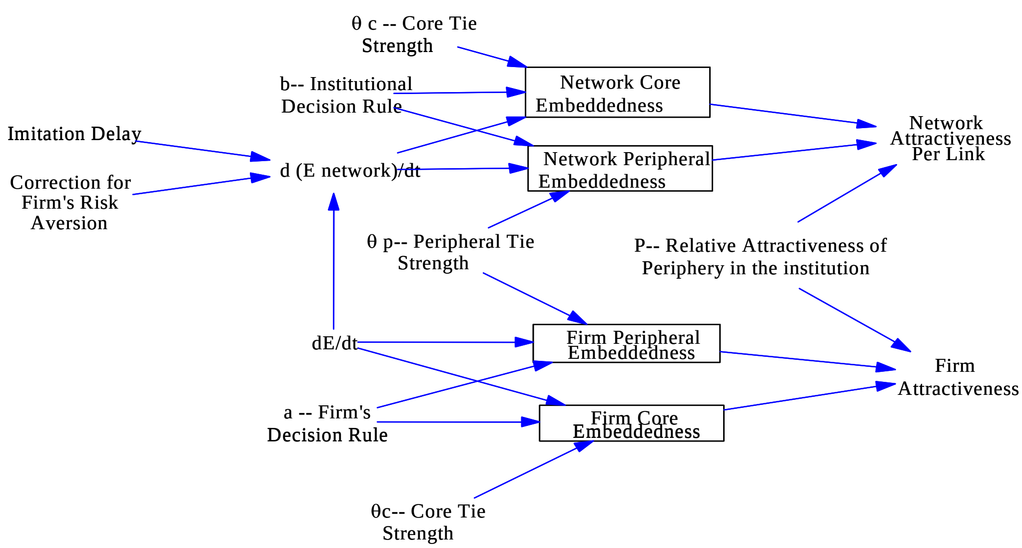

Figure 4: Decision Structure for Growing Two Pairs of Embeddedness Stocks

The second pair consists of institutional core embeddedness (I_{CE}) and institutional peripheral embeddedness (I_{PE}). This pair tracks the embeddedness associated with an "average" firm within the institution. Without a loss of generality, we will assume that the institutional decisions lag the firm decisions by a fixed time constant, termed as imitation delay (T_I), as shown in Figure 4.

Let 'a' (s.t. $0 \le a \le 1$) represent a non-dimensional decision parameter that captures the firm's assignment rule and 'b' (s.t. $0 \le b \le 1$) represent another non-dimensional parameter that captures the institution's assignment rule on average. Setting up either 'a' or 'b' above 0.5 indicates a bias in favor of growing the core embeddedness and vice versa. Then,

$$d F_{CE} /dt = a * \theta_c * dE/ dt \qquad \text{...........(2a)}$$
$$d F_{PE} /dt = (1-a) * \theta_p * dE/ dt \qquad \text{...........(2b)}$$

and

$$d I_{CE} (t-T_I)/dt = b * r * \theta_c * dE/ dt \qquad \text{...........(3a)}$$
$$d I_{PE} (t-T_I)//dt = (1-b) * r * \theta_p * dE/ dt \qquad \text{...........(3b)}$$

Here, r (≥ 0) is a correction for the risk averseness of the firm. The default value for r is set to 1.1, implying that the institution will reach a level 10% above ET for the firm. θ_c (s.t. $0\le \theta_c \le 1$) and θ_p (s.t. $0\le \theta_p \le 1$) capture the strength of ties within the core and the periphery respectively. We assume that the initial stocks F_{CE} (0), F_{PE} (0), I_{CE} (0), and I_{PE} (0) are known. We stipulate that $0 < F_{CE} (0) < I_{CE} (0) < ET$ and $0 < F_{PE} (0) < I_{PE} (0) < ET$. These stipulations restrict the follow on analyses to situations where the firm starts out with lower embeddedness than the institution.

We measure the attractiveness of the firm or the institution by combining respective core and peripheral embeddedness. We follow Uzzi's (1996) results to set up this specification: core embeddedness makes a linear contribution to attractiveness, but peripheral embeddedness makes a linear and a quadratic contribution. This specification ensures a convex attractiveness function, and allows the model to address both the under and the over embedded regimes.

Let p (≥ 0) be the parameter that defines the relative attractiveness of core and periphery and let q (≥ 0) be the multiplier on the quadratic terms. F_A and I_A, the firm and institutional attractiveness constructs are specified as:

$$F_A(t) = \{F_{CE}(t)/ET\} + p * \{ F_{PE}(t)/ET - q * (F_{PE}(t)/ ET)^2\} \quad \text{.......... (4)}$$
$$I_A(t) = \{I_{CE}(t)/(r*ET)\} + p * \{I_{PE}(t)/(r*ET) - q * (I_{PE}(t)/(r* ET))^2\} \quad \text{.......... (5)}$$

To mirror the proportions in Uzzi's data, the default values of p and q are set to be 1 and 0.5. With p=1, attractiveness is unbiased in terms of core and peripheral embeddedness. If p <1, attractiveness favors the core and vice versa.

3.3 Positional Advantage

March (1991) argues for inclusion of centrality and variance constructs while assessing the firm's position within a competition for primacy. Our definition of PA, a positional advantage construct, follows March's formulation for advantage within a competition for primacy:

$$PA(t) = F_A(t) / \{F_A(t)+ N(t) * I_A(t) \} \quad \text{........... (6)}$$

Here, N(t) is the size of the network at time t. This sector of the model is shown as a causal loop diagram in Figure 5.

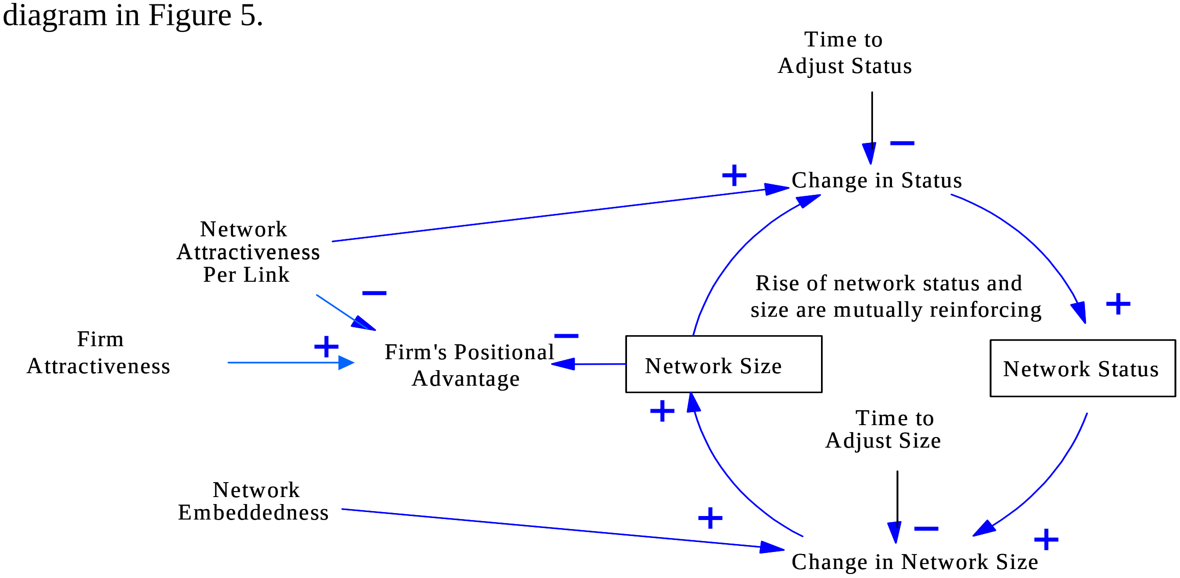

Figure 5: Evolution of Positional Advantage

We have drawn upon the work of Baum and Ingram (2002) and Baum et al (2003) to assess N(t) and allied status and interdependence constructs: S(t) and D(t).

Network Size:= $N(t) = C_1 * S(t) * \{ C_2 * I_{CE}(t) + C_3 * I_{PE}(t)\} / T_{AN}$ ……………. (7)
Network Status:= $S(t) = C_4 * N(t) * \{ C_5 * I_{CE}(t) + C_6 * I_{PE}(t)\} / T_{AS}$ ……………. (8)
Interdépendance:= $D(t) = 1 - A_1 * \{ C_7 * I_{CE}(t) + C_8 * I_{PE}(t)\} + A_2 * N(t)$ …………. (9)

C_i (> 0) for i=1,8 are scaling parameters set to be unity without loss of generality. T_{AN} (> 0) is the time to grow the network. T_{AS} (> 0) is the average cognition time needed to establish network status. A_1 and A_2 are positive fractions. The specification for interdependence in the face of transaction cost mirrors Baum and Ingram (2002)'s argument that interdependence reduces while embeddedness is building up. However, as the network size grows, the coordination burden increases and overcomes the reduction in interdependence due to the presence of embedded relationships.

3.4 Overall Model

Equations (1) through (8) are integrated to build the overall model. The structure of the overall model is shown in Figure 6. Feedbacks have been shown with dotted lines.

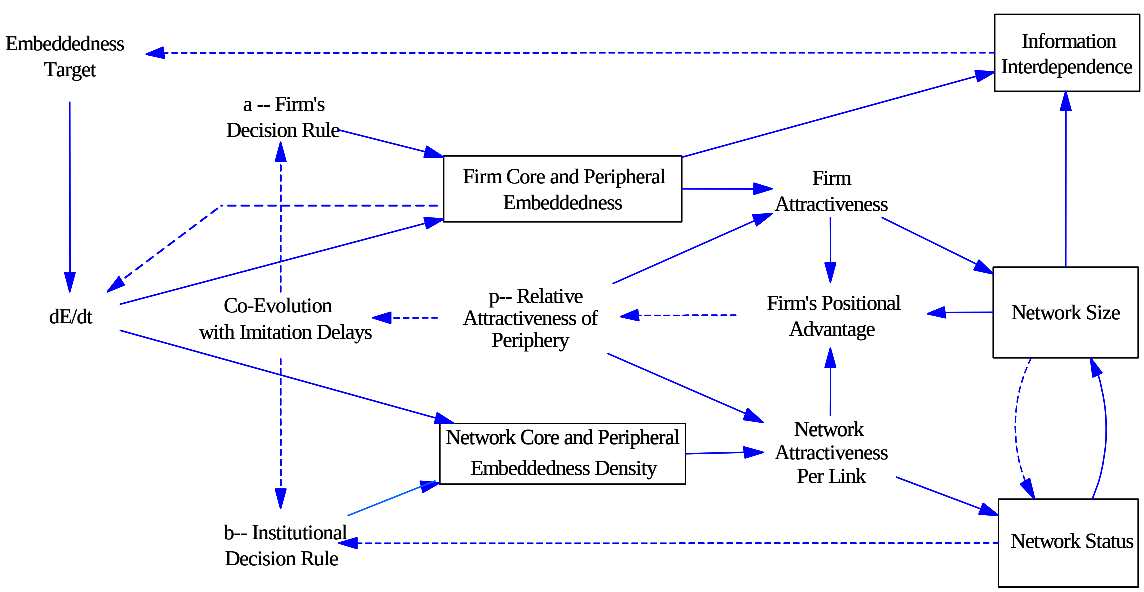

Figure 6: The Overall Model Structure
(Some constructs and polarity on the arrows omitted for ease of depiction)

Construct E(t) is linked with the outcome parameters in the assignment sector as follows:

$$E(t) = F_{CE}(t) + I_{PE}(t) \quad \text{or} \quad E(t) = \{I_{CE}(t) + I_{CE}(t)\}/ r \qquad \ldots\ldots\ldots\ldots(10)$$

Before setting up the base case, decision parameters ‘a’ and ‘b’ and the strength of ties θ_c and θ_p are kept as independent variables. These parameters are varied systematically to explore the response of the model over their entire range of validity. In the base case, these decision parameters have been set to be equal (i.e. a = b). In analyses that follow the base case, target embeddedness (ET) is set up as an endogenous parameter as follows:

$$ET(t) = C_9 * \max\{1- D(\tau)\}, \ \forall\ t \geq \ \tau > 0 \qquad \ldots\ldots\ldots\ldots..(11)$$

C_9 is a scaling parameter. The specification in (11) relates the target embeddedness with the evolution of the interdependence construct. We justify this specification based on transaction costs associated with information interdependence. When the interdependence falls, due to a rise in embeddedness, institutions are willing to raise the desired level of embeddedness. The desire for increased embeddedness is curbed when information interdependence rises due to increases in the network coordination costs.

4. Validation

Owing to a lack of empirical data for one to one comparison, we cannot calibrate the model performance against time series for each of construct of interest. Instead, we have selected a complete and reasonable range of input parameters and explored the evolution of the full model in a systematic manner. The goals of this exploration are to ensure that model performs consistently, internally and externally, against the theoretical underpinnings (e.g. paradox of embeddedness) and the dynamic hypotheses (a.k.a. the empirically observed changes in embeddedness parameters, network size, and interdependence over the entire life cycle of evolution).

Following standard practice in the system dynamics literature, we have set up a series of tests to explore the structure and the evolution of constructs in each sector. The term structure refers to the constituent relationships specified in the previous sections. These tests set up selected constructs, such as decision parameters ‘a’ and ‘b’ as exogenous parameters. Tests have been conducted over the entire span of the feasible values for each parameter (e.g. $0 \leq a \leq 1$), and for all reasonable combinations (e.g. changing $0 \leq a \leq 1$ and $0 \leq b \leq 1$). In this section, we present a subset of test results. The rest of the validation results are available upon request. The output parameter for these tests is the value of the average positional advantage (APA) over the entire duration of evolution. Results have been grouped under two headings: paradox of embeddedness and evolution of process parameters.

4.1 Paradox of Embeddedness

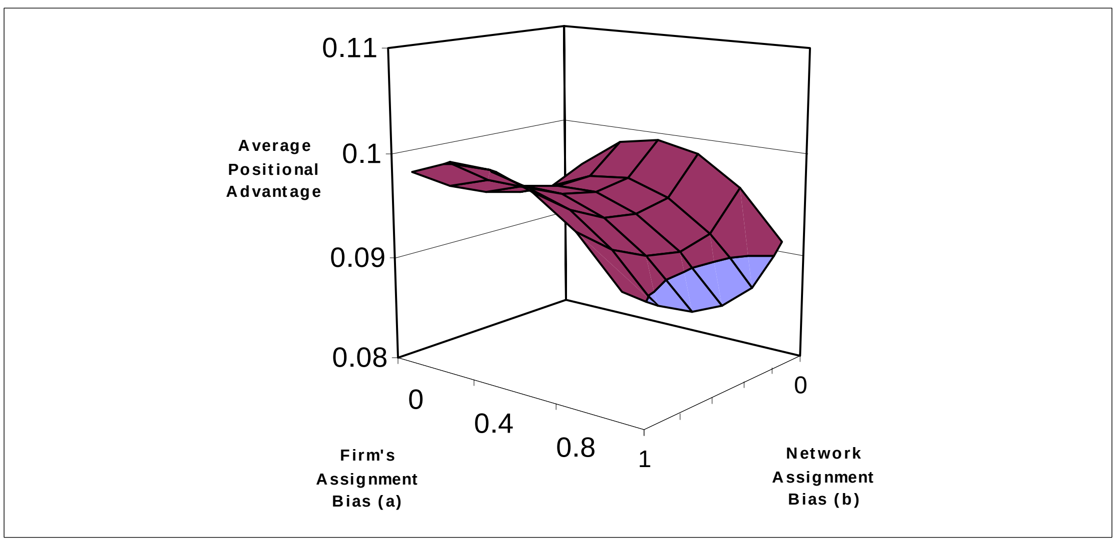

Figure 7: Response to Variation in the Decision Bias

Figure 7 shows the model response surface as a function of decision parameters ‘a’ and ‘b’. Recall that higher value of ‘a’ (a > 0.5) represent the firm’s bias towards building core embeddedness and lower values (a <0.5) are biased towards building the periphery. Similarly higher values of 'b' indicate the institution's bias towards building the core. The saddle shaped response surface confirms that the model can reproduce the paradox of embeddedness postulated by Uzzi (1996): setting 'a' (or 'b') to extremes will yield the lowest (or highest) positional advantage. Note that our outcome variable (Average Positional Advantage, APA) is not the same as the outcome variable used by Uzzi (Probability of Failure, POF). The functional form of APA and USF are analytically analogous, however POF accounts for the network effect implicitly by comparing the firm's performance against a constant value for the network attractiveness.

We have repeated (but not shown) our analyses using Uzzi's input parameters with both POF and APA as the outcome variables. Results are materially similar. Since we are interested in isolating APA and network size effects during policy analyses, rather than compare the survival probability, we have used APA as an outcome parameter in the rest of this paper.

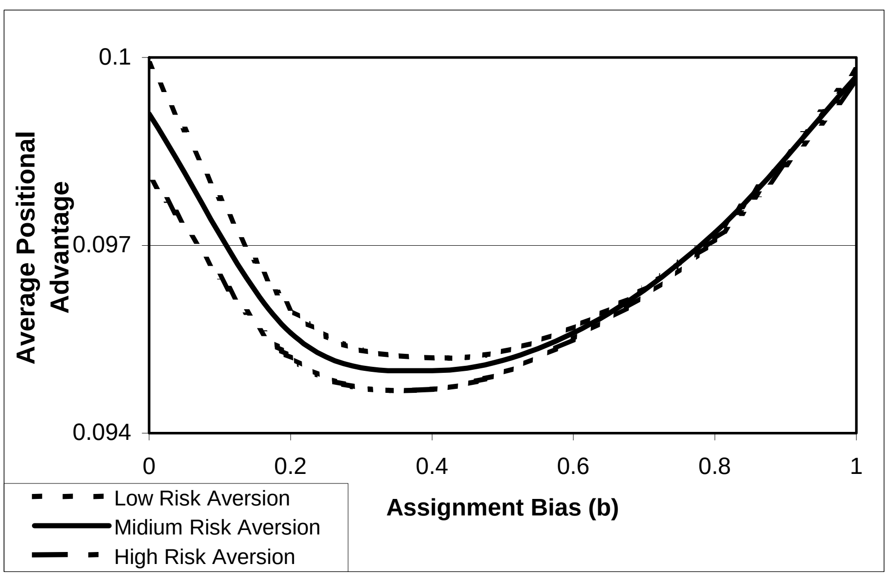

Figure 8: Effect of Changing Risk Aversion

Figure 8 shows that when the focal firm's risk aversion rises, its average positional advantage is reduced. Uzzi (1996) has reported similar results while using a POF formulation. We have also explored the model response beyond replication of Uzzi's results. For instance, we have varied the relative attractiveness of periphery (i.e. parameter p in Equation 5). Figure 9 illustrates that the APA for low values of network assignment bias will be diminished and when periphery (p) becomes more attractive.

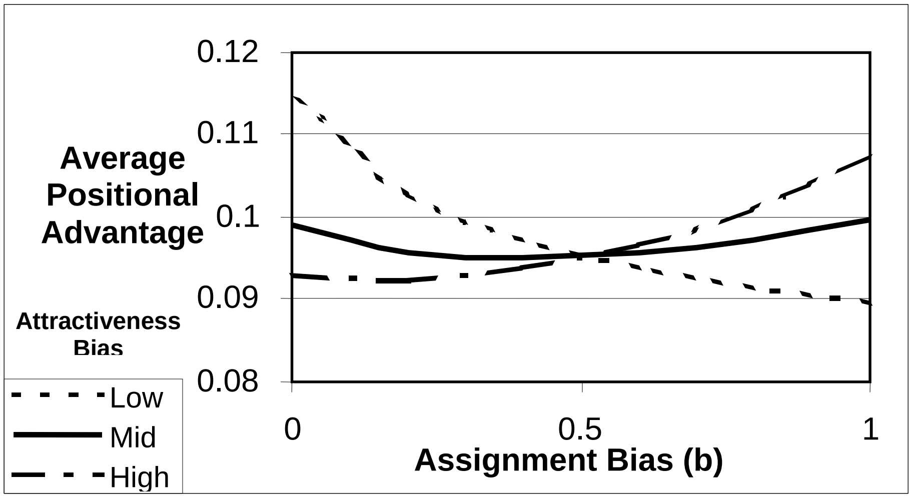

Figure 9: Effect of Varying Attractiveness Bias (p)

APA for high values of assignment bias (b) will increase with this increase in attractiveness.

4.2 Evolution of Embeddedness

In Figure 10, we illustrate evolution of key constructs assuming that the embedded target is set up as an exogenous parameter. These results mirror Baum and Ingram's dynamic hypotheses (described in §2.2), except that the interdependence curve in our results has two points of inflection.

We have repeated these results by making ET, the embeddedness target, endogenous within the model (as per specification in Equation 11). Figure 11 verifies that the dynamic hypotheses, i.e. the manner in which embeddedness, interdependence and network size evolve, remain materially similar, even with this change in the model structure.

We confirm (but do not show) that the above-mentioned dynamic hypotheses remain robust for entire feasible range of test parameters. This has increased our confidence that the model is suitable for setting up further policy analyses. Before discussing policy analysis, we direct reader’s attention to the transient nature of positional advantage in Figure 12.

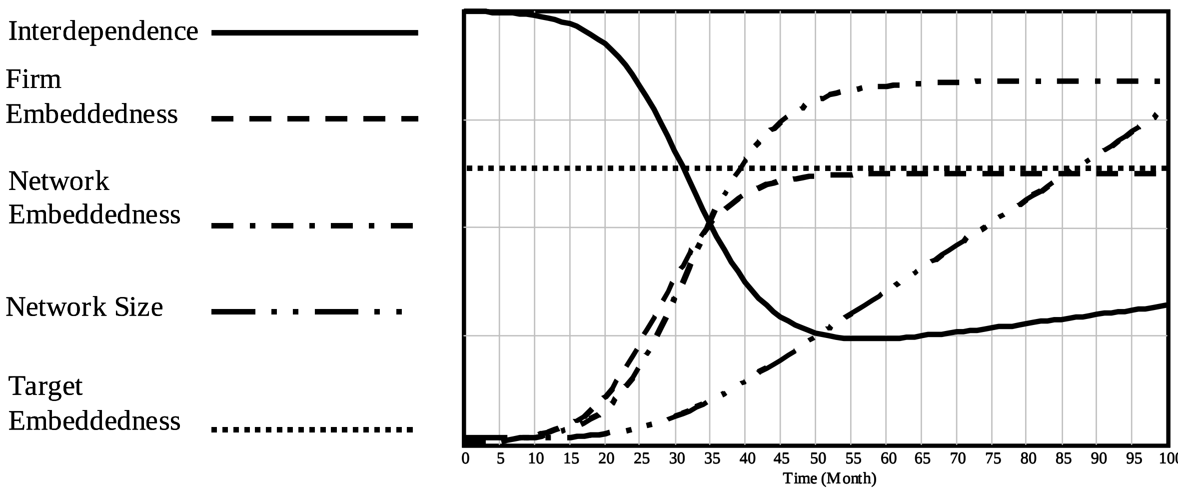

Figure 10: Evolution of Process Strength with Exogenous Target Embeddedness

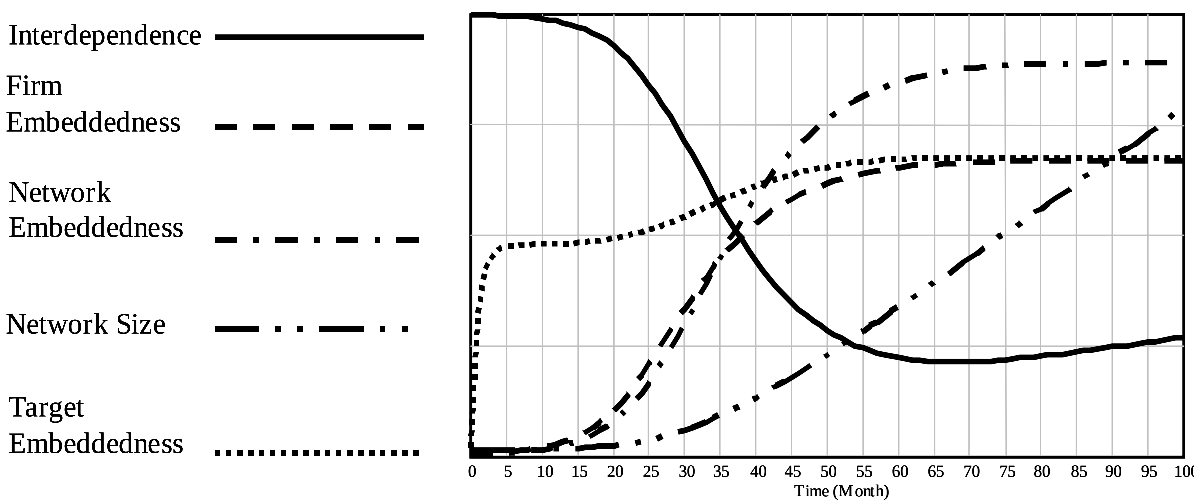

Figure 11: Evolution of Process Strength with Endogenous Target Embeddedness

Within the setup for our base case, positional advantage attains a maximum value early during the network evolution, however this advantage atrophies due to imitation and co-evolution (Powell et al. 2005) within the institution, while the network size attains a maximum at the end of our period of assessment. Hence, for the purpose of policy analysis, we include the following four constructs as outcome variables of interest: maximum positional advantage (MPA), the time at which MPA occurs (T-MPA), the average positional advantage (APA), and the maximum size of the network (N-max) accessed at the end of simulation. The first two variables characterize the positional advantage in the short run and the last two terms measure the advantage over the entire time period of observation.

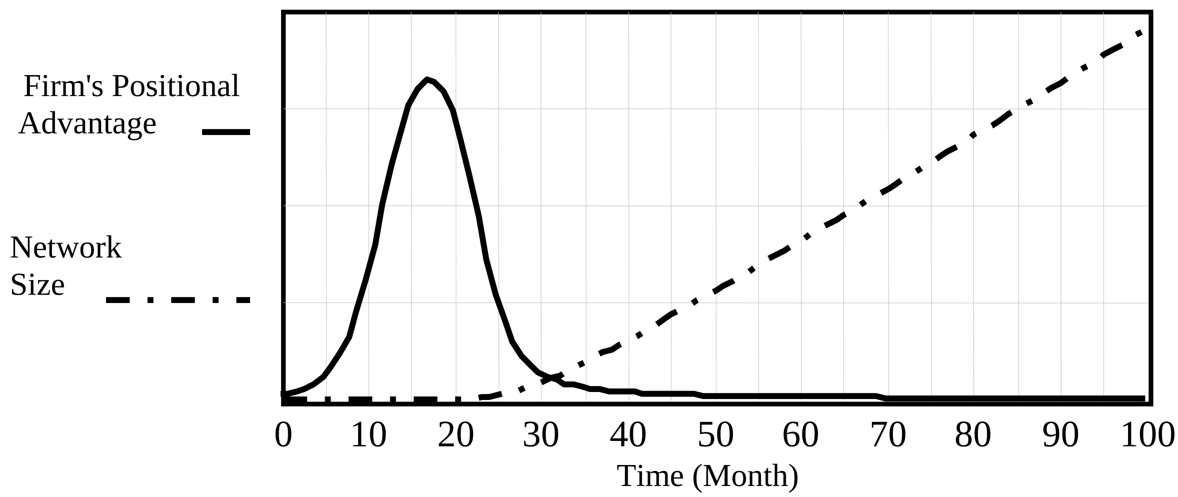

Figure 12: Evolution of Positional Advantage and Network Size

5. Policy Analysis

Recall from the literature discussion that the primary goal for policy analysis is to assess the efficacy of the strategies for exploration (and exploitation) of the core and the periphery. For ease of discussion, we label the input parameter as follows: we either set a = b = 0.75 or a =b = 0.25. The higher value represents a bias towards assigning ties to the core, and the lower value represents a bias towards assigning ties to the periphery. It is clear that both policies will build links into the core and the periphery. However an assignment bias towards the core is likely to yield a **connected network** and an assignment bias towards the periphery is likely to yield **structural holes** (Burt1992). We set the strength of tie parameter either at 1.0 or at 0.5. The higher value indicates a strong tie and the lower value represents a weak tie. We also set the value of ‘p’ to be either 1.5 or 0.5. The higher setting represents a bias towards the periphery while computing the positional advantage, and a lower value represents a bias towards the core.

While naming these policies, we presume that when the institution values the periphery more than the core (i.e. p =1.5), the focal firm and the institution are more likely to explore than exploit the core of a network. Hence we label these policies EPR#1 through EPR#8. On the other hand, when the institution values the core more than the periphery, the focal firm may wish to exploit the core, and the policies are labeled as EPT#1 through EPT #8. This allows us to test a total of sixteen policies as shown in Table 2. The following four constructs, defined in §4.3, are used to measure the performance: MAP, T-MPA, APA and N-Max. The last two columns rank the outputs based MPA and APA, respectively.

Table 2:Performance of Exploration and Exploitation Alternatives

	INPUT				Output					
	Embedded-ness Assignment Bias	Strength of Ties in the Core	Strength of Ties in the Periphery	Institution Bias in Valuing Advantage	Maximum Positional Advantage	Time at which MPA Occurs	Average Positional Advantage	Size of Network Accessed	Rank for MPA	Rank for APA
Policy Id #	a and b	θc	θp	p	MPA	T-MPA	APA	N-Max		
EPR#1	Connected	Strong	Strong	Periphery	0.582	22.4	0.1034	340	1	9
EPR#2	Connected	Weak	Strong	Periphery	0.528	26.3	0.1081	306	5	1
EPR#3	Connected	Strong	Weak	Periphery	0.350	43.3	0.1055	175	9	6
EPR#4	Connected	Weak	Weak	Periphery	0.256	62.6	0.1076	40	13	2
EPR#5	Hole	Strong	Strong	Periphery	0.554	23.1	0.0961	340	4	14
EPR#6	Hole	Weak	Strong	Periphery	0.350	43.3	0.1055	175	11	7
EPR#7	Hole	Strong	Weak	Periphery	0.481	27.6	0.0942	306	8	16
EPR#8	Hole	Weak	Weak	Periphery	0.233	64.6	0.0948	40	16	15
EXT#1	Connected	Strong	Weak	Core	0.519	26.7	0.1064	306	6	3
EXT#2	Connected	Strong	Strong	Core	0.576	22.6	0.1028	340	2	10
EXT#3	Connected	Weak	Strong	Core	0.350	43.3	0.1057	175	12	5
EXT#4	Connected	Weak	Weak	Core	0.250	63.2	0.1045	40	14	8
EXT#5	Hole	Strong	Weak	Core	0.350	43.3	0.1057	175	10	4
EXT#6	Hole	Strong	Strong	Core	0.563	22.8	0.0980	340	3	13
EXT#7	Hole	Weak	Weak	Core	0.241	63.9	0.0990	40	15	11
EXT#8	Hole	Weak	Strong	Core	0.498	27.0	0.0982	306	7	12

The outcome parameters confirm that in general, strong ties result in higher positional advantage (e.g. policies EPR#1 and EXT # 2) and weak ties yield a lower positional advantage and slow the diffusion process down (e.g. EPR#8 and EXT#7). Weak ties in combination with strong ties, either at the core or at the periphery, can yield high levels of positional advantage (e.g. EPR #2 and EXT #1). The top three policies for MPA show high levels of network growth (N-max), however only two of the top three APA policies come with large N-max. These rankings also show that in some instances (EPR#4) and (EXT#6), the maximum positional advantage (MPA) may not yield a high value for average positional advantage. In effect, these instances identify myopic search strategies (Levinthal and March 1993).

Thus, advantages accrued through exploration and exploitation policies are crucially affected by behavioral biases (e.g. parameters ‘a’ and ‘p’ in the table), imitation and target setting associated with the evolution of core and periphery embeddedness constructs.

6. Conclusion

We have formalized a behavior theory of network evolution using a system dynamics model. The modeling process has yielded insights about the internal consistencies within this theory (e.g. firm’s risk averseness raises network embeddedness above the firm’s embeddedness) and also allowed us to test new formulations (e.g. endogenous evolution of embeddedness targets). Our model quantifies multiple outcome constructs: the maximum positional advantage, the average positional advantage and the maximum network size. Policy analysis results for these constructs illustrate that, consistent with Baum and Ingram’s view shown in Table 1, it is a good idea to consider the strength of ties, and the degree of structural holes or connected nature of networks, while coming up with exploration or exploitation choices. Our results also show that aside from the focal firm's assignment biases, the institution's bias in valuing the advantage is a significant determinant of positional advantage.

These policy analysis results are preliminary and come with many limitations. Our modeling view is aggregate because it ignores individual attachment details and uncertainty addressed by an agent based model (Rahmandad and Sterman 2004). Hence, our results can only indicate aggregate performance. Owing to modeling assumptions, our results can only be tested over a selected range of parameters. For reasons of parsimony, we ignore many critical aspects of behavioral choices, e.g. trust and mental models. Moreover, labels may confound our results: exploration and exploitations are not mutually exclusive alternatives within our formulation. Exploration comes with some exploitation and vice versa. A sophisticated firm may be interested in altering its exploration and exploitation policies during different phases of network evolution. We are in the process of extending the model boundary to relax some of these assumptions so that we may test all the paradox of embedded hypotheses (Uzzi 1997). The model can then be used to address more sophisticated exploration and exploitation policies.

Our approach builds a bridge between social network research and the system dynamics methodology based on a behavioral theory of network evolution. The promise of this approach lies not only in the formalism and precision that it can bring into organization science but also in the theoretical justification it can provide for simulations of network evolution.

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Appendix: Model Parameters

Parameter	Equation #	Range	Base Case	Units
a	2	0 to 1	0.5	Dimensionless
A_1	9	0.005	0.005	Dimensionless
A_2	9	0.0001	0.0001	Dimensionless
b	3	0 to 1	0.5	Dimensionless
C_1 - C_8	7,8,9	1	1	Dimensionless
C_9	11	0.001-200	Not used	Dimensionless
ET	1 and 4	0.001-100	100	Dimensionless
$F_{CE}(t=0)$	Implicit in 2	0.0005	0.0005	Dimensionless
$F_{PE}(t=0)$	Implicit in 2	0.005	0.0005	Dimensionless
$I_{CE}(t=0)$	Implicit in 3	0.5	0.5	Dimensionless
$I_{PE}(t=0)$	Implicit in 3	0.5	0.5	Dimensionless
N(t=0)	Implicit in 7	1	1	Dimensionless
p	4	0.5-1.5	1	Dimensionless
q	5	0 – 2	0.5	Dimensionless
r	3, 6, 10	1-1.5	1.1	Dimensionless
S(t=0)	Implicit in 8	0.001	0.001	Dimensionless
T_{AB}	8	10-50	30	Month
T_{AE}	1	2-4	2	Month
T_{AN}	7	10-50	30	Month
T_I	3	2-4	3	Month
θ_C	2	0-1	1	Dimensionless
θ_P	2	0-1	1	Dimensionless