INDUSTRY STUDIES ASSOCIATION
WORKING PAPER SERIES

Strategic Research Connections: Implementing Funding Policy in a Dynamic Network

By

Michael C. Farmer
Center for Paper Business and Industry Studies
Georgia Institute of Technology
Atlanta, GA 30318

2004
Industry Studies Association
Working Papers

WP-2004-18
http://isapapers.pitt.edu/

Strategic Research Connections:
Implementing Funding Policy in a Dynamic Network

By

Michael C. Farmer, 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

Strategic Research Connections:
Implementing Funding Policy in a Dynamic Network

ABSTRACT

Since the early phone-book experiments that produced the term "six degrees of separation," renewed interest in network theory ranges from sociology and organizational management to economic development and new economic geography. More formal 'small world' studies today underline the importance for an agent to navigate a network efficiently to accomplish, say, a successful job search. Field work has produced a wealth of network data and data collection protocols growing in sophistication continuously. Lagging behind are proactive analytic tools that use this data to locate strategic connections among network agents to leverage better outcomes, such as research output.

This work employs a network map of collaborations among venture capitalists in Silicon Valley to locate unexploited strategic connections. From the literature, I test several rules suggested as to how network connections might evolve, simple rules in the style of cellular automata, and I compare connection choice strategies. One strategy may be especially attractive. A "smart small world" policy robustly achieves two ends: it improves overall output and flattens the informal hierarchy of the network to improve connectivity and increase competition. Since the smart small world strategy does not require any form of dynamic optimization or recursive programming but relies on field data directly, it is more accessible to policy-makers.

Our Research group tested the rule on a research network which is still under construction. This initial application of a strategic connection search uncovered a divide between European and North American researchers that participating scholars readily recognize as a concern, providing a face validity test of the program.

Strategic Research Connections: Implementing Funding Policy in a Dynamic Network

Interest in social, research and business Networks has blossomed into an enormous research field, rich in diversity and able now to report an impressive cache of both field data and developed protocols to map and to represent social networks. This work suggests that a relatively established network map often contains information on network dynamics that are not fully utilized by analysts. It is conceivable that analysts can extract more efficient estimates of how a network will evolve *in response to* a policy initiative: how agents enter and exit a network; how associations form; and how certain tasks are affected by specific connections.

I take the lead provided by the 'small world' concept to explore a network mapped by Castilla et al. (2000) and analyzed by Castilla (2003) of venture capital firms engaged in joint ventures in Silicon Valley. We examine plausible rules of dynamic evolution that networks might obey and use those general properties to select and compare the reaction of the network over time to connections seeded, ostensibly with public funds, to help energize the productive investment activity of joint ventures among these venture capitalists. I compare the performance and robustness across different rules and conduct sensitivity analysis over several evolutionary structures that a network might obey. The most important sensitivity analysis compares constant returns to scale (CRTS), where each collaboration is of equal import regardless of the number of collaborators with whom an investor partners, versus increasing returns to scale (IRTS) where each collaboration has a better probability of success as the number of other connections, or other partners grows. So centrality of position carries with it strong hierarchy reinforcement.

In comparing strategic connections to fund, I find that somewhat obvious rules to maximize connections in a static network map, such as connecting successful nodal centers are common in social network analysis. Other rules seek to reduce the average path length to navigate the system, recommendations that emerge from physics in their explorations of small world phenomenon. Also fairness rules that flow from digital divide debates seek to link up agents so as to enfranchise peripheral members and shelter these disadvantaged clusters while building them from within. Each of these rules is outperformed in these simulations by a rather simple rule of thumb to improve local connectivity: to choose to fund collaborations that maximize the number of associations within two steps of the least connected nodes: a fairness – output blending rule that I label 'Smart Small World.' In these simulations, the smart small world rule generates more output over time than a static maximization rule to link productive centers to each other. Also it is at least as fair, or more fair, than fairness rules themselves and it beats an important rule suggested from physics. Fortunately, the rules are relatively easy to calculate from an existing network as they do not require complex dynamic programming optimization rules which are computationally expensive. This type of formal dynamic analysis and simulation complements the quality of field work collected as it better uses that information.

In a progressed network with strong and distinct centers of unequal strength, the rule presented here, to select connections so that the most unconnected nodes have as many collaborators within two degrees of separation as funding allows, proves valuable to increase performance on selected tasks because it encourages the evolution of nascent, productive clusters. By empowering these emergent groups a predictable social network style result emerges: this boosts output with the added benefit that it enhances fairness by increasing access and making room for more agents to participate and enter the network. To seed emerging clusters reduces the disadvantages of hierarchic centralization, echoed in both sociological and economic literatures using network tools. There is a vibrant quasi-Schumpeterian flavor, absent the aggressive protectionism that accompanies that development strategy, to a rule that dovetails nicely into the new economic growth literature with its focus on the creativity of monopolistically competitive, 'increasing return' industries. In these industrial organization structures a local network of linked producers capitalize on their complementary human capital skills (Krugman, 1980; Romer, 1987) yet resist a slide into more centralized, possibly *decreasing returns* oligopoly structures.

Background

Creative descriptive diagnostics have evolved in the social network literature to characterize and compare networks by various density and clustering characteristics. The statistics themselves are valuable but they might mislead a policy-maker who frames policy directly from those properties to, say, fund those specific research collaborations that *immediately* improve measures of density or of clustering, such as connecting up the most connected nodes. This seemingly intuitive policy can damage progress on the desired task (e.g. publications, high tech jobs, investments); and this warning is wholly consistent with suggestions from several literatures on how networks evolve. If a policy changes the starting point by deliberately altering connections in the network, adding a few strategic collaborations, then the analysis is no longer a static query but a dynamic one that must anticipate how the network will react, or evolve, as a consequence of policy.

I simulate several plausible dynamics: an individual collaboration becomes more effective with sequential experience or breaks apart if the partnership fails to perform several times in a row. Also consistently successful collaborations attract new partners or services; those with lots of collaborations realize a better success rate for *each* collaboration than those with fewer associations (IRTS); or, conversely, chance for a success from a collaboration is everywhere equal. Since the network chosen is already a progressed and mature system, I also test if cutting the number of connections in half makes a qualitative difference to the results.

I measure success by the number of successful joint venture investments and I use this metric to compare different policy rules. I also report the total number of network participants at the end of the simulation (three policy cycles) as another indicator of success and fairness. I graph each outcome to illustrate visually how the character of the network is altered by quite modest inventions, 5 funded connections out of 264 initial connections among 104 nodes. I suggest that policies drawn from a well-mapped network can be sharpened with data available if the network is sufficiently rich to suggest how a network will evolve.

Small World Networks and 'Task'

Many applications explore networks among researchers, business leaders or financiers to uncover social arrangements among these agents that contribute to their economic activity. As a research goal itself, these maps reveal extensive connectivity. Network mapping motivated by a policy objective adds another dimension: the analyst ultimately must come to terms with the reaction and subsequent evolution of a network to an external policy stimulus, *ex ante*.

Diverse applications of networks show an effort to locate key positions in a network that 'grease the path' toward the completion of a *task* that the policy-maker hopes to stimulate. Response top task depends on how agents in a network have (or will) embed themselves (Granovetter, 1985): more successful job hunts (Granovetter, 1974), successful associations in a friendship network (Moody, 2002); navigation by welfare parents through a complex welfare to work programs to achieve meaningful personal progress (Green County, 1999). Embedding gives the agent a modal perspective to accomplish a task that affects the type and quality of the task completed. Whether public-private partnerships embed themselves as public agencies or as business-like entities while shift their emphases and the tasks that they best achieve (Kingsley and Farmer, 2002). Sensitivity to the dynamics of how tasks are accomplished and how the quality of the task changes as the character of interactions shift in response to policy can be an essential ingredient in framing policy; so the best dynamic information available, node by node and connection by connection, becomes a critical *ex ante* concern for policy implementation

It is this focus on task, a task completed by agents who participate in a network that interests the policy-maker. To use network analysis for public goals, focused on task, could reduce data demands on network mapping if, for example, joint rotary club membership is wholly redundant to some other observed connection (e.g. rotary club associations of venture capitalists always correlate to joint membership on venture capital advisory boards). Clearly, the opposite may hold true if rotary club membership contributes to the task but is not captured by other connections. Those associations can affect embedding changes for those association types.

The overall impact, I suggest, is likely to lower the heavy demands on the traditional social network analyst but task does add a specific demand. Orientation on task means that each association, depending on the mix of characteristics that define that connection, needs to be distinguished from other connections by overall expected contribute to the given task: scientific co-authorship, successful high tech joint venture, jobs et cetera. In these cases a sharper focus on the history of collaborations will record some empirical precedent for how the network and individual network associations evolve. This could be more demanding but it may be easy to add this information as much of the history is already collected but not always explicitly coded. If an analytic instrument can make better use of the added coding step, the burden may be modest.

Not All Connections Are Of Equal Task Weight: A problem with dynamic assessment

A focus on task is worthy of examination as the public policy literature and social network literature expose an obvious problem: in most cases, the power of one connection will not necessarily be equal to another connection in generating a particular outcome.

Emerging analyses, however, sometimes nest a latent assumption that every connection is equally valued, or normalized to unity (Watts and Strogatz, 1999). This assumption makes sense for disease spread, social familiarity or actions that often fall into discrete categories: sick or well, known or unknown. This literature has produced a key statistic to measures navigability by average path length, defined as L(p) / C(p). L measures the path length from one node to another by how many steps or degrees of separation stand between two points; and C is the total number of connections in the network (from hundreds to billions). Adding up all path lengths for each node and dividing the number by the number of connections, yields an *average* distance measure (Watts, 1999). The average of these distances is the L(p)/C(p) statistic where a shorter average path length speeds up the spread of disease or abbreviates a job search. If associations are of equally import, this single measure conveys enormous information on the character of the network *and* its subsequent dynamics (Dodds and Watts, 2004).

Two other measures signal overall connectivity across a network. A dense network that is also highly clustered typically has the features of a navigable network, or a low L/C ratio. Generally, a program to select a handful of the highest ranked policy candidates suggests a policy to connect centers of clusters in a dense map to intensify connectivity generally, leading to similar recommendations. Yet task orientation calls this direct method into question.

If separate collaborations are more or less likely to succeed at a specific task, analysts need to track how associations might change subsequent to a policy stimulus. If, as we expect, connections are qualitatively different, a focus on emerging clusters, not necessarily the most central today, may be more productive targets to complete the task of interest.

Taking Bottom-Up Policy Implementation Seriously

As one looks closely, the technical concerns raised underlay debates in the policy literature regarding bottom up or top down policy implementation and policy formation.

Public managers have been eager to know which contingencies link policy inputs to policy outcomes. After several decades, 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, 266). This technical question is directly related to network mapping and 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). Top-down models can be quite hierarchic, so modelers focus on the degree to which officials or affected citizens act in concert with or in opposition to policy goals (Matland, 1995; Mazmanian and Sabatier, 1989). Simply, top-down models must anticipate the reaction of a network, with its own nested hierarchy (Moody, 2003), to implement policy. Once again, predicting something about network evolution is important.

Bottom-up models by contrast focus on how service providers themselves 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 can differ, thereby occluding a uniform, formulaic management scheme and this, of course, is nearly definitional to the bottom-up objective. Simply these policy modelers and analysts require highly case specific tools to address formally agent adaptability in order to predict the response of citizen agents who receive resources and pursue a particular task. In this case, dynamic assessment tools, flexible enough to be context specific, rise even more in importance.

Network analysis fortified to anticipate better the reaction of agents promises to add a new analytic instrument to the bottom-up policy tool kit; and a lot is at stake. So I simulate plausible dynamics, drawn for the literature, that may affect network evolution following a small injection of resources and conduct sensitivity tests of those processes on a real world map of venture capitalists in Silicon Valley. Fortunately, the policies are quite accessible researcher skilled more in network data analysis than in recursive computational dynamic programming.

The Network

Below are experiments on an existing network of venture capital collaborations in silicon-valley assembled by Castilla (2003). I propose different rules for the evolution of that network under which to test the performance of different funding policies that select strategic joint ventures based on static network diagnostic measures.

Figure 1 illustrates the initial network of joint venture collaborations among venture capitalists in Silicon Valley collected by Castilla et al. (2000). The network is planar, so it can be represented in two dimensions; but the map provides the visual distinctions we need to compare various policies and the collaborations targeted by each selection rule.

The network exhibits several interesting features. First, there are 260 connections among 156 participants. 20 are isolates and have never collaborated, leaving 136 nodes in the network for simulations. The network also demonstrates three other properties that reflect important public policy interests, which is why this map was chosen for simulation.

First, the network is divided and Castilla et al. (2000) discusses this evolution. Critically, the property interests policy makers concerned with digital divide questions or disadvantaged high tech groups who, though successful and emergent, are nonetheless overshadowed by a more developed set of associations. This is more than creating a new technology center *ex nihilo* since productive collaborations already exist. To jump start local development (Burt, R.S. 1992; Malecki & Tootle, 1996; Williamson, 1985; Williamson, 1975; Krugman and Smith, 1994), managing development in the face of a divided network to salvage a severed yet emergent group that is less progressed than its corollary is a critical and common policy concern.

Second the network is dense, especially on the RHS. Castilla (2003) measures the density factor in the overall map in Silicon Valley and reports greater concentration, density and greater overall activity compared to Route 128. So policy injections engage an active and vibrant collaborative structure to advance high tech industries. From a bottom-up perspective, fashioning policy around the network seems essential; yet with such a progressed structure it raises the question if modest interventions, such as seeding only five new collaborations among 264, in a dense network can 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 an informal hierarchy (Moody, 2003). There are a few individuals who are less well connected overall but straddle clusters. In other words there exists a class of nodes that are only a few degrees of freedom from two or more central nodes. Within this class, for those more than two degrees of freedom apart (not in the same cluster), they evidence far fewer collaborations on average than centrally positioned nodes. This property has been located in research networks among public and private technical laboratories as well as academic researchers and high tech collaborations (Malecki, 1997).

Cellular Automata Processes and Policy Selection

A serious and numerically intensive exploration led by physicists attempts to examine the structure of connected networks, in particular their small world properties(Watts&Strogatz,1999).

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). This system-wide function is often quite complex and, as found in bottom up studies, seldom replicable from network to network; yet if associations are of rather uniform quality, such as infectious disease spread, single system dynamics can be quite predictive.

Another approach considers each node to be connected to other nodes where the properties of change for any given association obey rather simple properties. Complexity emerges from these very simple rules, but cast over a non-uniform initial state of inter-actions (or different nodes are positioned differently). Connections may break in response to a network stimulus as others deepen, but individual connections experience different results based on the initial position or state in which an agent exists. As connectivity ripples through the network and as each change produces its own ripple effect, these simple processes turn out highly diverse, complex outcomes for a system. This sort of dynamic is considered realistic for social network systems (Smith and Steven, 1999). In this model, to divine universal properties from a given dynamic trajectory misses the point. So it is initial conditions, i.e. a good network map, coupled with rather simple or general rules of evolution that matter. White (2003) charts network shapes by linking key diagnostics directly to different social concepts and principles. With enough randomness, or probabilistic distinctions centered on how each individual association evolves or acts to affect its particular tasks, dynamic analyses not centered on association by association characteristics can be a highly suspect endeavor that can mask core conceptual distinctions – a warning emphasized in recent works on network analysis and diagnostics (White et al, 2003). If the warning is taken seriously, this turns around the empirical and the computational demands from one that treats the unit of analysis as the system itself where its evolution as more or less deterministic (and this includes systems where random, long range weak ties generate a small world outcome) to analyses that evolve as the product of reactions of each node in a positional context for completing a task.

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 locating rather simple *dynamic* properties or ‘cellular automata’ rules from first principles that flow from the theory behind the network organization mapped, connection by connection. It turns out this is not as hard as it sounds. Quite the contrary, rather than attempting singular system-wide operations, estimation of direct expectation into how individual associations might change under a probability distribution of choices or outcomes in a given period can be simulated numerous times to generate a picture of the various ways the network might evolve. This keeps the *dynamic* estimation structurally close to the theory that the network analyst employs to describe the network. A program to model the distribution of plausible dynamic outcomes easily can introduce a policy that alters the initial network and then track a distribution of outcomes that flow from that intervention where the dynamics are premised directly on the data of association characteristics that the analyst used to map and describe the network.

Cellular Automata Rules

The network of collaborations in joint ventures is used to simulate system effects from some simple properties of association.

First the output of a connection is weighted. Not all connections are equal. In this case each connection is assigned a probability of success. Simulations here allow connections to succeed 10% of the time, 30 % of the time or 60% of the time. Second, the chance of output success is not static. From an initial assignment, success in one period improves the chance of success in the next: moving from 10% to 30%, 30% to 60% or 60% to 90% (where it peaks); or down along the ladder past 10% to 3% (its nadir). Third, the number of raw number nodes and connections is also not static. Following the policy literature, a policy cycle is three periods. Any connection that fails three times in sequence is broken; any node that fails to succeed in any collaboration over three periods exits the network.[1] Any connection that succeeds three periods in row, adds a node, connected to both collaborators with a probability of success for each. Added sensitivity analysis was conducted over different probabilities and by cutting connections in half.

Finally, we compare increasing returns to constant 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 nodes with six or more collaborators has a 60% chance of succeeding in any period with each connection, rising or falling from there as periods pass; those with fewer connections had either a 30% or a 10% chance of success on each connection in the first period. This is compared to a structure where the chance of success for any given collaboration was randomly distributed over the map; or we did not model any positive returns to scale.[2] Scenarios run 100 times to create a histogram of outcome distributions.

The data to generate these rules are not so onerous. In a companion paper we employ a Bayesian logit model (Albert and Chib, 1993) that uses co-authorship data in a progressed research area to gasify cellulose and waste products at existing pulp mills. Research falls into several sub-topics. The chance hat a given co-authorship collaboration will successfully publish on a given sub-topic from a DOE project is predicted from historic information on funding sources and amounts, the authors engaged an their individual track record (why the Bayesian

---

[1] The few, after a three period cycle, that rise to 90% and then fail three times in row occurred only once in over 6,500,000 connection events simulated

[2] The number six was selected to keep the static, period one productivity for the network stable: or the overall probability of success for a connection in period one was 37.5 versus 37.875 % making period one output 99 successes under constant returns and 100 successes under increasing returns.

approach was chosen), the research institution of each co-author where work was conducted, records of patents, comments as to how researchers entered this research area and why others left. That is enough to estimate connection dynamics map a network and predict responses of a given connection. These success chances form the rules of the cellular automata and the map, predicated on interactions and spill-over relationships allows the type of analysis suggested to be completed with relatively accessible methods and current practices.

Joint ventures are funded in the initial year; but policy does not stop. At the end of a policy cycle, three periods in these simulations, a new network map is constructed. Policy-makers re-map the network at that time and the policy rule is redeployed and at the start of period four to sponsor another bevy of joint ventures. The policy analysis, implementation and evaluation process repeats again at the end of period six and a final set of collaborations are funded. Total output cumulative up to the end of period nine is compared as well as the overall shape and character of the final emergent network.

One policy selection rule is **Direct Optimization.** This selection process seeks those collaborations that would immediately maximize total output – or highest expected output under the probability regime characterizing the static network map. The connections are illustrated in red on Figure 2 below. The rule tends to draw links between highly connected points on one side to highly connected points on the other.

Policy Choices

A second selection criteria is the so-called **Smart Small World** rule. The rule maximizes the number of two degree of separation connections of the least connected nodes. It emphasizes density yet penalizes centrality *per se*. Smart small world, in blue on Figure 2, targets nodes that overlap prominent clusters rather than simple link across clusters well centered nodes in a cluster that enjoy positional hierarchic influence - examined by Moody (2003). Another way to frame the policy in terms of new growth theory is that the rules aspire to maximize the diversity and the industrial complementarity of monopolistic competition without degenerating into an oligopoly (Fujita, 1993) or coordination between decomposition and centrality (Jackson & Watts, 2002).

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.[3] 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.[4] As shown below the rule is premised on fairness and does not approximate the lowest average path length recommended by Watts (1999) and Watts and Strogatz (1999). It does configure the network with the five selected connections so that the five longest paths in the network are as small as possible.

Critically, the policy injections are quite modest. Only 5 connections are chosen at each policy decision point which occurs only every third period. The number of connections per node is scenario dependent but remains close or above 3 over the scenarios and there are on average in the range of 150 active nodes over the cycle as the map grows and shrinks. So the number of total connectivity actions between nodes runs to the order of 4000 total decisions or engagements, taking the policy incursions less than one-third of one percent of total network activity.

Outcome Comparisons

Table 1 summarizes the principle results of the simulations and sensitivity analyses preserve the rankings of the five reported data measures on the table. There are several curious trends which hold up under sensitivity analysis for this network. First, direct optimization does outperform the

[3] Again, we eliminated the isolates from examination as they were not networked to any other agent.

[4] 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. With a less progressed and more diffuse network, the best application of the rule became very difficult to locate and the one by one rule compared to the optimum did make a difference.

baseline, do nothing, strategy. If the policy-maker uses the static measures of density and clustering to appraise output generation, the immediate impact appears attractive and the evolution of the system shows improvement. This comparison holds if centrality is privileged only by its volume of connections and if centrality benefits from increasing returns as many theorists suspect in knowledge networks. Cutting the number of total connections in half (randomly removing half of the connections), produced similar results. So direct optimization, a policy that flows neatly from static measures of the character of the network appears productive.

Finally, there are eight different visual representations of the final networks for each policy represented on Table 1. We can see that more than output is affected. These very small incursions into the network change the shape and character of the network in subtle but interesting ways.

Key Comparisons:

First, Direct Optimization does generate the highest output in the immediate period. That rule, in this network, corresponds everywhere to a lower L/C ratio (path length minimization) over the other policy suggestions. Unfortunately this policy rule performs poorly, generating less aggregate output and drawing fewer new members to the network.

Another property not reported on Table 1 is a slow decline in output from period to period for both the Baseline and Direct Optimization alternatives. This dynamic is not inevitable but it does expose a vulnerability, consistent with organizational theory in economics, from a too narrow reliance on clustering, density and path length reduction to guide policy.

The creative opportunities from clustering and informal hierarchy can drive diversity and niche organizations to the overall benefit of system performance. That is one reason networks are important to study (Williamson, 1975). Economists find similar increasing returns to scale benefits from connectivity in so-called monopolistic competition where clusters form in an industry to produce differentiated products as producers take advantage of some novelty (Romer, 1987). The 'spill-overs,' loosely speaking, are important here as each producer who generates a slightly different product still takes advantage of specialized supply chain producers that service all firms: industry specialists in law, marketing, tailor-made public infrastructure as well as physical manufactured goods used by all (Krugman and Smith, 1994); yet clustering cannot be so hierarchic as to deliver too much control to a single entity or a single cluster so that the system begins to devolve into a more centralized oligopoly that reduces competition, diversity, supply and the number of engaged actors (Fujita, 1993).

Curiously this slow and modest deterioration prevails in the baseline and Direct Optimization regimes even under increasing returns to scale scenarios where tolerance for clustering and centrality is given lots of room before inefficient crowding out of more productive upstarts evolves; and the result holds up even as half of the connections are broken in the network. That Smart Small World resists this unproductive deterioration and extends creative diversity by rewarding emerging clusters is instructive as it mirrors the power of intersection across specialties in social organizations generally (Ennis, 1992) over simple position *per se*. Moreover, the effect may be more pronounced in the real world. The model builds-in an advantage to Direct Optimization as it formally treats a subgroup cross-over as an obstacle only of initial conditions (the shape of the initial network) but does not add any penalty or difficulty to bridge subgroups, added friction that likely explains their distinction in the initial network map (Frank and Yasumoto; 1998). So comparing the powerful influence of persons who already straddle or cross-over groups and subgroups from the beginning and are therefore targeted by the Smart Small World Policy relative to connecting central nodes *per se* as Direct Optimization largely rewards, the stronger performance of Smart Small World is consistent with theory and even may be understated in these examples.

Other key results are read directly from Table 1. A policy to target connections to lower the overall L(p)/C(p) ratio is not adequate when different connections are qualitatively different. The Smart Small World option does not immediately enhance navigability under this measure compared to Direct Optimization – and this holds under every scenario; yet the rule outperforms the baseline, the direct optimization rule and the Fairness rule in task performance for every case considered. Just as direct optimization does not in the end optimize output so fairness does not necessarily best introduce and retain network actors. Under CRTS Fairness is less fair than the Smart Small World policy on this measure of enfranchisement and, on over 100 simulations, is virtually identical to the number of persons engaged in this network under IRTS.

For reasons indicated, the Smart Small World rule is both easy to deploy and rather successful on both output and fairness objectives. It resists, for longer at least, the evolution to strong hierarchies that posthole only a few product centers that benefit a few central actors. It is this leveling that avoids the rapid oligopoly control; yet attention to provide multiple pathways to centers still presupposes the retention of creative centers that can realize collaborative scale. It is for this reason that the rule recruits new members: adding productive vibrancy along with access.

Comparing Network Maps

Below are three graphs drawn from representative cases of policy alternatives for increasing returns scenarios. That is, from over 100 scenarios, a scenario whose performance is close to the mean aggregate output *and* the mean number of final actors is chosen to map; and the pictures reinforce the main message here.

Figures 3, 4 and 5 compare are final period network maps under the Fairness Rule, Direct Optimization and Smart Small World respectively. Some results are striking as others require closer inspection. Again, of the total interactions in the system, less than one-third of one percent are subject to deliberate policy injections (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 they also are connected to other well-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. These points protect pathways for nodes to reach more than one center and for the centers themselves to interact, by direct collaboration or by sharing common venture capitalist firms in separate joint ventures. The network is relatively more 'ringed' in that there are multiple pathways for points to reach relatively connected nodes. The ring of inter-connectivity among the less connected outlier nodes on the right hand illustrates this property and 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 3 roughly mirror the evolution of right hand side and left hand side nodes on Figure 2 above. Fairness concentrates on building left hand side activity as it rewards emerging causeways to link up the two networks as viewed through the blue connection nodes that largely perform this function of linking up the left side to the right side and providing many alternative routes for those links to occur; and the dual objectives (adding muscle to the less dense and active node as it bridges the two systems) occur immediately in policy choices, from the very first policy injections.

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 rule and the choices are instructive. 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.

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, premised on maximizing expected output in a static position by linked up productive actors to each other, displays three overlapping properties that inhibit task performance by the network and a subsequent weakness in recruiting new actors to the network. This network is less 'ringed.' The bottom part of the graph corresponds to the more dense nodal associations on the right hand side on Figure 2 (or right hand side on Figure 3) 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 at the periphery to draw resources from the center is evidenced by clear dependence by the less developed segment on the top part of the graph (corresponding to the less developed left hand side on Figure 2) on a few strands of relatively less productive associations that embed a greater probability of de-coupling and this is reinforced by the location of the blue, critical connectivity nodes in the map. Those nodes are critical as they are successful actors in the system who shore up a very few critical linkages for entire nodal strings that are, within themselves, relatively less interactive and therefore more vulnerable to separation, followed by erosion of their engagement in this network. The role of these critical connectors is less able to enjoy the dual function of providing alternative paths but rather sustains productivity and navigability by re-enforcing connectivity to a single nodal center.

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.

Conclusions

The goal here is not to insist on broad generalizability of the maximin rule presented which maximizes the minimum number of connections that are two degree of freedom away from any node. Rather the point is to illustrate that the statistics routinely used to measure and compare network success (Wasserman and Faust; 1994), while very useful for that purpose, can be very poor candidates to employ as policy targets.

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. The good results scholars measure from connectivity and density statistics are the processes of emergent connections often latent in the initial map that build connectivity and density via critical links and this distinction is noted by Wasserman and Faust (1994) as they cover the waterfront of Network Analysis tools and applications. A geometric analogy for policy purposes is that the blocks that build the highest pyramids that cover the largest space beneath are those that establish the broadest secure base, though at any moment, the single block that increases elevation immediately is the one that goes atop the highest standing point. If we are measuring elevation and area covered, the best way to that goal is not to increase those measures with each act.

The reason for the focus on the increasing returns to scale case, that draws out the distinction between policy choice and success measure most, is deeply rooted in what we are finding out from social networks that are defined by task. In human systems, position counts and as tasks evolve and draw more resources to a system, success begets success (Faust, 1997). The tension then is to recognize hierarchy, formal and informal, and reward its productive collection of complementary skills and actors without endowing centrality with a sort of feudal power that

Balkanizes the system and secures productive activity at the center at the expense of even more productive activity at the margin. 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 naturally. 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.

Indeed 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 can be spurious. The limited use of regression here is to locate rules of individual connectivity efficiently in place of prediction directly over the trajectory of the system. The computational system such as the one constructed here, operable node by node and connection by connection under a probability distribution, is more permissive (imposes less structure *a priori*) to the variety of outcomes that the analyst expects could emerge; and that suggestion is premised on the reason for network analysis itself, its dependence on initial conditions and a complexity of outcomes that flow from potentially modest changes in the performance or decisions of individual associations that are not predetermined, or forced. The rules located are simple and given the ever sharper quality of network data a parallel effort at analytic methods more able to introduce the richness of information being assembled shows promise.

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 Rowen, 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 Wesley 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.

Smith, T. & Stevens, G. 1999. "The Architecture of Small Networks: Strong Interaction and Dynamic Organization in Small Social Systems." *American Sociological Review.* v64: p. 403-420.

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. Powell, W.W. Owen-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.

Table 1
Policy Outcomes

Constant Returns	Static Analysis Output	L/C Ratio	Output after Three Funding Cycles* (mean)	Final Number of Researchers (mean)*
Baseline	68.0	1.8357	59.0	175
Direct Optimization	68.6	4.3599	60.4	179
Smart Small World	68.5	4.5068	69.0	189
Connectivity Fairness	68.4	5.8359	62.3	179
Increasing Returns	**Static Analysis Output**	**L/C Ratio**	**Output after Three Funding Cycles (mean)**	**Final Number of Researchers (mean)**
Baseline	71.5	1.8357	63.9	175
Direct Optimization	74.5	4.3599	69.7	202
Smart Small World	75.9	4.5068	76.7	210
Connectivity Fairness	73.9	5.8359	73.5	211

*Average Values over 100 simulations.

Direct Optimization
Final Network

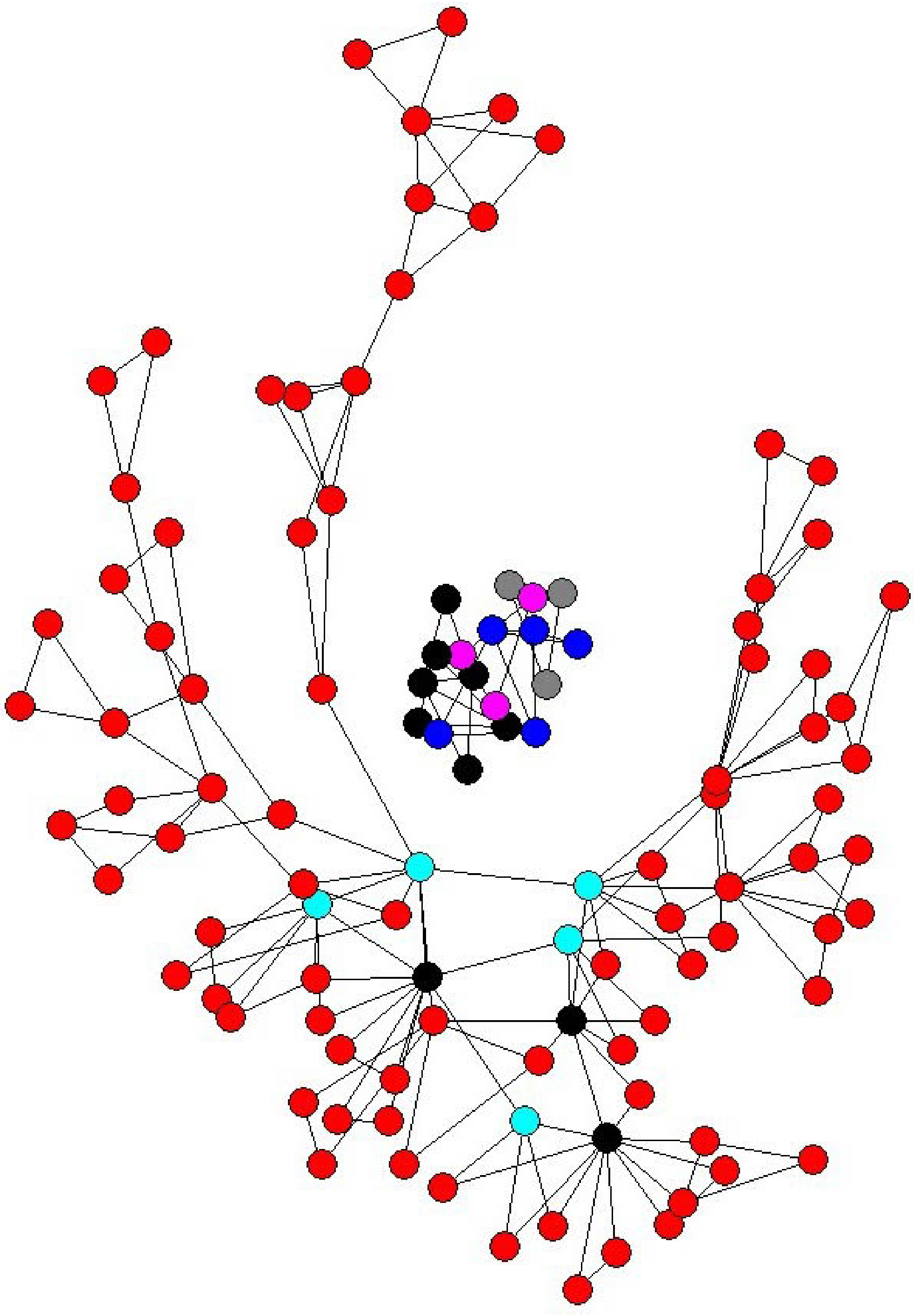


Figure 4

*Isolates and Nodes of Degree 1 Removed

Fairness Rule
Final Network

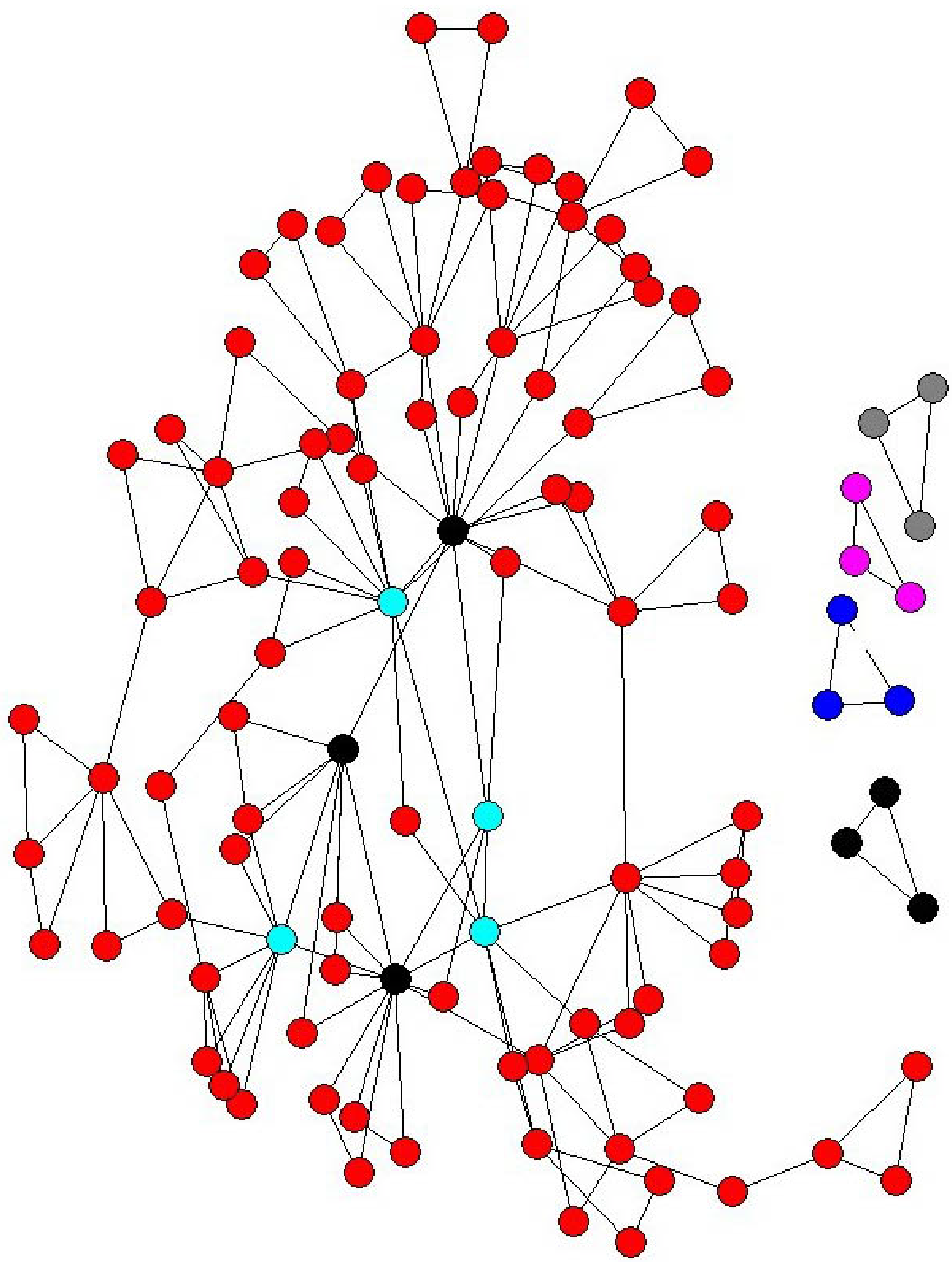


Figure 3
*Isolates and Nodes of Degree 1 Removed

Smart Small World
Final Network

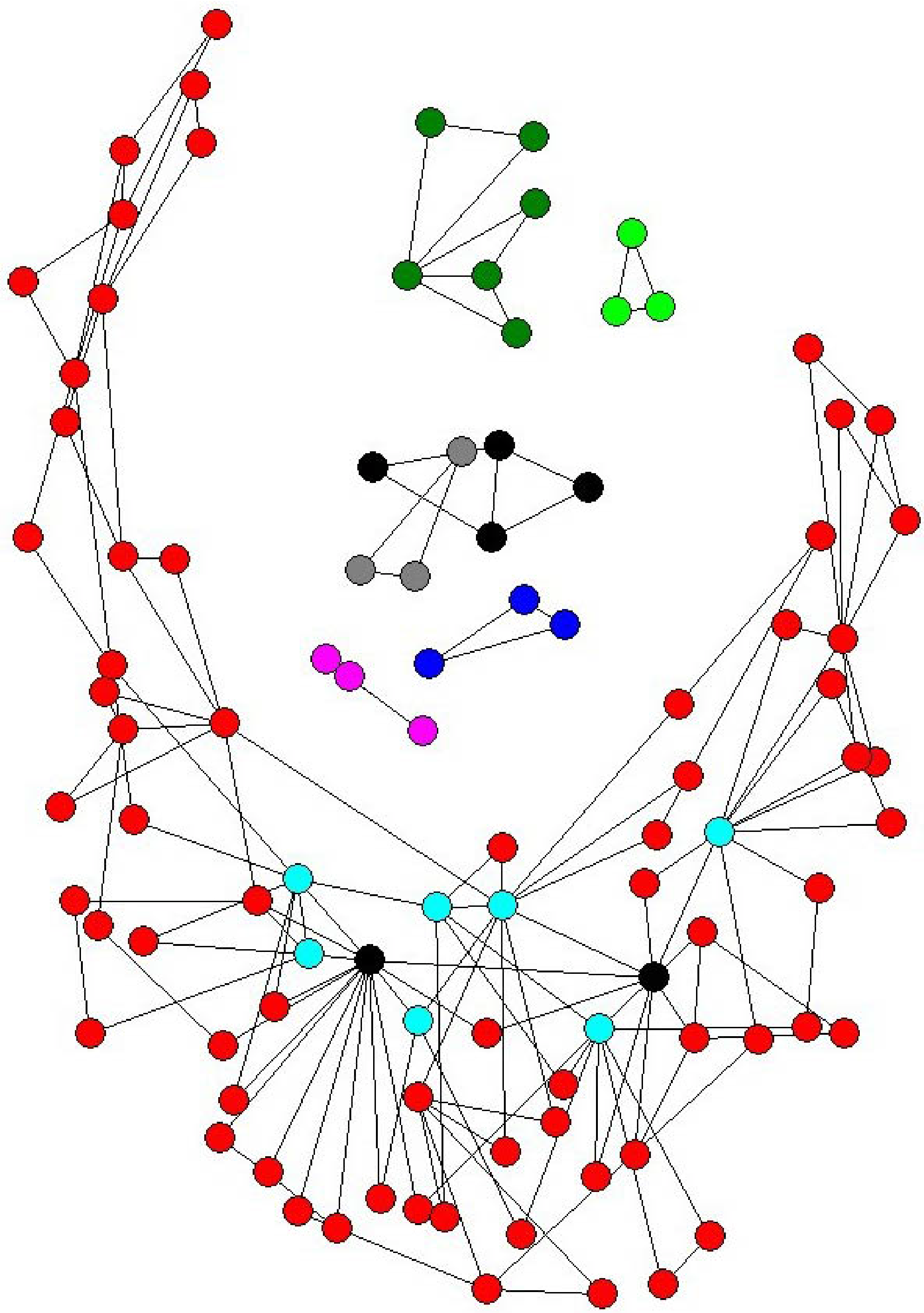
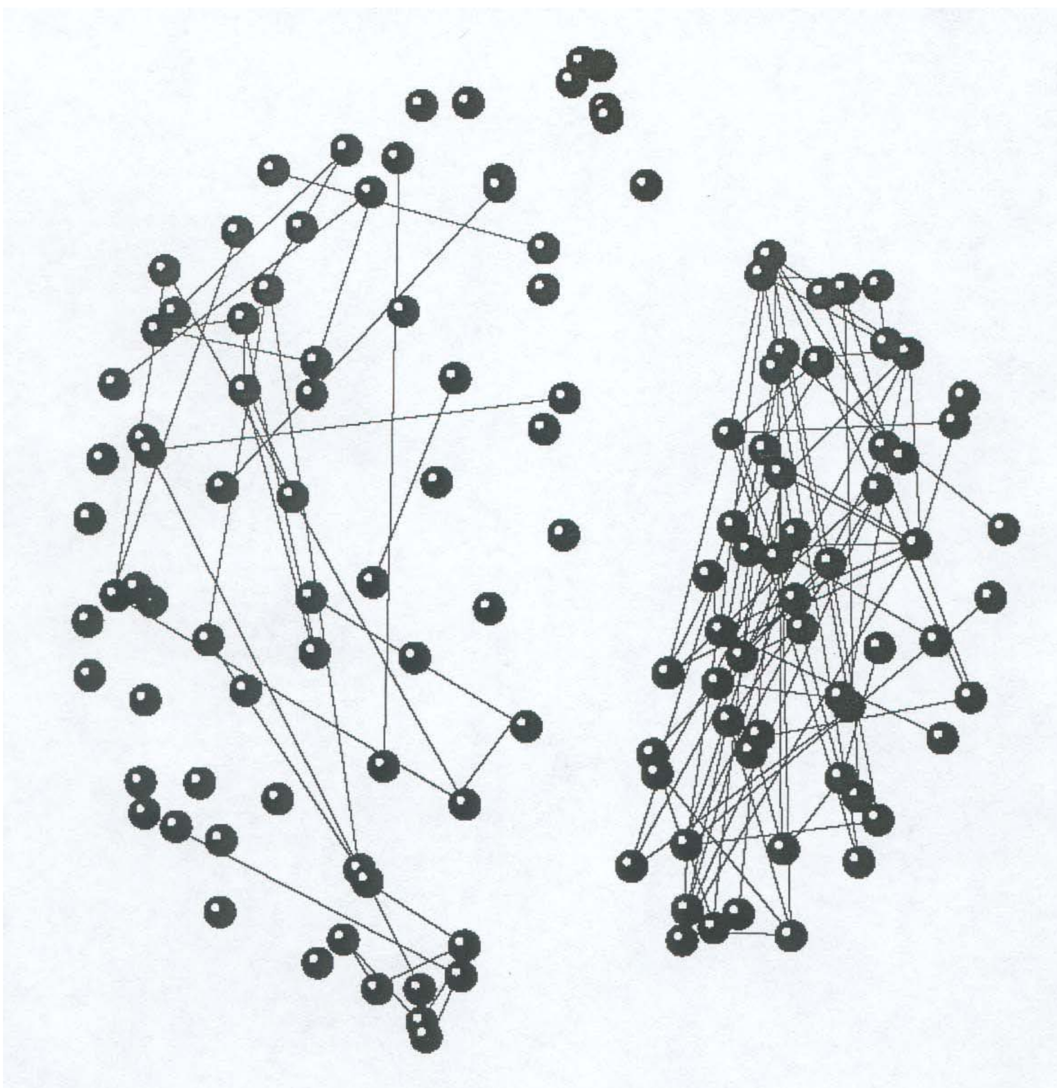


Figure 5

***** Isolates and Nodes of Degree 1 Removed

Initial Network of
Venture Capital Collaborations
(Silicon Valley)*



*Courtesy of Castillo et al. (2000): Warton School of Business

Figure 1

Strategic Connections
Direct Optimization vs. Smart Small World Policy

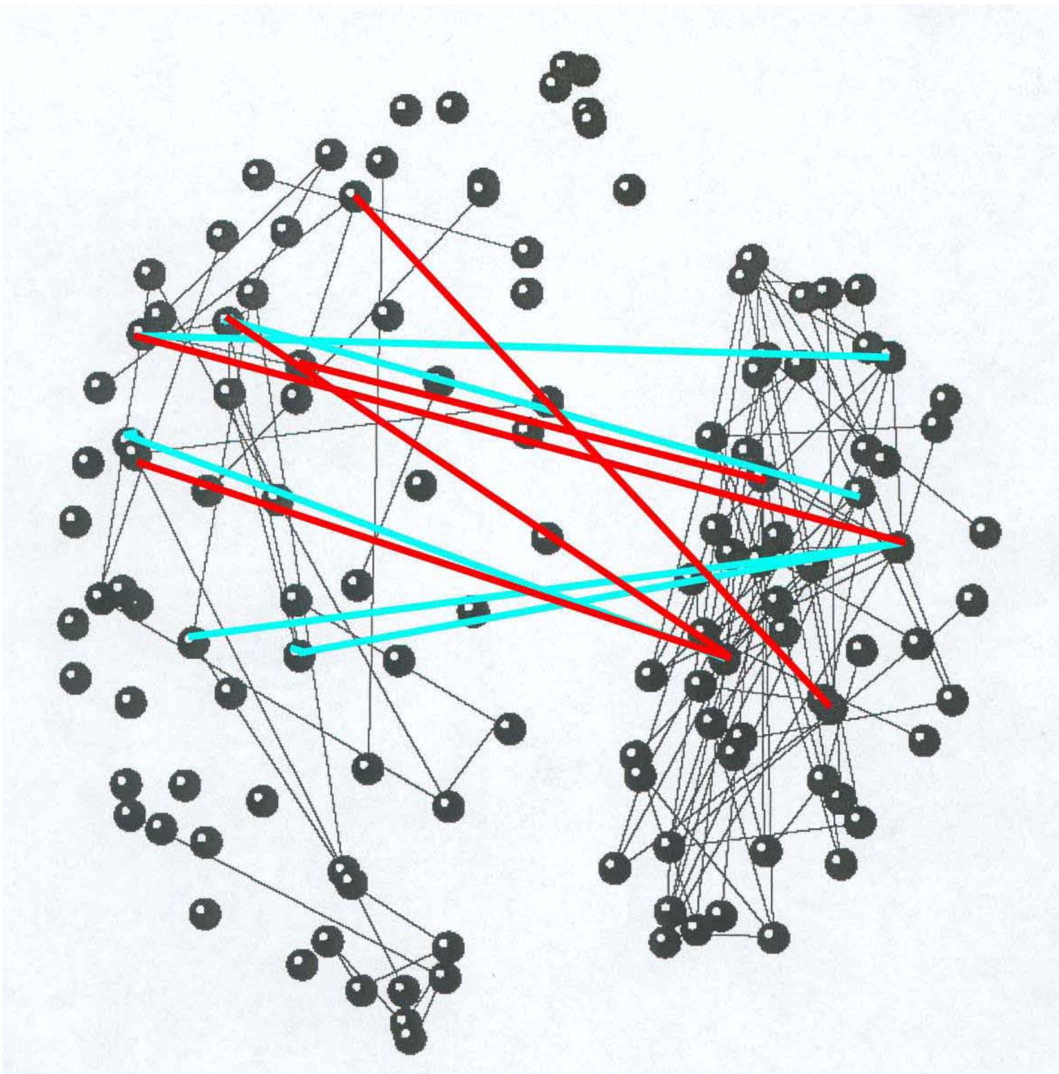


Figure 2