Making Strategic Connections:
Stimulative Policies for a Dynamic Network

By

Michael C. Farmer, PhD., Research Associate*
Center for Paper Business and Industry Studies
Georgia Institute of Technology
500 West Tenth Street, NW
Atlanta, GA 30318 – 0621

Michael.Farmer@ipst.gatech.edu

and

Steven Burke, MS., Graduate Research Assistant
The School of Public Policy
Georgia Institute of Technology
500 West Tenth Street, NW
Atlanta, GA 30318 – 0621

ABSTRACT

We perform simulations on a network of venture capitalists in Silicon Valley. We test several rules implied by the literature to identify ways to make strategic connections that enhance a policy-maker's goals. Some rules target fairness and others target connectivity; but one strategy may be especially attractive. A 'smart small world' rule attends to agent diversity as a way to facilitate both output and social fairness by using a cellular automata approach to predict network evolution. The information in social networks might contribute to overall output yet flatten the informal hierarchy to bring peripheral members closer to the network center.

*** Lead Contact**

Making Strategic Connections: Stimulative Policies for a Dynamic Network

ABSTRACT

We perform simulations on a network of venture capitalists in Silicon Valley. We test several rules implied by the literature to identify ways to make strategic connections that enhance a policy-maker's goals. Some rules target fairness and others target connectivity; but one strategy may be especially attractive. A 'smart small world' rule attends to agent diversity as a way to facilitate both output and social fairness by using a cellular automata approach to predict network evolution. The information in social networks might contribute to overall output yet flatten the informal hierarchy to bring peripheral members closer to the network center.

Making Strategic Connections: Stimulative Policies for a Dynamic Network

Excitement over network theory has spread from sociology and organizational theory to economic development and technology growth management. Studies now report an impressive cache of field data through ever sharper mapping protocols that construct social networks. In the pursuit of more powerful dynamic predictors of how a network might evolve, researchers now model disease spread or broad connectedness patterns (e.g. phone book exercises) by analytic techniques drawn from the natural and physical sciences by the 'small world' features operating in social networks. These recent technical advances are especially promising because 'small world' connectivity closely mirrors the 'strength of weak ties' phenomenon emphasized decades ago by Grannovetter (1973) in social networks. So-called 'small world' studies can be viewed in part as formal representations of the 'strength of weak ties' phenomenon that underlines an important social characteristic central to many network theory applications: to accomplish a task in a large social network, agents need to navigate that network efficiently to conduct, say, a job search (Grannovetter, 1973). As field applications grow in sophistication through progressed data collection and mapping protocols, lagging behind somewhat is the construction of tools able to use all of this data more fully, especially information on individuals regarding how they acquire resources and accomplish specific tasks.

Our goal is to assist the policy-maker in a search for strategic connections that facilitate clear public goals such as research output or high tech investment. We suggest a more micro-focus - on the individual node (person or institution) - may be a more efficient way to use the rich data often available from modern social network maps. To this end, we suggest that there is a set of other dynamic methods that can be more applicable to certain types of networks, yet still honor the basic small world insight of long-range ties that, while weak or tenuous or rare, exercise an enormous influence on the performance and subsequent dynamics of the network. When public administrators wish to encourage *specific ties* as a mechanism to facilitate high tech job creation or to stimulate research or encourage investment or mobilize more vigorous community action, the growing quality of social network mappings may contain more information than emerging system-wide analytic techniques typically are able to use. Specifically, connectivity patterns may be quite diverse among individuals and between specific connections; or some connections may differ enough *qualitatively* from others to warrant a closer accounting of particular connections.

To motivate this search to expand the set of dynamic assessment tools, a policy analyst may want to know, for example, how nodes (agents or institutions) enter or exit a network; how collaborative associations form or how they break; how *specific* tasks are accomplished or how they fail; and how network position affects the quality of specific outcomes. If these outcomes are conditioned on specific persons, an organic system-wide approach that analyzes connectivity patterns alone might not fully capture individualized data. We present an approach to network dynamics that will track different agents and specific alliances that differ qualitatively; and we build out from this micro-behavior to examine how the network as a whole may develop in response to directed policy stimuli. In the spirit of the small world insight where a small number of long-range connections makes a great difference, we intentionally restrict diversity to a modest set of key observable differences - all small in number yet still meaningful. We allow differences to center on the scale of agent connectivity and agent position within the network, but also on the *history* of a particular connection or of a particular agent. If this type of information is available in a real network, the policy analyst may be able to target with more precision those key leverage points within a social network that can implement a publicly valued end with modest resources.

Our approach constructs *cellular automata* rules – basic rules about how given 'cells' or connections mature and how they change based on the quality of their prior inter-actions (e.g. expectation that an association forms, breaks, or becomes more productive and the variance around these expectations). Analysts can extract how a network is likely to evolve *as a system,* but only first by using the collective movement of these individual associations in a 'bottom-up' method. Since individual outcomes are subject to uncertainty, the analyst can report an array of final expected outcomes for the entire system under a probability distribution formed from hundreds of simulations that account for individual variation in expected cell outcomes. Loosely we take each cell (or connection), its history and its position in the network to predict how that connection will evolve (will the tie strengthen, will it produce more output, will it recruit a new member or fall away?).[1] We run hundreds of randomized simulations over the different estimated chances (drawing randomly from the probability distribution) that each particular result will succeed or fail and then map a distribution over network-wide patterns that emerge. We obtain a histogram of likely outcomes (i.e. output or overall connectivity) so that a policy analyst can compare both expected outcomes and the incidence of undesired outcomes.

This approach is deeply consistent with the primary motivation for *much* of social network analysis in that the formal and informal structure of association matters yet individual differences must operate within the social network and its flux. One way to interpret the turn toward social network theory is a reaction against simple, single line regression analyses that may efficiently characterize the *mean individual experience* but bypass the nuanced *structural features* of that network, such as social hierarchy. Similarly, single system-wide analytic techniques that focus on macro-structure, robust for some purposes, tend to minimize individual diversity among network participants in an effort to explain how a network might evolve as a single 'organic' system. Somewhere between statistical approaches that average over individuals or analytic models that analyze a system-wide autonomous structure, the cellular automata promises to bridge these methods and preserve the individual and structural intuitions about how social networks emerge, how agents act within them and how the system evolves through this inter-play.

This work is a proof of concept exercise. We explore a network mapped by Castilla et al.

---

[1] The 'rules' as Wolfram calls them can be approximated by regression analysis. The dependent variable is the probability of an outcome (e.g. a successful investment venture) and Albert and Chib (1993) detail a Bayesian logit model that can assign a different beta-coefficient vector to each association. Individual, institutional, positional, resource access and historical experiences are independent variables. In a work in progress, we map a community of researchers engaged in a topic for 20 years and use regression to define the 'rules' of motion for individual connections. Critically, regression is limited to prediction about individual connectivity outcomes only – *not to* system-wide analytic prediction. Expected possibilities are programmed from cell movements (success, not success) in 500 simulations.

in 2000 and analyzed by Castilla in 2003 of venture capitalists who have engaged in joint ventures in Silicon Valley over a quarter century. We examine plausible differences in successful outcomes between collaborators and investigate if even modest differences dictate very different patterns for network evolution. We inspect whether policy-makers can exploit these expected differences and this information to exploit network connectivity in order to target strategically a few collaborations that might realize a noticeably large impact through the system.

We list four rules to target collaborations that a policy-maker might adopt: 1] A policy-maker may maximize connectivity by connecting the most successful nodal centers in a social network, increasing density or clustering measures directly; 2] A policy-maker may reduce the average path length to navigate the system – a recommendation consistent with the small world phenomenon, but numerically expensive; 3] A policy-maker may attempt to affect fairness to enfranchise and build up the peripheral members from disadvantaged clusters, consistent with digital divide or Schumpeterian theories; or 4] a policy-makers may seek a blended rule that embodies fairness, output maximization and path length reduction. Described below, we define a Smart Small World rule to locate those collaborations/connections that realize the greatest *increase* in the expected output due to their successful collaboration to capture dynamic trends in a network from static data. It turns out that in a hierarchic system undergoing dynamic change, policies to increase output do not necessarily favor rules that target the hierarchic centers directly but rather those that exploit hierarchy *and* embed several fairness ends as well.

The 'Smart Small World' rule emphasizes density yet it penalizes centrality or hierarchic *per se;* so in this exercise it performs well on several counts. In these simulations, the smart small world rule generates more output over time than a connectivity maximization rule (1); it is at least as fair as the fairness rules (3); and it realizes a non-trivial *final* path length reduction that indicates the rule enhances weak ties among key 'hub' nodes, without imposing rule (2). Paradoxically, the initial average path length is quite high; but it is the final path length at the end of the exercise that matters and results from these simulations prove quite attractive.

Background

Policy makers may hope to maximize output of new investments; increase or widen access to the network for less integrated members (e.g. digital divide concerns); or simply accelerate the number of participants that operate in the network. Equipped with a detailed network map, policy analysts have to decide how to best use that information to a policy end.

Creative descriptive diagnostics have evolved in the social network literature to characterize and to compare networks by various density and clustering characteristics at a given point in time (Wasserman and Faust, 1994). The statistics themselves have proven valuable diagnostics, but they could mislead the policy-maker if the policy-maker funds, say, research collaborations that *immediately* improve measures of density or clustering by connecting the most connected nodes (White, 2993; White, Smith and Moody, 2003). If the network is mature, stable and relatively static, that rule may make sense, but most policy applications that at least reference the network language in regional economic development (Krugman, 1994; Romer, 1987), local technology transfer (Burt, R.S. 1992; Malecki & Tootle, 1996) or job searches in a shifting market (Grannovetter, 1973) are premised on the desire to steer a network in the throws of dynamic change toward a defined social end.

Not All Connections Are Of Equal Task Weight

For a network in motion, the policy-maker possesses only the existing structural features of the network and any information on individual agents and partnerships. Absent the later, or if network movement is dominated by the former, prediction about how the network might respond to a policy stimulus will rely on structural features and key structural indicators alone.

Emerging analyses often nest a latent operational assumption that connections are more or less equally valued (Watts and Strogatz, 1999), and this makes good sense for questions of disease spread where total exposure, or dose level, is the key structural characteristic. Also social familiarity, where basic connectivity (yes or no) is the operative feature is conducive to this approach. Small world analytics[2] from this literature have produced another intriguing key statistic, or diagnostic, to measure overall navigability; one that complements the density and clustering measures above: average path length. Average Path length is defined as L(p) / C(p) where L measures the path length from one node to another defined by how many steps or degrees of separation stand between any two points; and C is the total number of connections in the network (from hundreds to billions). Adding up all path lengths from every node to every other node and then dividing that number by the total number of connections yields an *average* distance measure (Watts, 1999). A low value for average distance, L(p)/C(p), corresponds to accelerated disease spread or a more abbreviation of a job search. If associations are of relatively equal import, this single measure conveys enormous information on the character of the network *and* its subsequent dynamics (Dodds and Watts, 2004).[3]

Just as researchers use measures of 'density' or 'clustering' to signal a well connected, i.e. navigable, network, these measures frequently coincide with a low L/C ratio. Yet agent diversity where performance on a task may differ from node to node immediately implies that dynamics may differ from neighborhood to neighborhood across the map; *and this calls into question the use of these otherwise robust diagnostics as fully implementable prescriptions for pro-active policy*. The warning is consistent with observations by Smith and Stevens (1999), earlier reviews by Wasserman and Faust (1994), and even the analytic rationale in White (2003).

Taking Bottom-Up Policy Implementation Seriously

If the reaction of the network to a policy act of, say, the funding of a research collaboration or an investment partnership between institutions, is key to a successful policy action yet as that reaction is largely an autonomous response beyond the reach of the policy-maker, the network dynamics become the central concern for policy implementation.

The technical concerns raised above underlay debates in the policy literature regarding

[2] I distinguish analytic methods where solutions exist to a general canonical form without programming.
[3] The researchers are aware of this concern and do underscore this assumption nested in a given application.

bottom up or top down policy implementation and policy formation. We submit that when the cellular automata approach applies, it is particularly useful for bottom-up policy implementation.

Public managers have been eager to know which contingencies link policy inputs to policy outcomes. After several decades of a dedicated struggle in political theory and applied public administration, it turns out that it is the 'who' and the 'how' that often exceeds the what, why, and when; so studies have expressed an interest in developing "systematic knowledge regarding what emerges, or is induced, as actors deal with a policy." (O'Toole, 2000; p. 266); and this technical question directly relates to network mapping and to its dynamics.

In 'top-down' models the administrative concern is how to fit the managerial authority, its structures and its operations to the scope of the task (Mazmanian and Sabatier, 1989), particularly when the policy impetus comes from outside the bureaucratic organization (Stewart, 1996). Predicting something about network evolution is important; but that query itself may change the focus from fitting authority to the scope of the work.

Bottom-up models by contrast focus on how service providers can fit their policy to the environment, allowing policy formation to be more endogenous to the network onto which it acts. Policy implementation involves local agents who react to a policy: policies must be shaped to local conditions and permit significant autonomy by "street-level" bureaucrats (Hjern, 1982; Lipsky, 1980; Maynard-Moody, Musheno, and Palumbo, 1990) and later, by citizens themselves. Unfortunately, policies that call for bottom-up adaptability are fraught with uncertainty. Each individual network onto which a policy acts is likely to be different, thereby occluding a uniform policy management approach. This, of course, is emblematic of the bottom-up objective; and predictably these policy makers require case specific tools to predict the response of individual citizen agents in a given network to a specific policy stimulus. For these cases, dynamic assessment tools that are flexible enough to be context specific will rise in importance.

The Network

Below are experiments on an existing network of venture capital collaborations in silicon-valley assembled by Castilla (2003). Figure 1 illustrates the initial network of joint venture collaborations among venture capitalists in Silicon Valley collected by Castilla et al. (2000). The network has 260 connections among 156 participants. 20 nodes are isolates and have never collaborated, leaving 136 nodes for our simulations. Critically, this network exhibits three interesting features that reflect common public policy interests.

First, the network is divided in two and Castilla et al. (2000) discuss this evolution. Critically, this property interests policy makers concerned with digital divide questions or with disadvantaged groups who, though successful and emergent, are nonetheless overshadowed by a more developed set of associations. The policy choice is not to create a new technology center *ex nihilo* but to jump start local development in progress (Burt, R.S. 1992; Malecki & Tootle, 1996; Williamson, 1985; Williamson, 1975; Krugman and Smith, 1994). To salvage a severed yet clearly emergent group that is less progressed is a familiar policy concern.

Second the network is dense, especially on the right hand side (RHS). In a subsequent work, Castilla (2003) measures the density factor in this overall map in Silicon Valley and reports greater concentration, density and overall activity than another map of Massachusetts Route 128 firms. Such a progressed structure raises the question if a modest intervention, such as seeding only five new collaborations every third period can hope to meaningfully impact outcomes or alter the character of the network that ultimately emerges?

Third the network has defined clusters that somewhat overlap but with one or two clear lead actors in each cluster – or the network displays informal hierarchy (Moody, 2003). There are a few individuals who are less connected overall but straddle clusters (not all of them meet the technical property of a hub). In other words there exists a class of nodes that are only a few degrees of separation from two or more central nodes. Within this class, they evidence far fewer collaborations on average than centrally positioned nodes; yet as this structural property has been located in research networks among public and private technical laboratories as well as academic researchers and high tech collaborations (Malecki, 1997), the value or use of these nodes to affect a policy outcome has been the subject of much discussion since Burt (1992).

Cellular Automata Processes and Policy Selection

If the movement or response of a network to a policy act is crucial to policy success and if the provision of resources has a powerful impact on network outcomes, then key connections are paramount. If the largest differences among agents are relatively accessible from the history of each agent or partnership and also from their position within the network, it may be feasible to predict under a confidence interval how well a given connection between two agents is likely to do, both with and without any resources provided by policy initiatives. This process of estimating performance at each step is the foundational "cellular automata" process through which a policy-maker can begin to access how the network as a whole might respond to a policy choice.

One approach is to view the network as a single system whose dynamic is accessible by a system-wide dynamic function, typically a highly non-linear dynamic structure (Dodds and Watts, 2004). System-wide functions are often quite complex. Yet when associations exhibit relative uniform quality, such as infectious disease spread, then these analytic system dynamics predict very well.

Another approach is to consider that any given association might obey rather simple properties and that *complexity for the system arises out of the cumulative interactions among network agents.* But the operation of similar rules does not mean all connections enjoy a uniform experience in their pursuits. As one connection breaks in response to a network stimulus, others may deepen if the character of their connection is different. As connectivity ripples through the network, these simple processes turn out to generate highly diverse, complex outcomes for the system overall - an outcome considered realistic for social network systems (Smith and Steven, 1999). In this construct, it is the initial conditions, i.e. a good network map, coupled with general rules of interaction and task performance that matter.

Researchers have coined the phrase "cellular automata" (Wolfram, 1983) to underscore the independent choices of individuals or of particular connections as cells in a system that operate with relative autonomy, connected by the inter-lacing of their autonomous actions in a network. So dynamics reduce to estimating rather simple *dynamic* properties or 'cellular automata' rules from first principles; and this flows from several prominent theories behind the network focus. It turns out this is not as hard as it sounds. Rather than attempt a single system-wide operation, estimation by individual associations of how task performance might change (under a probability distribution) can be simulated to generate an aggregate system picture of the various ways the network might evolve. This keeps the *dynamic* estimation structurally close to the theory employed by many network analysts.

A program to model the distribution of plausible dynamic outcomes that evolve from individual connections and resources available to each individual to accomplish a particular task promise to inform the policy analyst to better describe how the network might respond to a policy stimulus; and the literature recognizes both this opportunity and the risk of using aggregate, system-wide indicators to make policy choices from a well-mapped social network.

For example, White (2003) charts network shapes by linking key diagnostics directly to different social concepts and principles. With enough randomness, or distinctions among individual associations to affect particular tasks, dynamic analyses not centered on individual association characteristics can be highly suspect – a warning emphasized in recent works on network analysis and diagnostics (White et al, 2003). Taking that warning seriously, we make the unit of analysis the connection, not the network system *per se*; and from this we introduce analyses that evolve from the collective impacts of individual nodal associations: each differing in the manner and effectiveness through which they complete a task.

Cellular Automata Rules Used for Simulation

The rules of expected movement, node by node, would be derived from the same information used to build the network map. For simulation purposes, all we need to entertain is some chance of a specific outcome with variation around that outcome (e.g. 30% success, 70% otherwise); so we use simple probabilities of success for illustration.

First expected output from a given connection is weighted: Not all connections are equal; and their performance *history* matters. In this case each connection is assigned a probability of success. Simulations allow connections to succeed 10% of the time, 30 % of the time or 60% of the time, sometimes randomly assigned and sometimes a product of network position (so-called increasing returns, or hierarchy benefits). Output success is dynamic in that success in one period improves the chance of success in the next: moving up along the ladder with each success from 10% to 30%, 30% to 60% or 60% to 90% (where it peaks); or down along the same ladder for a sequence of failures, falling eventually to 3% from 10%.[4] Second *the number of nodes* or actors in the game *is not static*. A policy cycle lasts three periods. Any connection that fails three times in a row is broken;[5] yet connections that succeed three periods in row add another node which is connected to both collaborators. Those two new connections are assigned an initial probability of success (sometimes randomly) and then experience the same dynamics as any other actor thereafter. Sensitivity analyses use different probabilities and randomly cut the number of connections in half across the network.

Finally, we examine increasing returns success structures. Simply, for those central nodes with a gross high number of collaborations, the probability of success on each connection is higher than nodes with few connections: or in these simulations, those nodes with six or more collaborators have a 60% chance of succeeding at each connection. The chance of success still rises or falls from period to period along the ladder, but those with fewer connections start with a 30% or a 10% chance of success on each connection in the very first period. We compare this network structure to one where the chance of success for any given collaboration is randomly

[4] Sometimes associations are randomly assigned, other times the *initial* probability of success is determined by network position and the number of connections a node enjoys.
[5] Those that rise to 90% and then fail 3 times occurred only once in over 6,500,000 connections simulated

distributed, or individual differences on the productivity of a collaboration are not determined by scale of total association. Clearly, both types of networks exist; so we examine both.

Policy enters by selective funding of joint ventures in the initial year. At the end of a policy cycle (three periods for these simulations), there is a new network map. Policy-makers redeploy the same policy to select joint ventures to fund at the start of period four and again at the start of period seven. Evaluation of the rule to select collaborations to fund is determined by the total cumulative output through the nine periods and the shape of the final emergent network. Since simulations involve probabilities of success at each node over each of the nine periods (a highly individualized inspection), output evaluation is reported as the mean output after 500 simulations with a histogram recorded to represent the distribution (or variance) of outcomes.

Policy Choices

A policy-maker in possession of the foregoing maps and expectations of success for individual partnerships has some information on how any injected resources might affect change in the network trajectory. One could search over all possible choices and reactions to make an 'optimal' choice; but that is computationally expensive (can take weeks or longer) even with this relatively small network and the search can require a high acumen with programming. That approach also begs the question if the quality of the information warrants such a precise search even if it can be done. So we offer a few initial plausible policy choice rules that a policy-maker can adopt with relative ease and then compare the performance of these different options, including sensitivity analysis, for the simulation exercises.

We consider four different rules to make policy funding choices. One policy selection rule is **Direct Optimization.** This selection process seeks to link those collaborations that would immediately maximize the total number of connections in the network; and these connections are illustrated in red on Figure 2. The rule tends to draw links between highly connected points on one side to highly connected points on the other. Mathematically the rule chooses a Connection, C_{ij} among the set of nodes {N} where $C_{ij} \square n_i, n_j \ni \{N\}$ so as to obey:

$$[1].\ \text{Max}\ \sum C_{i,k} + \sum C_{jm} + C_{ij}, \text{ where}$$

i] i, j are singletons; ii] $k, m \in \{N\}$; iii] $\{n_k\} \subset N, \ni C_{i,k}$ exists; iv] $k \neq j$;

v] $\{n_m\} \subset N, \ni C_{j,m}$ exists; vi] $\{n_m\} \cap \{n_i\} = \varnothing$; vii] $\{n_i, n_k\} \cap \{n_j, n_m\} = \varnothing$.

Simply, connections are chosen so that the total number of final connections that attach to each of the two nodes linked is as large as possible;[6] or the rule links up already well-connected nodes not connected to each other currently. In general there are many to choose from (15 or more typically reach the same maximum value); so the policy-maker is not limited to such a small set of options that they cannot avoid unworkable collaborations.

A second selection criterion is the so-called **Smart Small World** rule. This rule locates the greatest increase in *expected output* from single a connection. It uses information beyond connectivity, based on expected collaboration success.

We define a collaboration success as S_{np} for any two nodes $n, p \in \{N\}$ that have formed a collaboration, C_{np}. We define the probability of success for that collaborating in any period as Pr (S_{np}), where $0 \leq \Pr(S_{np}) < 1$. If a given vector of node and collaboration specific characteristics, **x**, affects the probability of success on a given task for a collaboration, then we define the function $\Pr(S_{np}) = S(C_{np}(\mathbf{x}))$ to represent the probability of success over a distribution. In these simulations, **x** are characteristics such as the number of total collaborators that a node enjoys and the history of past successes for that collaboration, C_{np}. Technically, the **Smart Small World**[7] rule searches for a collaboration, C_{np}, to obey the objective:

---

[6] A variant is to maximize the total number of connections two steps away to capture local spill-overs. We tested this variant to optimization and it did improve output and fairness over Direct Optimization used, but the improvement was not dramatic in these simulations and still dominated by the 'Smart Small World Process.' To program this variant, choose the following maximand: Max $\sum C_{i,k} + \sum C_{im} + C_{ij} + \sum C_{,kt} + \sum C_{mp}$, adding to the 7 conditions: $\{n_t, n_k\} \cap \{n_i, n_k\} = \varnothing$; $\{n_t, n_k\} \cap \{n_p, n_m\} = \varnothing$; $\{n_p, n_m\} \cap \{n_j, n_m\} = \varnothing$.

[7] It is called "Smart," not because we are smart but because small world properties analyze the effects of largely random (or unmodeled) long range connections. Here we consciously *select* weak ties, or long range connections expected to do the most good rather than rely on randomness in long range connections.

$$[2]. \text{ Max } \sum \Pr(S_{ik}) + \sum \Pr(S_{jm}) + \Pr(S_{ij}),$$

with identical restrictions on collaborations listed in [1] for Direct Optimization. Simulations allow for the probability of success ($\Pr(S_{np})$) and of failure ($1 - \Pr(S_{np})$) at each period during a multi-period simulation. Success depends on the characteristics, **x**, operating at that period of time for that collaboration. Equation [2] can be expressed in terms of collaboration success functions as well; or,

$$[2a]. \text{ Max } \sum S(C_{ik}(\mathbf{x_{ik}})) + \sum S(C_{jm}(\mathbf{x_{jm}})) + S(C_{ij}(\mathbf{x_{ij}})).$$

Typically chosen connections are drawn from less connected nodes than those chosen by direct optimization; but the smart small world collaboration choices display high marginal improvement in output expected from a given connection. The rule continues to emphasize density in the spirit of Direct Optimization, yet it also penalizes centrality *per se* as it searches for long distance 'weak' ties that exhibit strong effects.

Represented on Figure 1, the Smart Small World rule differs from the Direct Optimization rule that maximizes the number of connections between the most highly connected nodes, emphasizing instead connections that contribute the largest expected *marginal* gain. Measuring the instantaneous output gain for the two nodes linked and spill-over impacts on all of their collaborators, the rule picks those connections that are emergent productive collaborations that have not fully matured (a fairness property).

An important practical value for the policy-maker is that it is rather simple to operate, accessible from a linear program that can be performed on an Excel spreadsheet. Often the rule does pick the same connections as Direct Optimization, especially in increasing returns to scale cases, but there is an important difference. What are prized in Smart Small World selections are nodes that enjoy generous collaborations today but not yet the gains from collaborative resources enjoyed by the most central actors. Notably, the nodes chosen are those that are thought to illustrate greater dynamism since their contributions escalate more quickly from their baseline.

These are prized because they are productive *at the margin* and, in the increasing returns cases analyzed, they improve productivity of all of their other collaborators as well.

The operative nodes for the Smart small world rule, in blue on Figure 2, target nodes that overlap prominent clusters rather than link across clusters from one well centered node to another. Choices are involved in a cluster that exhibits strong positional hierarchic influence - examined by Moody (2003); but are not the central nodes at the top of that hierarchy. Another way to frame the policy is in terms of new growth theory to maximize the diversity and the industrial complementarity of monopolistic competition without degenerating into an oligopoly (Fujita, 1993) or to coordinate between decomposition and centrality (Jackson & Watts, 2002) – a subtlety this economics literature bemoans as beyond standard regression analysis (Smith & Krugman,1994).

Two other alternatives are compared. One is a **Baseline Rule** that leaves the network on Figure 1 to evolve on its own with no external impetus. All other polices select five candidate collaborations to seed.[8]

A final rule is **Connectivity Fairness** that extends the properties of the Smart Small World to reduce the path length for the nodes most disconnected to some distant colleague. The rule maximizes the minimum number connections by the least connected node – or a MaxiMin fairness rule.[9] The rule simply picks connections, C_{ij} □ n_i, n_j $\ni$ $\{N\}$ by amending [1] to obey:

$$[3].\ \text{Max Min } \sum C_{i,k} + \sum C_{jm} + C_{ij,}$$

retaining all the conditions in [1] but adding: viii] $\sum C_{i,k} = \{\varnothing\}$ and $\sum C_{jm} = \{\varnothing\}$.

Simply, collaborations are chosen to make the number of total connections for the least connected nodes as large as possible, provided that each node already enjoys at least one collaboration.

---

[8] We eliminated the isolates from examination as they were not networked to any other agent.

[9] This 'do-loop' search process is computationally expensive. In this case it made little difference except when the number of connections was cut in half.

As shown on Table 1 the rule is premised on fairness and does not approximate the lowest average path length recommended by Watts (1999) and Watts and Strogatz (1999); yet it does configure the network to select 5 connections so that the five longest paths in the network are as small as possible. This observance turns out to have a long term benefit that does reduce path length *over time* as the system evolves.

Critically, the policy injections are quite modest. Only 5 connections are chosen at each policy decision point and this occurs only every third period. The number of connections stays in the range of 150 nodes over most of the evolution cycle; so the total number of connections in any period runs to the order of 4000 total decisions or engagements. This means pro-active policy connections account for less than one-third of one percent of total network activity.

Outcome Comparisons

Overall, all of the rules show positive impact and this is encouraging. In addition, some impacts are more sensitive to changes in conditions (density, connectivity, cellular automata processes) than others and this is instructive. Table 1 summarizes the principle simulation results.

There are several trends, robust to sensitivity analysis for this network. First, direct optimization outperforms the baseline (do nothing) strategy. If the policy-maker targets larger immediate measures of density and clustering for output generation, the immediate impact appears attractive and system evolution system shows clear improvement. Cutting the number of total connections in half (randomly removing half of all the connections), produced similar results; so direct optimization, a policy that flows neatly from static measures on the character of the network, does demonstrate productive gains even with these very small incursions into the network. The rule, in this network, also corresponds everywhere to an immediately lower L/C ratio (path length minimization) than the other two policy suggestions (Table 1). Unfortunately this policy rule performs poorly compared to other rules over time.

Key Comparisons:

Table 1 compares results for a representative run among the four policy options. First, after three rounds of funding policy selections, fairness exhibits some very attractive features that dominate the baseline in these simulations. Fairness, motivated by Schumpeterian rules, is a good producer and surprisingly outperforms direct optimization on both fronts: *mean* output is noticeably higher and fairness recruits many more new members, especially in the increasing returns cases. For increasing returns cases, the fairness rule reflects some of the economic growth concepts from Rostow (1990) and Schumpeter (1942) to Krugman (1995) who speculate in different ways that a 'take-off' condition might be ignited by policies akin to the fairness rule. However, variation around the mean output is high for this rule (see Figure 6 histograms). The intuition is that a few key connections at the periphery of the network which have a reasonable chance of succeeding can fail in the critical early periods. If these critical connections fall away or fail to recruit new members quickly, the cohesion effect necessary for 'take-off' fails. This added variance alone could cause a policy-maker to defend Direct Optimization over Fairness in these scenarios. Though the variance is roughly the same on the histogram (Figure 6), when conditions that dictate success and 'take-off' are less generous than those presented, sensitivity analyses (discussed below) show this rule to be *much* more sensitive than direct optimization.

The hybrid small world inspired rule also rewards take-off potential but it operates through more secure agents in the network. Smart Small World connections induce recruitment of new members and deliver a high degree of output. The rule dominates both other rules on each count – recruitment and output: more fair than the fairness rule for this criterion under the best performance conditions for fairness and more output than rules that create partnerships directly between the network's best producers even under conditions most conducive to hierarchy advantage (increasing returns).

The dominance of Small World policy choices holds for several sensitivity tests: Cutting the number of connections in half; increasing the probabilities of success in both increasing and decreasing returns cases (3%, 10%, 30%, 60%, 90% ***to*** 5.91%, 19%, 51%, 84%, 99% as a *symmetric* increase); *decreasing* the probabilities of success in both cases (from 3,10,30,60 and

90 ***to*** 1.5%, 5%, 15%, 30% and 45%); and a combination that cuts network membership in half and changes the probabilities. Predictably, the performance of the Fairness rule was less robust to shifts in overall density and connectivity: output slips noticeably and variance increases dramatically as the number of nodes drops and as the probabilities of success falls because these shifts compromise the chances of success for critical connections in the early periods that are so necessary for 'take-off.' Yet Smart Small World maintains its first rank for output generation and for recruitment under in *all* scenarios. Paradoxically, the Smart Small World rule enters the map with a very high L(p) / C(p) ratio, but yields a low L/C ratio in the end;[10] or the robust *diagnostic* property of high small world connectivity may not function as a robust policy *prescription*.

In these scenarios, there also at times is a slow and modest deterioration of output under the baseline and Direct Optimization regimes over the policy cycles (compare static output to final cycle output on Table 1). Density and clustering suggest a potential for a type of hierarchy that can fail to sustain network momentum – or a hierarchy that eventually over-centralizes the network. The Smart Small World rule avoids (or delays) conditions where the center benefits *at the expense* of overall network productivity since the rule deliberately links nodes that access more than one center. The rule builds out from hubs to make connections that help to level network peaks and 'fill the valleys' in a multi-centric network hierarchy.

The result mirrors the power of 'intersection across specialties' emphasized by Ennis (1992) among others. Rather than simple position *per se,* it is the influence of persons who already *straddle* (Ennis' term) or cross-over groups and subgroups that the Smart Small World Policy targets; so stronger *sustained* performance of the Smart Small World is consistent with several strands in sociology and economic theory.

---

[10] Final L/C statistics are difficult to compare across the rules as they each produce disconnected spin-offs of four to six each (leading to division by zero for no connectivity cases). Also the number of agents differs in the end: the smart small world rule recruits more persons with more to involve. However, calculating the L/C ratio is *lowest* for the large continuous portion from the smart small world output (see Figures 3-5).

For reasons indicated, the Smart Small World rule, or a rule that focuses on similar sorts of targets, is both easy to deploy and rather successful on output and fairness objectives. It resists, or delays at least, the evolution to strong hierarchies that posthole only a few product centers that benefit the few central actors at the expense of the many; and it is this leveling that avoids the rapid 'oligopoly' control and *provides multiple pathways to centers* that allows for aggressive recruitment of new members: adding productive vibrancy by greater access.

Comparing Network Maps

To visualize the comparisons are three graphs drawn from representative cases of the policy alternatives. We chose scenarios whose performance is close to the mean aggregate output *and* the number of final actors to represent each case.

Figures 3, 4 and 5 compare final period network maps under the Fairness Rule, Direct Optimization and Smart Small World. Some results are striking and others require closer inspection. Again, of the total policy injections into the system is less than one-third of one percent of total collaborations (15 out of about 4000). Even so some character differences emerge to suggest the path of a network is far from predetermined, even when guided by simple dynamics processes and even when the network is already highly progressed.

The Fairness Rule on Figure 3 exhibits a great deal of connectivity and navigability. The three black nodes are nodes that enjoy numerous collaborations – eight or more – and the bottom black node is connected to otherwise ill-positioned actors. Using NetTool, the blue points locate critical connectivity junctures that perform critical conduits for less central nodes toward more than one central point (loosely, hub points though not all meet the technical definition of a hub). These points protect pathways for nodes to reach more than one center and for the centers themselves to interact. On average, the Fairness rule fuses the division in the network between the right hand and left hand sides (Figure 1). When the Fairness rule performs less well, it is the failure to secure, early on, the success of the outliers to strengthen their ties and recruit new members – or failure of 'take-off' at a vulnerable point.

As the reader compares the Fairness outcome on Figure 3 to the Direct Optimization outcome on Figure 4, the vulnerability of outliers is more pronounced. First the policy already has produced more spin-off communities of relatively densely connected nodes of 5 and 7 actors.

Direct Optimization displays three overlapping properties that inhibit task performance and subsequent weakness in recruiting new actors to the network. The bottom part of the graph corresponds to the more dense nodal associations represented on the right hand side on Figure 1 and these actors, among themselves, are noticeably less interactive, more dependent on a single center or pathway. The navigability from point to point is relatively singular compared to the variety of options open to members of the Fairness network. This vulnerability of members at the periphery is evidenced by clear dependence on the top part of the graph (corresponding to the less developed left hand side on Figure 2). The blue nodes are critical as they shore up a very few critical linkages that prevent those relatively less interactive nodes at the periphery from erosion or disengagement. The role of these critical connectors is to perform the dual function of providing alternative paths and sustaining productivity by enabling connectivity to a single nodal center; but pathways are quite singular for the long string of 14 nodes connected by many steps to a blue (or hub) node via a single and poorly connected node. In other words the strength of weak ties characteristic, related to the small world property that allows navigation to be enhanced by a long distance connection to end run these bottlenecks is severely impaired in the Direct Optimization alternative.

Finally, the Smart Small World network on Figure 5 uncovers a fruitful blend of these two activities: inclusiveness in connectivity and overall productivity, in the end outperforming or matching the target objectives (numbers engaged and closely accessible or task performance).

Immediately, the Smart Small World network is more ‘ringed’- a signal of strength among peripheral nodes to sustain productive engagement. Yet the overall shape retains the flavor of the direct optimization map where the top and bottom correspond to the left and right on Figure 2; or developed and less developed remain distinct with a more visible retained lag in performance. Unlike central nodes (black) concentrated in the weaker sector for the Fairness Rule, the Smart Small World sustains and consciously empowers two central nodes, one from each sector, but builds deep critical connectivity to link peripheral strings to both centers, able to position more critical links (blue) across sectors with more options to collaborate near the stable, productive center. The very top and the very bottom are much less likely to disconnect from the network and, with greater internal interaction, are more sustainable which helps them to pull resources more effectively from the center but also among themselves. That a central node and a critical connection penetrate deeper into the bottom segment of the graph, buttressing these peripheral nodes with more accessible navigability. Also the array of pathways available through several critical connectivity nodes on the top half of the graph performs the same task.

The 'ringed' property opens multiple pathways (an important small world feature) to reach relatively connected nodes (strengthening weak ties). The ring of inter-connectivity leaves very few places where a single break could sever a string of nodes from the network system. The nodes on the right and left on Figure 5 roughly mirror the evolution of right hand side and left hand side nodes on Figure 2 above. Fairness on Figure 3 does concentrate on building the left hand side as it rewards emerging causeways to link up the two networks.

Policy perspectives concerned with digital divide, or emergent research or industry activities in developing regions within a world economy, find a strong Schumpeterian quality to the Fairness rule but the fairness qualities of the Smart Small World suggestion should not be overlooked. Full protection in the early development is not the sole policy focus though it is a concern. In this sense, the old trade and industrial development rules of 'Import Substitution' focused solely on building the less developed sector do not seem as robust in this system for a rule highly geared to providing resources to isolated network sectors.

Conclusions

The goal here is not to insist on broad generalizability of the Smart Small World *per se* but to point out that the statistics routinely used to diagnose and to compare network success

(Wasserman and Faust; 1994) may be poor candidates for policy prescription. This is expected. The theory about how dynamics operate in many of the appeals to the use of social networks suggests that vibrant evolution would *not* be captured directly in these descriptive statistics.

Dynamics matter and many of the reasons why social networks are so interesting is that they explore or explain evolutionary processes that are not captured by these diagnostics alone. Connectivity and density statistics are the end products of emergent connections that build connectivity and density via critical links. This distinction is noted by Wasserman and Faust (1994) in their waterfront coverage of then current Network Analysis tools and applications. A geometric analogy is pyramid-building. The blocks that build the highest pyramids are those that establish the broadest secure base; yet at any moment, the single block that increases elevation is the one that stacks atop the highest point. If we measure success by elevation, the best way to that goal is not to increase elevation with each act but to create conditions that assist this end.

The reason for the focus on the increasing returns to scale case is deeply rooted in what we are learning from social networks. In human systems, network position counts in one's ability to draw resources from the system, and successful use of network associations rises geometrically as one positions better, or success begets success (Faust, 1997). The tension then is to recognize hierarchy, formal and informal, and to reward its *productive* collection of complementary skills and actors without endowing centrality with a sort of feudal power that Balkanizes the system where productive activity at the center occurs at the expense of more productive activity at the margins (or periphery). The approach here is no more than a proof of concept and should be read as the warning it is rather than *fait au complet* policy profile. That the cellular automata rules embed the types of dynamics and interpersonal associations reported in the literature and applied to an association network collected from a real world venture capital collaboration network suggests a program worth pursuit. Additionally, the system of network analysis offers up a different analytic perspective. A single line time series regression with output as a dependent variable and the character of individual collaborations as independent observations to be used as independent variables will generate highly network specific conclusions that may tell us little about robust properties across networks or even the real guiding impetus of network dynamics. Many appeals to networks and network theory do just that and skip entirely the actual network mapping exercise itself.

Likewise, single system-wide evaluations not premised on the details of each individual connection can yield quite statistically efficient and highly complex, non-linear processes that nonetheless could be spurious in some cases. Our suggested use of regression is limited only to the estimation of cellular automata rules, not the projection of network movement in its entirety. So this dynamic estimation process is more permissive in that it imposes less structure *a priori* yet continues to admit a variety of outcomes that could emerge, letting the shape of the initial map and the characteristics of existing association inform the evolution directly.

Our general suggestion of how to approach a network for policy-purposes is premised on many of the reasons for network analysis itself, its dependence on initial conditions; a complexity of outcomes that flow from potentially modest changes in the performance; or decisions of individual associations. That these changes are not predetermined, or forced, means the rules to be estimated are simple and take advantage of the ever sharper quality of network data assembled.

References:

Albert, J.H., and Chib, S. 1993. "Bayesian Analysis of binary and polychotomous response data," *Journal of the American Statistical Association.* v88. *pp.* 669-679.

Burt, R.S. 1992. *Structural holes: the social structure of competition.* Harvard University Press: Cambridge, MA.

Castilla, Emilio J., Hokyu Hwang. Mark Granovetter and Ellen Granovetter. 2000. "Social Networks in Silicon Valley." Pp. 218-247 (Chapter 11) in *The Silicon Valley Edge: A Habitat for Innovation and Entrepreneurship*, edited by Chong-Moon Lee, William F. Miller, Henry Roin, and Marguerite Hancock. Stanford: Stanford University Press.

Castilla, Emilio J. 2003. "Networks of venture capital firms in Silicon Valley," *International Journal of management Technology.* V25. #1-2. pp 113-135.

Chase, Ivan. 1980. "Social process and hierarchy formation in small groups: A comparative perspective," *American Sociological Review*. v45.

deLeon, Peter. 1999. The Missing Link Revisited: Contemporary Implementation Research. *Policy Studies Review*. 17. 311-338.

deLeon, Peter and Linda deLeon. 2002. What Ever Happened to Policy Implementation? An Alternative Approach. *Journal of Public Administration Research and Theory*, 12, 4, 467-492.

Dodds, P.S. and Watts, D. J. 2004 (forthcoming). "Universal Behavior in a Generalized Model of Contagion." *Physical Review Letters.*

Ennis, James G. 1992. "The Social Organization of Sociological Knowledge: Modeling the Intersection of Specialties." *American Sociological Review. v*57. pp 259-265.

Faust, Katherine. 1997. "Centrality in Affiliation Networks" *Social Networks* v19. pp. 157-191.

Frank, K. and Yasumoto, J. 1998. "Social Capital Within and Between Subgroups." *American Journal of Sociology.* v104. #3. pp. 642-86.

Fujita, M. 1993. "Monopolistic competition and urban systems," *European Economic Review* v.37. p. 308-315.

Goggin, Malcolm L, Ann O'M. Bowman, James P. Lester, Laurence J. O'Toole Jr. 1990. *Implementation Theory and Practice: Toward a Third Generation.* Glenview, IL: Scott, Foresman/Little, Brown.

Granovetter, M. 1985. "Economic Action and Social Structure: The Problem of Embeddedness," *American Journal of Sociology.* v81. pp. 481-510.

Granovetter, M. 1974. *Getting a Job: A Case Study of Contracts and Careers.* Harvard University Press. Cambridge, MA.

Green County Gazette. 1999.

Hjern, Benny, 1982. Implementation Research: The Link Gone Missing. *Journal of Public Policy*, 2, 301-308.

Ingram, Helen M. and Anne L. Scheider, 1990. Improving Implementation by Framing Smarter Statutes. *Journal of Public Policy,* 10, 67-88.

Jackson, M. and Watts, Alison. 2002. "The Evolution of Economic and Social Networks." *Journal of Economic Theory.* v106. pp. 265-295.

Krugman, Paul. 1980. "Scale economies, product differentiation and the pattern of trade." *American Economic Review*, v70. p. 950 - 959.

Krugman, P. and Smith, A. 1994. *Empirical Studies of Strategic Trade Policy.* University of Chicago Press. Chicago, Ill.

Lipsky, Michael, 1980. *Street-Level Bureaucracy.* New York: Russell Sage Foundation.

Lynn, Laurence E. Jr. 1996. *Public Management as Art, Science, and Profession.* Chatham, NJ: Chatham House.

Malecki, E.J. 1997. *Technology and economic development, 2nd edition.* Addison Isley Longman Limited: Harlow, England.

Malecki, E.J. and Tootle, D.M. 1996. "The role of networks in small firm competitiveness." *International Journal of Technology Management*, 11, 43-57.

Matland, Richard E. 1995. Synthesizing the Implementation Literature: The Ambiguity-Conflict Model of Policy Implementation. *Journal of Public Administration Research and Theory*, 5, 145-174.

Maynard-Moody, Stephen and Suzanne Leland, 1999. Stories from the Front-lines of Public Management: Street-level Workers as Responsible Actors. In H.G. Rainey, J.L Brudney, L.J. O'Toole, Jr. (eds) *Advancing Public Management: New Developments in Theory, Methods, and Practice.* Washington, DC: Georgetown University Press.

Mazmanian, Daniel A. and Paul A. Sabatier, 1983. *Implementation and Public Policy*. Glenville, IL: Scott, Foresman.

Moody, J. and White, DR. 2003. "Social Cohesion and Embeddedness: A Hierarchical Concept of Social Groups." *American Sociological Review.* v68. #1. pp.1-25.

O'Toole, Laurence J. Jr. 2000. Research on Policy Implementation: Assessment and Prospects. *Journal of Public Administration Research and Theory*, 20, 263-288.

Romer, Paul. 1987. "Growth based on increasing returns due to specialization." *American Economic Review*, v77. #2. p. 56-62.

Rostow, W.W. 1990.*Theories of Economic Growth from David Hume to the Present Day.*

Schumpeter, J.A. 1942. *Capitalism, Socialism and Democracy.* Harvard Univ. Press.

Smith, T. & Stevens, G. 1999. "The Architecture of Small Networks: Strong Interaction and Dynamic Organization in Small Social Systems." *American Sociological Review.* v64: p. 403-20.

Wasserman, S. and Faust, K. 1994. *Social Network Analysis: Methods and Applications.* Cambridge: Cambridge University Press.

Watts, D.J. and Steven H. Strogatz. 1998. "Collective Dynamics of 'small-world' networks." *Nature.* v393. pp. 440-442.

Watts, D.J. 1999. *Small Worlds: The Dynamics of Networks Between Order and Randomness.* Princeton: Princeton University Press.

White, D. R. 2003. "Network Analysis, Social Dynamics and Feedback in Social Systems." *Cybernetics and Systems.* v35. #2-3. pp. 173-192.

White, D.R. Poill, W.W. Oin-Smith, J. and Moody, J. 2003. "Network Models and Organization Theory: from embeddedness to ridge structure." In *Computational and Mathematical Organization Theory.* eds. Alessandro Lomi and Phillipa Pattison.

Williamson, Oliver E. 1975. *Market and Hierarchies: Analysis and Antitrust Implications.* Free Press. New York, NY.

Williamson, Oliver E. 1985. *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting* Free Press. New York, NY.

Wolfram, S. 1983. "Statistical Mechanics of Cellular Automata," *Reviews of Modern Physics.* v55. pp. 601-644.