ABSTRACT

Title of Document: NETWORK MODELS OF REGIONAL INNOVATION CLUSTERS AND THEIR IMPACT ON ECONOMIC GROWTH

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This research uses social network analysis to develop models of regional innovation clusters using data from patent applications and other sources. These new models are more detailed than current industry cluster models, and they reveal actual and potential relationships among firms that industry cluster models cannot. The network models can identify specific clusters of firms with high potential for manufacturing job growth where business retention and expansion efforts may be targeted. They can also identify dense clusters of talent where innovation and entrepreneurial efforts may be targeted. Finally, this research measures relationships between network structure at the time of patent application and manufacturing job growth in subsequent years. This will permit the translation of a wide range of network-building activities into the ubiquitous "jobs created" metric. These new tools will help economic developers focus resources on high-yield activities, and measure the results of networking activities more effectively.

There are three parts to this research. First, it evaluates the uses of social network analysis (SNA) in planning, reviewing the literature and empirical research where SNA has been used in planning related studies. Second, it presents the construction if innovation network models, covering methodology, data, results and direct applications of the network models themselves. Models are constructed for Pennsylvania between 1990 and 2007. The methodology presents a significant innovation in how networks and geography are modeled, embedding counties in the network as *place nodes*. The resulting network models more accurately reflect the complex and multiple relationships that firms and inventors have with each other and the locations where they interact. This approach makes it possible to evaluate relationships between innovation and economic growth at a smaller geographic level (counties) than previous research. Third, this research presents an econometric model that evaluates the influence of network structure on county-level manufacturing employment and value added. Network structure is measured in the year of patent application, with manufacturing employment and value added being measured annually for each subsequent year. Differences in network structure generally reflect differences in the level of social capital embedded in different parts of the network. I find that network structure influences manufacturing employment within three years (longer for medical devices and pharmaceuticals) but does not influence value added.

NETWORK MODELS OF REGIONAL INNOVATION CLUSTERS AND THEIR IMPACT ON ECONOMIC GROWTH

By

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Preface

In many respects the seeds of this research were planted in a failed 2004 grant application for Pennsylvania's new Keystone Innovation Zone (KOZ) program. The program, which was launched that year by newly elected governor Ed Rendell, was based on the success of recent redevelopment activities in West Philadelphia, most notably in the area around the University of Pennsylvania. It was consistent with the emerging view at that time that universities played a critical role in the innovation ecosystem. Those views suggested that investment in the areas around universities would promote the commercialization of new technologies and foster new company formation and job creation. Around that same time the U.S. Council on Competitiveness published a new methodology for assessing regional innovation capacity.

As an economic developer in York, Pennsylvania I was charged with writing the county's KOZ application. Naturally, one of my first tasks was to apply the Council's new methodology to assess the innovative capacity of York County. To my horror this new methodology suggested that York had very little innovation capacity. This finding ran counter to my knowledge of York's long history of both innovation and manufacturing, and my experience with present day innovation through factory visits related to my job as an economic developer. I *knew* York had innovation capacity, yet somehow it was not showing up in the metrics developed by the Council. One of major the reasons was that York did not have a tier one research university, even though Johns Hopkins, the University of Pennsylvania, Penn State, the University of Maryland and Drexel – to name just a few – were just a short drive away. York College and Penn State York were both fine institutions with capable faculty, but they were focused primarily on teaching rather than research.

That same year Sean Safford completed his dissertation at MIT, using social network analysis to examine the response of Allentown and Youngstown – cities in many ways comparable to York – to the patterns of deindustrialization prevalent in the 1980's and '90's. His research won the MIT dissertation prize and was later published by Harvard University Press as the book *Why the Garden Club Couldn't Save Youngstown.* Sean's work introduced me to social network analysis for the first time and prompted me to propose a network-based approach for our KOZ. Despite vigorous discussions with state officials the application was rejected. Afterward, York County Economic Development Corporation president Darrell Auterson remarked that it was "one of the most innovative applications he had ever seen".

I have written many grant applications over my career and have come to accept that sometimes even good applications don't get funded. I have learned not to take it personally. Yet something about this application continued to gnaw at me as I began my Master's studies at Temple the following year, and later my PhD studies at the University of Maryland. The Council on Competitiveness metrics along with several other innovation indicators tended to be university-centric. They seemed to be driven in several respects by data availability, with measures like "number of advanced degrees" and "patent counts". Yet there were significant gaps in other measures where data was hard to come by. They did not, for example, have any measure of localized skills required to actually make things. Through my factory visits in York I observed that many people on the factory floor were deeply involved in innovative and creative work, yet their knowledge and skill had been developed though years of experience. Many of them had minimal formal education. It was clear to me that a significant amount of innovative activity was undetected by the available metrics. This problem also appeared to be especially acute in second tier regions that had significant manufacturing capacity but that were also limited in terms of the institutional infrastructure that was currently being associated with innovation.

Economic developers in these second tier regions (and elsewhere) faced a second measurement-based problem associated with public funding for economic development. That problem was – and remains – the overwhelming use of "jobs created" as the metric by which public funding is committed to economic development activities. This obsession over the past decade or two has had the subtle effect, in my view, of shifting economic development priorities towards investments in capital projects where input-output software can easily translate "dollars invested" into "jobs created". As an economic development practitioner I saw budgets for networking activities slashed, while capital budgets continued to increase. Public opinion of networking events and activities soured, they were increasingly viewed as a waste of public money.

This trend, it seemed to me, was especially devastating to second tier regions because the threshold level of capital investment necessary for an institutional approach to supporting innovation was simply too high. On the one hand, capital investments in these regions were likely to produce some good, but ultimately would be seen as underperforming when compared to major metro regions with deep institutional resources. On the other hand these regions were starved of resources for networking activities to support innovation because they had no way to document the number of jobs created by these activities.

Yet at a core level it is precisely this practice of networking, of connecting people, firms, resources and ideas, that is the very foundation of economic development practice. Economic developers know instinctively that strong networking leads to economic growth. The problem is they haven't been able to measure it in terms of the job creation metric.

This dissertation seeks to address both these problems. Through the use of social network analysis and vivid network graphics it reveals the broad geography of innovation. What is striking is that the findings reinforce the importance of major metropolitan regions and research universities in the innovation ecosystem. There are no major disputes with prior innovation and cluster research. However this new approach reveals both visually and empirically that innovation is not limited to those places. It is everywhere, and it is more interconnected than we ever imagined. In similar fashion they reveal previously unobserved and unmeasured aspects of clusters that allow us to see the emergence of new technologies and clusters at the firm level, well before they show up in the industry data. Finally, this research shows that networking matters to economic development by revealing the relationship between network structure and the rate of manufacturing job growth in subsequent years. While much more work is needed, the ability to translate "dollars invested" in networking activities into "jobs created" is on the horizon. The creation of this and other "big data" tools for economic development form the basis of my research agenda going forward.

Dedication

This work is dedicated to my friends and family whose support and encouragement has sustained me through the hours, days, weeks and years. To Christopher, I have learned more from you than you know, and the trips to Wyoming and Arizona provided welcome interludes and fresh perspectives. To Cassandra, you challenge me to write well, to shape ideas with both evidence and the craft of writing. To Kim, your love and support has been unwavering through all the challenges – thank you. Finally, to my mom who always had words of encouragement when I called you on my way home from class. This is for you.

Acknowledgements

The research presented in this document focuses broadly on the structure and outcomes of collaboration in the process of innovation. Quite simply it says that if we understand the social structure of collaboration in the innovation process we will in turn have a better understanding of at least some of the economic outcomes of innovation. Yet, as a dissertation this research is by definition an individualized work – a test of one person's capacity to make a unique contribution to human knowledge. This notion of individual work has been useful in helping me define a specific niche within the academy and has helped me develop strong, logical, evidence based arguments to support my claims.

I am grateful to many people for engaging in those arguments with me, for sharing their insights and criticism, and for pushing me to continually refine and simplify my ideas and arguments. Foremost among them is my advisor, colleague and friend, Marie Howland, who over the past five years has sharpened my perspective, clarified my arguments and simplified my writing. The members of my committee – Jim Cohen, Jerry Hage, and Gerrit Knaap from the University of Maryland, and Peter Meyer from the Bureau of Labor Statistics – have also shaped my thinking and clarified my arguments in many ways. So too has Jay Liebowitz of University of Maryland's University College, an early advisor and committee member.

Many people beyond my committee also provided useful guidance, information, support and feedback. A few of these include the faculty involved in the 2010 ACSP Dissertation Workshop at Georgia Tech – Bruce Stiftels, Steve French, and especially Nancey Green Leigh, whose support and insights have been invaluable. John Landis' early critique of my proposal was extremely useful in establishing the level of rigor that my research needed to meet to make a useful contribution. This group was also responsible for putting me together with Ward Lyles from UNC Chapel Hill whose work with social network analysis complemented my own. Ultimately Ward and I co-author *The Uses of Social Network Analysis in Planning: a Review of the Literature*, published in the February 2012 issue of the Journal of Planning Literature. A version of that paper is included as chapter 3 of this dissertation, with Ward's direct contributions noted throughout.

Immediately following that ACSP workshop in the summer of 2010 I had the opportunity to work with Steve Herzenberg and the Keystone Research Center on issues related to manufacturing employment in Pennsylvania and beyond. Steve's insights and support of my research came at a critical and formative stage in my dissertation. His contribution to my research has proven invaluable.

Tim Franklin of TRE Networks, Ed Morrison from Purdue, and Emily DeRocco from the Manufacturing Institute have all provided important insights and feedback through the annual TRE Roundtable meetings, as well as through correspondence and conversations. The 2011 Roundtable led to a subsequent collaboration with Meredith Aronson and the New Jersey Institute of Technology which has been very productive. Russ Montgomery (formerly) from REDDI has also been a friend, a constant sounding board, and strong supporter of my research for many years. John Voeller from Black and Veatch, and Julia Lane (formerly) from NSF helped me frame my research within a policy context.

Within the University of Maryland I am also grateful to several people for their support and collaboration. To Dean Carmello at the graduate school, Provost Ann Wylie, and Dean Cronrath from the School of Architecture, Planning and Preservation, I am very grateful for financial support provided through the Wylie Dissertation Fellowship and other grants and fellowships which supported my doctoral studies at Maryland. In the Office of Research I am grateful to Vice President Patrick O'Shea for his interest in my research and for supporting the continuation of my research with a seed grant. I am also very grateful to Associate Vice President Brian Darmody for his counsel and support in connecting me to people both inside and outside the University who have helped with my research. In the Human Computer Interaction Lab my collaboration with fellow doctoral student Cody Dunne has been invaluable. Likewise, the support and encouragement of Ben Shneiderman and Ping Wang, along with Marc Smith from Connected Action have been energizing as I have made the transition to Node XL as my preferred network software package.

There are of course many others in my network of friends, supporters and collaborators that have contributed in both direct and subtle ways to this "individual" work. The limitations of time, memory and space do not permit me to name all of you, and there will inevitably be that moment in the future when the sudden realization that I didn't mention you by name will cause me to whack myself in the head. To all of you – named and unnamed – please accept my sincere thanks for your interest, support and help over these many years. While I am necessarily the author of this dissertation it is truly the result of a long collaborative effort. Thank you.

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Chapter 1: Introduction

A broad consensus exists among scholars in multiple disciplines that there is a causal relationship between innovation and economic growth. However there are divergent perspectives on the particulars of this relationship, in part due to difficulties in defining and measuring innovation. Many economists have focused on the relationship directly (for example Marshall, 1932; Solow, 1957; Griliches, 1996; Pianta, 2004, Verspagen, 2005). Other researchers have focused on identifying and measuring the inputs to innovation (for example Bresnehan, Gambardella & Saxenian, 2004; Fagerberg, Mowery & Nelson, 2005). Economic geographers have explored the spatial nature of innovation and why it seems to cluster in certain urban centers (for example Polenske, 2007; Carter, 2007; Feldman, 2007). Business and social science researchers have sought to understand the process of innovation and its connection to entrepreneurship (for example Porter, Whittington & Powell, 2005; Pavitt, 2005; Lam, 2005). They have focused on issues such as the tacit knowledge and face-to-face communications (for example Cowan, 2005; Gertler, 2005, 2007; Malerba & Breschi, 2005; Storper & Venables, 2005; Keilbach, 2000); the conditions under which entrepreneurial opportunities emerge (for example Burt, 1995; Granovetter, 1973); environments in which innovative people are found (for example Florida, 2002, 2005); and how new knowledge clusters are born (for example Saxenian & Hsu, 2001).

Two basic problems with innovation research have frustrated progress in the field. The first is that innovation is not well defined and there is little precision in the definitions that do exist. The second problem is that as hard as innovation is to define, it is even more difficult to measure. For example, a recent U.S. Commerce Department report on potential innovation measurements illustrates both of these difficulties. The report defined innovation as "*the design, invention, development and/or implementation of new or altered products, services, processes, systems, organizational structures, or business models for the purpose of creating new value for customers in a way that improves the financial returns for the firm*" (Schramm, et. al., 2008). Not surprisingly, the report offered only broad principles for developing measures of innovation. Still, researchers continue to be motivated by the needs of Economic Development (ED) policy and practice. They continue asking how, why and where innovation influences economic growth, and what conditions support the growth of innovative activity.

This paper approaches these questions from an economic development perspective and is motivated by the difficulties many smaller manufacturing communities face in transitioning to new products and markets in an increasingly global economy (Mayer, 2009). The plight of the so-called "rust belt" is now well documented, but economic development policies and practices to date have had limited success in addressing the core issues in these regions. One core issue is a pressing need for more innovation in communities and regions that apparently lack the resources and institutional density upon which most cluster-based economic development policies and practices are based. This paper builds on existing strands of thought within the literature and promising methods of Social Network Analysis to advance a new model of the relationships between the structures of innovation networks; the inventive activities undertaken by actors within those networks; and the spatial distribution of manufacturing job growth and value added measured at the county level. This new model is used to answer a specific research question with implications for manufacturing regions in the U.S.: ***Are "innovation networks" drivers of economic development in regions that lack the institutions and density present in agglomeration economies?***

1.1 Defining, Measuring and Representing Innovation and Innovation Networks

As noted above the lack of clear and widely accepted definition and measures of innovation has impeded progress on understanding and managing its process and outcomes. Many scholars have addressed this problem, however there seems to be little consensus, in part because innovation cuts across so many disciplines that it literally has different meanings depending on the perspective, and the measures of innovation are used in different ways depending on the discipline.

One way to add structure to this definition problem is to identify different types of innovation. For example, there is a common distinction between product and process innovation (Hage and Meeus, 2009). This distinguishes new and improved products from innovations in the processes it takes to make those products. Process innovation may also extend into services as well. Less common but equally important is distinguishing organizational innovation from products and processes (Hage 2003). Organizational innovation refers to new or altered business models, practices and structures that lead to better organizational performance. A second way to add structure is to look at innovation as a dynamic process in which these different types of innovation may be applicable at different points in the process. One such approach identifies six "arenas" in which different types of innovation shape the overall innovation process. These arenas include 1) basic research; 2) applied research; 3) product development; 4) manufacturing research / process innovation; 5) quality control research; and 6) commercialization research (Hage, 2011; Hage and Hollingsworth, 2000).

On the measurement side the number and variety of metrics developed to measure innovation is equally diverse. Thamhain (2003) offers a useful summary of the metrics used to measure innovation performance, primarily from the firm perspective. Mote, Jordan and Hage (2007) provide metrics for radical (as opposed to incremental) innovation that may be used in real time to help manage the innovation process. Ratanawaraha and Polenske (2007) provide yet another summary from the geographic perspective and there are many others as well. What quickly becomes clear is that the measures that are used and the validity of those measures depends very much on what part of the innovation process they are measuring and which perspective the results will be interpreted.

Indeed, debate over the definition and measures of innovation seems to have evolved into an academic sport of sorts. This paper acknowledges this debate but chooses not to engage in it. A few of its contours are discussed above; however this paper deliberately focuses on a narrow slice of the innovation spectrum (product innovation) with a clear discussion of the limitations of this focus in light of the ongoing debate over definitions and measures of innovation.

Innovation Networks

An important difference in this research is the modeling and measurement of innovation networks. Innovation networks are simply networks of people and organizations involved in the process of innovation and the relationships between them. This difference is important for two reasons. First, innovation networks are not proxies for innovation in the same way as say, patent counts. Innovation networks are something different. They are historical records of innovative activity by specific people and organizations. They are "footprints of complex dynamic [process]" (Leydesdorff, 2006 p2).

It is precisely this complex dynamic process that makes innovation so difficult to measure and leads researchers to use proxies like patent counts in the first place (Thamhain, 2003). This sets up the second reason why the use of innovation networks is important to this research. The reason is that the research question asks whether the presence and structure of *innovation networks*, not innovation itself, influences economic growth. In so doing this research does not seek to reduce the whole of innovation to a single simple measure or proxy. Instead it asks whether there is subsequent economic growth in places where we observe these footprints of complex dynamic processes. If the answer is yes, then the debate over how that complex dynamic process we call innovation is defined need not be resolved in order to demonstrate its influence on economic growth.

Why Networks and Why Now

As discussed in more detail in the next chapter, innovation increasingly requires the involvement of many different people and organizations. Americans in particular have developed a certain cultural mythology around the lone inventor / entrepreneur with larger than life example like Henry Ford, Thomas Edison, Bill Gates, Steve Jobs and Mark Zuckerberg. Their unique visions have earned them a rightful place in history; however each one would quickly say that they didn't do it alone. The process of innovation, form the initial flash of discovery, through invention, product development, manufacturing process, and quality control to large scale production takes many skills and many people. There are, however, many different models and different arrangements of people and organizations based on specific products, technologies, skill sets, and many other factors. Moreover, the need for different skills, people and organizations tend to arise as the innovation process moves through different stages or "arenas" (Hage, 2011). The process of innovation, as Hage points out, often slows down or stalls between these arenas.

The complexity of the innovation process and the organizational structures designed to manage it, along with the variability of these structures from one industry to another makes it very difficult to model innovation consistently using traditional means. Such models would specify a set of innovation inputs, an innovation process defined by a mathematical model, and a set of innovation outputs. However there is little agreement on what the inputs are and what their precise relationships are to innovation outputs. What has filled this void are a variety of innovation indexes that provide some correlation between various sets of innovation inputs and certain economic performance indicators. These include metrics by the Council on Competitiveness, the Milken Institute, the Information Technology and Innovation

Foundation and many others. These metrics are useful for comparing two or more places, but they provide little insight into the innovation process itself.

The idea of using social network analysis to model various aspects of the innovation process has been explored by several researchers. For example, Mote, Jordan, Hage, and Whitstone (2007) reviewed its use as a tool for evaluating research and development. This and several other efforts will be reviewed in the next chapter. Interest in using SNA to model innovation has been driven in part by the continuing elusiveness of satisfactory models using traditional methods. It has also been driven by an increasing awareness of SNA along with relatively recent availability of software, data and computing power sufficient to handle large complex networks. A third factor, at least for the research presented in this paper, is the recognition that the types of interpersonal interactions required in the innovation process involve significant levels of trust, the suspension of opportunistic behavior among those involved in the process, and the sharing of information and resources. In other words, the innovation process requires social capital. Formally defined, social capital is embedded in the networks of actors involved in innovation and the ties that connect them (Lin, 2001; Lin, Cook and Burt, 2001). Although some have tried to allocate social capital to individual actors for the purpose of empirical analysis, the results have been unsatisfactory (most notably Glaeser, Laibson & Sacerdote, 2002, reviewed in the next chapter. Recent extensions of network analysis to include different types of nodes other than strictly people or organizations have also made this type of investigation possible (for example Monge and Contractor, 2005, reviewed in the next chapter).

Networks, Geography and an Innovative Approach to Analysis and Representation

A confluence of technical, methodological and substantive factors presents an opportunity to advance the study of innovation using network analysis. These factors have also laid the foundation for an innovative resolution of the so-called areal unit of analysis problem. On the one hand, selection of small geographic units – say counties – compromised the integrity of network structures that spanned the boundaries of those small units. On the other hand, selecting geographic units large enough to fully contain most networks – say states or countries – limited the usefulness of the results. In using SNA to model innovation networks this research makes a second important departure from prior studies. Instead of attempting to force network structures into a geographic analysis frame, this research simply interprets geographic units, in this case counties, as nodes in the network. As will be shown in the next three chapters, this use of a network analytic frame rather than a geographic one preserves important networks structures, allowing measurements of the social capital embedded in those structures.

The graphic rendering of the network models in later chapters presents "places" in a format quite different from the geographic maps people are accustomed to and this tends to be a little disorienting at first. In part this is because we are so accustomed to seeing geographic maps that we accept them as "real" rather than as the symbolic representations that they are. In similar fashion we tend to think of spatial distance as "real" and social distance as "imaginary" even though both are symbolic constructs. One may be more familiar, but both are legitimate symbolic representations or reality.

The research presented here is organized as follows. Chapter 2 reviews relevant literature at the intersection of innovation, clusters, networks and economic growth to establish a foundation for the research question and methodological approach. Chapter 3 examines the uses of social network analysis in planning since the approach and methods of SNA are relatively new within planning research and practice. Chapter 4 presents the research methodology in two parts. First, it details the creation of network models using patent data and other sources. It also discusses the measurement of network structure. Second, it presents an econometric model that measures the influence of network structure on economic growth. Chapters 5 and 6 discuss the results of network model and econometric model respectively. Chapter 7 presents conclusions, discusses limitations of the current research, and presents directions for future research.

Chapter 2: Literature Review

Over the past two decades a large volume of literature has focused on the complex nexus of regional clusters, innovation and networks, with several significant edited volumes being published. These include *Technological Change and Mature Industrial Regions: Firms, Knowledge and Policy* (Farschi, Janne & McCann, 2009); *The Economics of Regional Clusters* (Blien & Maier, 2008); *The Economic Geography of Innovation* (Polenske, 2007); *Cluster Genesis* (Braujnerhelm & Feldman, 2006); *Clusters, Innovation and Networks* (Breschi & Malerba, 2005); *Industrial Clusters and Inter-Firm Networks* (Karlsson, Johansson & Stough, 2005); *The Oxford Handbook of Innovation* (Fagerberg, Mowry and Nelson, 2005); *Innovation Clusters and Interregional Competition* (Brocker, Dohse & Soltwedel, 2003); *Innovation Policy in the Knowledge-Based Economy* (Feldman and Link, 2001); *The Oxford Handbook of Economic Geography* (Clark, Feldman & Gertler, 2000); *Innovation Behaviour in Space and Time* (Bertuglia, Lombardo and Nijkamp, 1997); *Innovation, Networks and Learning Regions* (Simmie, 1997); and *Innovation Networks: Spatial Perspectives* (Camagni, 1991). This far-from-exhaustive list of focused edited volumes presents over 200 peer-review papers by at least as many scholars and the totals more than double with the addition of journal articles, conference proceedings, books and research reports. These scholars and their publications provide much of the foundation for research presented in this paper, thus relevant highlights are briefly reviewed here.

Some of these scholars have focused specifically on one part of the innovation process – invention – and on the spatial distribution of inventors. Researchers along this line have used disaggregated patent data and Social Network Analysis (SNA) to reconstruct and analyze networks of inventors (discussed in chapter 3). They have used this approach along with traditional social science analysis methods to determine the effects on metropolitan size on patenting activity (Bettencourt, Lobo and Strumsky 2004); the effects of inventor networks on patenting activity (Strumsky, Lobo and Fleming ,2005); and the effects of enforcement of non-compete agreements on inventor mobility (Marx, Strumsky and Fleming ,2009).

This literature review draws together three strands of research literature that focus on the relationship between innovation and economic growth; the notion that entrepreneurial opportunity is embedded in network structure; and the interplay between innovation networks and spatial agglomeration. The first strand includes Alfred Marshall's notion that innovation is "in the air" (1932) and Robert Solow's measurement of technological change as a "residual" (1957). These examples illustrate a long history within economics of attempts to measure the effects of innovation on economic growth, and the difficulties in doing so. They also illustrate the importance of technology focus and alignment – concepts which also underpin most cluster theories. The second strand integrates Granovetter's concept of *weak ties* (1973) and Burt's theory of *structural holes* (1995) as indicators of entrepreneurial opportunity embedded in the network structure. They demonstrate that opportunities for growth often emerge out of the network structure. In so doing, they open the door to the concept of innovation networks and offer an alternative way to conceptualize innovation. The third strand involves the debate over spatial agglomeration vs. network effects on the spatial distribution of innovative activity. This strand anchors the first two strands in a spatial context while they, in turn, offer a particular framework for interpreting the agglomeration / network effects debate. For example, it is known that networks have significant effects on the growth of mature clusters (Saxenian, 1994) and especially on the development of nascent industry clusters (Saxenian & Hsu, 2001). Some researchers are now moving beyond an either/or debate to a dynamic conceptual framework where both agglomeration and network effects exist. The extent to which one or the other is dominant depends on initial conditions and industry sector dynamics (Prevezer, 2008; Ter Wal & Boschma, 2009).

2.1 Economic Literature

The theoretical foundation of this research begins with an important strand of economic thought concerning the aggregate measurement of innovation. Inspiration is drawn from the classic ideas that innovation is something that is "in the air" (Marshall, 1932), and that innovation (more specifically, "technological progress") is best measured as a "residual" (Solow, 1957)[1,2]. At issue here are not so much the arguments and theoretical contributions that these and many other economists have made to the measurement of various factors of production and their impact on

[1] To be clear, the research proposed herein only draws inspiration from Solow's recognition that the components of technological progress, one of which is innovation, are manifested in the "space" between inputs and outputs. I do not intend any specific comparison between the research proposed herein and concepts of total factor productivity.

[2] Solow was one of several economists working on an Output/Total Input index which identified a "residual" which was associated with technological change. See Griliches (1996) for a detailed historical account.

economic growth. Rather, it is the observation that a consistent thread throughout this literature is a frustration with the intangible nature of innovation that is best exemplified in the quotes above. What is implicit in these two examples and throughout the economic literature concerning the measurement of innovation and its impact on economic growth is that the current system of data collection and analysis has so far not identified adequate measures of innovation. Moreover, these examples seem to imply that the elusive process of innovation is something that happens in the "space" between the measurable attributes that could be analyzed. In short, identifying specific metrics and analysis methods to *directly* assess the influence of innovation on economic growth remains a significant gap in the economics literature.

2.2 Management and Sociology Literature

The second strand of thought woven into this research is found in social network research, primarily the concepts of *weak ties* (Granovetter, 1973) and *structural holes* (Burt, 1995). Relationships are referred to as "ties" in SNA, and those ties may be considered "strong" or "weak" depending on the type of relationship. Evidence suggests that *new* information and *new* opportunities are more likely to come through indirect relationships - weak ties - rather than through well established relationships (Granovetter, 1973). The opportunities represented by weak ties cannot be measured directly, since they are by definition indirect relationships. The strength of weak ties comes from their *potential* to become direct relationships.

Following a similar line of inquiry, Burt (1995) identified certain patterns of relationships in the structure of social networks that were related to the level of entrepreneurial opportunity available to actors in the network. He called these patterns *structural holes* because the opportunity was manifested by the absence of direct ties between certain actors, and the ability of a third actor to broker a new relationship between them. Thus structural holes quite literally refer to ties that do not exist. It is arrangement of ties in the network structure relative to the *ego*[3] that determines whether structural holes represent opportunity or constraint (Burt, 1995). The absence of ties between alters represents high opportunity for the ego to broker relationships. However if there are many ties between alters, the ego's opportunity for brokerage is constrained. Burt's measure is called "constraint" and it is an indicator of the extent to which the ego's alters have ties with one another.

Weak ties and structural holes are related in terms of network structure by the idea that weak ties have the potential to bridge structural holes, allowing the ego to capitalize on the opportunity presented by a structural hole (Burt, 1995). Both Burt and Granovetter effectively argue that the seeds of economic opportunity are sown within the structure of the network. The literature provides ample empirical evidence that opportunity and growth emerge out of the network structure (discussed further in chapter 3).

Social Capital

The theories of Granovetter and Burt have become widely associated with *social capital,* and Burt's constraint is frequently presented as a measure of social capital (Ahuja, 2000; Walker, Kogut and Shan, 1997). Despite popular use of the term social capital in a variety of contexts in recent years, sociologists have

[3] When the network is modeled from the perspective of a single actor it is called an *ego network*. The actor from whose perspective we are viewing the network is called the *ego*, and all the other actors he is connected to are called *alters.*

developed specific definitions, leading to the construction of a theory of social capital that provides a solid foundation for empirical measures. Social capital may be defined as *resources embedded in a social structure (or network) which are accessed and /or mobilized for purposive action* (Lin, 2001; Lin, Cook and Burt, 2001). Network structure is critical to both the embedded nature of social capital and the individual actor's ability to access and mobilize that capital, because networks not only connect individuals; they connect the multiple hierarchies within which those individuals are embedded. The positions that network actors hold in those hierarchies determine the set of positional resources available to that actor and thus the level of social capital that may be accessed through a network connection. Lin states "interactions should be analyzed and understood not only as relationship patterns among individual actors or nodes, but much more importantly, as resource patterns linked to interaction patterns" (Lin, 2001, p38). This perspective seems particularly relevant to the process of innovation across multiple arenas as described by Hage, 2011, and may offer some insight into some of the measurement difficulties noted in Chapter 1. The "resource patterns" referred to by Lin corresponds loosely to "innovation inputs" in traditional innovation models or indexes. However, where the traditional models are not clear or consistent in how those innovation inputs are brought to bear on the process of innovation, Lin's statement makes it clear that these resources are made available to the innovation process (*i.e. purposive action*) as social capital through interaction patterns in a network structure. This perspective seems able to reconcile the broader structure of the innovation process described by Hage and others, with the seemingly highly individualized nature of innovation and apparent variability in organizational structures that are able to produce successful innovation. Under Lin's perspective the broader structure of the innovation process would correspond to the highly structured hierarchies and patterns of resources accessed through social capital, while the variety of network paths leading to those resources would represent the perceived variability in organizational structure surrounding each individual innovation.

2.3 Economic Geography Literature

The third strand of literature shaping this research emerges from a debate within economic geography. The debate is whether spatial agglomeration or network effects have a controlling influence on the spatial distribution of innovation activity. Those advocating agglomeration and knowledge spillover effects have held the high ground in the argument for some time, and have had significant influence on economic development policies and practice (for example Florida, 2002, 2005; Porter, 1998a, 1998b, 1998c; Muro & Katz, 2010). While acknowledging the underlying importance of networks, agglomeration-based analyses have nevertheless focused almost exclusively on spatial structure and the attributes of place. Little attention is paid to relationships or network structure.

For example, in recent years the concept of *social capital* has increasingly been associated with economic performance, innovation and entrepreneurship within the literature on these topics as discussed above (see also Putnam, 2000, for example). Quite often the term social capital is used conceptually, referring generally to the value of relationships. As discussed in the previous section, sociologists have developed specific definitions and measures that emphasize the importance of networks structure (Lin, 2001; Lin, Cook and Burt, 2001). Several scholars have also focused on economic definitions and empirical measures (Burt, 2004; 1992; Hansson, et.al., 2005; Westlun & Bolton, 2003; Glaeser, Laibson & Sacerdote, 2002; Durlauf, 2002). Many of those focused on economic definitions acknowledge the "community" nature of social capital and observe that social capital is a relational emergent, attributable to the relationships between actors rather than the actors themselves. Lin's theory of social capital is anchored in classical and neoclassical theories of capital (broadly defined), however clear distinctions between social capital and other forms of capital. One of the features that distinguishes social capital from, say, financial or human capital is that social capital is embedded in the network, while financial and human capital may be attributable to individual actors (Lin, 2001).

Yet this community or network view of social capital has made empirical analysis in economic terms more difficult (Glaeser, Laibson & Sacerdote, 2002) and empirical results more questionable (Durlauf, 2002). In response, Glaeser, Laibson & Sacerdote opted for an "actor attribute" definition of individual social capital that is more congruent with conventional economic theory and analysis rather than the "community" definition of social capital. Although the approach was analytically more tractable, this simplification ignores a defining characteristic of social capital – that it is relationship-specific (perhaps what they refer to as "interpersonal externalities" in the passage below). That is, a particular "unit" of social capital only has value in the context of a *specific* relationship or set of relationships. It was a useful experiment that did not yield particularly satisfying results. Glaeser and his colleagues concluded the following:

> Our analysis shows that social capital accumulation patterns are consistent with the standard economic investment model. Individuals accumulate social capital when the private incentives for such accumulation are high. However, profound differences distinguish social capital from other forms of capital. *Most of these differences stem from the interpersonal externalities that can be generated by social capital.* These externalities make the aggregation process extremely complex. It is not at all clear whether we should think about social capital as networks (with positive externalities) or as status (with negative externalities). While we think that the basic economic model does quite well at helping us understand individual social capital investment, ***we also believe that future work must develop a new set of tools to address the complicated and important aggregation/externality issues.*** *(2002, emphasis added)*

On the other side of the debate, those advocating network effects of innovation have suggested that the co-location of firms that leads to agglomeration effects are actually spatial manifestations of underlying network dynamics (i.e. interactions and changes over time), and that network growth is a catalyst for spatial agglomeration. (Prevezer, Opsahl & Panzaraza, 2008; Powell, 1996; Sorenson, 2003) They also suggest that within spatial agglomerations, innovation and cluster growth results from the interaction of multiple overlapping networks (Granovetter, 1973; Sorenson, 2005; Porter, Whittington & Powell, 2005; Owen-Smith and Powell, 2006). Differences in cluster performance have been linked to the effectiveness of such networks (Saxenian, 1994). More recently, researchers have begun to consider the effects that industry sector (i.e. technological) differences may have in network development and co-location (Malerba, 2004, Breschi, 2000). Industry differences are believed to influence communication styles and methods (Cowan, 2005), labor mobility, and communities of practice (Saxenian and Hsu, 2001).

Owen-Smith & Powell (2004, 2006) demonstrated that network structure and composition played significant roles in shaping the market focus and related development of the biotech industry between Boston and the San Francisco Bay area. Network structure has also been associated with differences in community resilience in response to significant economic restructuring between Allentown, Pennsylvania and Youngstown, Ohio (Safford, 2009). Certain elemental network structures have been identified as controlling structures in so-called "scale free" networks (Xu, Zhang, Li, & Small, 2011). Scale free networks are networks in which the degree distribution follows a power law. They are characterized by multiple "hubs" that are highly interconnected with lower degree nodes. This creates a structure that is generally resilient in the face of localized failure. Xu, Zhang, Li, & Small (2011) demonstrate that the structures that connect the high-degree hubs into "rich clubs" exhibit some controlling characteristics on the structure and performance of the larger network. Innovation networks generally exhibit the characteristics of scale free networks, thus an examination of the structure of the core of the innovation network may reveal clues as to the structure and dynamics of the broader innovation network[4].

While the academic debate has been fairly balanced, the policy debate has clearly tipped in favor of agglomeration. This has led to an economic development policy environment that is heavily skewed towards an interpretation that spatial density and concentrated institutional resources are the primary factors that influence innovation. Such policies have been based in large measure on *cluster* concepts advanced by Michael Porter, and to a lesser extent on *creative class* concepts

[4] Scale free networks are mentioned here because they suggest a promising direction for future research. They are however beyond the scope of this paper.

advanced by Richard Florida (Porter, 1998a,b,c; Florida, 2002, 2005; Muro & Katz, 2010). These ideas have found greater acceptance within a policy environment that tends to favor place-based strategies (Bolton, 1993). Widespread implementation of strategies based on these concepts has yielded mixed results (Mayer, 2011; Feldman, 2007), but one clear observation can be made. Both concepts are manifestations of agglomeration theory and are therefore based on certain assumptions about population and institutional resource density. Under these theories, spatial density and depth in both talent and institutional resources are necessary to drive the knowledge spillovers that are fundamental to the growth of innovation clusters. The emergence of research universities as central actors in such strategies exemplifies these assumptions (Bowman & Darmody, 2008; SSTI, 2006). In the network models[5] there is a clear migration of universities from the periphery to the core of the network between 1990 and 2001.

Interestingly, many universities are turning to network-based approaches to community engagement. Transformative Regional Engagement (TRE) Networks, for example, is a network of universities and related organizations focused on transforming the process and effectiveness of university economic development at regional, national and international scales. Central to this transformation is the recognition that such engagements occur in the form of open networks and that planning meaningful action within such environments requires new approaches and new tools of practice (Franklin, et. al. 2010, 2011; Morrison, 2010a, 2010b, 2011).

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[5] www.terpconnect.umd.edu/~dempy/research.html

Over the past decade or so there has been a gradual shift in perceptions and policies concerning the role of research universities in the innovation process. While early cluster literature noted that universities played important supporting roles (Porter, 1998a, for example) what has emerged is a more widespread perception among policymakers and practitioners that research universities are an essential and necessary part of regional clusters. This perspective has emerged in large part due to the limited number and character of regional clusters that have been studied, notably Silicon Valley, Boston / Rt.128, and North Carolina's Research Triangle (Mayer, 2011; Braunerhjelm &Feldman, 2006). If this perception is true then large portions of the U.S. and other nations will be left out of the innovation economy. It also fails to explain the observed emergence of innovative clusters in regions without research universities; or why some regions with research universities fail to develop innovative clusters. Mayer (2011) finds that the presence of research universities are neither a necessary nor sufficient condition for the emergence of innovation clusters, however connections with universities become more important as the cluster matures. In her case studies of Portland, OR, Kansas City, MO and Boise, ID, Mayer found that firms served as "surrogate universities" and that cluster emerged through the entrepreneurial activities of employees / former employees of those firms. The knowledge of processes, and business practices that entrepreneurs learned at these firms spilled over into their new ventures and their connections to markets allowed them to quickly establish functional networks of customers and suppliers.

2.4 Using Social Network Analysis and Patent Data

As noted in the introduction to this literature review several recent studies have been undertaken using theoretical frameworks, methods, and data similar to those proposed herein. These studies also reference much of the literature just reviewed but emphasize slightly different aspects. The first of these studies examines the relationship between patenting activity and the population size of metropolitan areas (MSA's) using patent data. The study draws several important conclusions. First, that patenting activity is disproportionately located in larger metropolitan areas, exhibiting increasing returns to scale with respect to population size. Second, the distribution of inventors follows a very similar pattern to patenting activity with a nearly identical relationship between the number of inventors and metropolitan population size. Third and of particular interest, the researchers found that patents per inventor per year (inventor productivity) was approximately constant across all metropolitan areas. Fourth, the distribution of R&D / Creative Class activity followed a similar scaling pattern as patent activity and inventor location although the exponents are different (Bettencourt, Lobo and Strumsky, 2004). While the first, second and fourth findings above tend to reinforce well-established theories of spatial agglomeration, the third finding suggests that spatial agglomerations are not structurally more efficient in terms of inventor productivity. In considering the distribution of inventors, the researchers used network size to model "agglomeration effects," and network density to model "network effects." Their analysis showed that density was weakly correlated but not sufficient to explain the differences. Network size was highly correlated and super-linear (i.e. the terms in the equation have exponents between 1 and 2; see finding 2 above). If inventors in more populous MSA's were more productive because they had better, denser networks, one would expect to find structural differences in the network reflected in more strongly correlated density measures. This was not the case. Larger metro areas produced more patents because they had more inventors, not because the inventors there were part of denser, more productive networks.

The second paper by Strumsky, Lobo and Fleming (2005) extends the research presented above, focusing more intently on the differential effects of network size and density on patenting activity while introducing control variables to account for differences in patent technology (for example drugs, electronics, machinery, etc); differences in industry technology; and differences in socio-economic conditions across MSA's. Attempts were also made to account for inter-regional collaborations between inventors. Their findings were consistent with the first paper. The researchers were openly disappointed that their expanded model did not find stronger network influences (measured by network density) than the previous model. As will be shown in the next section, much of this disappointment may be rooted in the way that they define the network; how they defined what agglomeration effects are; what network effects are; and the network measures they chose to use.

The third paper by Marx, Strumsky and Fleming (2009) examines how changes in the enforcement of "non-compete" agreements in Michigan influenced inventor mobility. While maintaining the same basic structure and assumptions about the inventor network, the nature of the research question demanded a more sophisticated approach to the relationship between inventors and patent technology.

Notably, the paper introduces the use of a Shannon entropy index to identify more prolific inventors who they label as *specialists* and *stars,* based on patent citations. This approach effectively illustrates two important aspects of technology with respect to market demand. The first is that *what* inventors are inventing matters. That is, different products have different demand schedules in the marketplace. For example demand for the latest *iPad* technology is much higher than, say, demand for new mechanical pencil technology. The second important aspect is that *timing* matters. The notion of *product life cycle* is an important part of multiple planning and business theoretical approaches, several of which are reviewed by the authors. The rapid pace of innovation means that the length of time for which a particular technology remains influential is limited. Portable computer data storage for example, has evolved from tape storage to floppy disks, to CD's to flash drives. These two aspects of patent technology have important implications for modeling innovation and the Shannon entropy index effectively captures these influences.

Limitations and Critiques of Patent Data in Innovation Research

The perceived dangers and limitations associated with the use of patent data in innovation research have reached near mythic proportions. Thus no such research would be complete without prominent acknowledgement of the limitations of patent data, both real and perceived. In simple terms, patents provide specific information about a certain set of activities. Researchers must exercise caution in how they use and interpret patent data, as they should with all data sets. Analytic errors can arise when researchers do not fully understand or account for idiosyncrasies in the data set. They may also arise when researchers make unfounded assumptions about the data set or use the data as a proxy for something else. Many of the problems that have become associated with patent data are in fact research design problems. Several of these are quite common, and are discussed below.

Understanding the patent process and the nature of the information provided in that process helps to minimize problems related to idiosyncrasies in the data set. Inventors and/or their assignees are afforded protection of their intellectual property rights through the patent system. In the course of seeking that protection they provide certain pieces of information as a matter of public record in their patent application. Some information provided by the applicant should be used with caution. For example, inventor addresses typically refer to their address of residence, not their place of work. Assignee (firm) addresses may refer to an establishment where the invention was developed, or may refer to the location of the corporate headquarters. Thus it is important to use caution in interpreting locations. The patent application is then reviewed by a patent examiner, who may alter or augment certain parts of the application in the process of granting a patent, most notably citations of prior art, and patent classifications identifying the specific technology class to which the invention belongs. These changes may also be made by a patent agent or patent attorney in the process of applying for a patent on behalf of the inventor(s). Thus caution should be used in assuming certain relationships exist based on citations listed in the patent (USPTO, 2012; Griliches, 1990).

Often a number of years may pass between the application and granting of a patent. Some inventions may me patented but never commercialized. Some patents may be granted for relatively minor improvements that represent minimal economic value, while others may represent enormous financial potential. These factors become problematic if patents are used as proxies for innovation, because they are records of invention, not necessarily innovation. Further, one cannot assume that patent applications represent a consistent time reference in the innovation process, or that all patents are of comparable value. These are all well known limitations of patent data, discussed by Griliches (1990), and Schmookler (1966), among others.

Additional problems arise if patents are used as a proxy for innovation. This problem is twofold. First, as noted previously patents are records of invention, not necessarily innovation. Inventions that are patented but never commercialized would yield “false positive” results. This situation may arise for a variety of reasons. Inventors may be satisfied with the patent alone and may lack the desire or resources to pursue commercialization. Patents may be obtained during the course of academic or other research and may be subject to onerous university licensing requirements that inhibit commercialization. Patents may be obtained as defensive measures in order to protect a firm’s current profitable products from competition. Finally, patents may be assigned to or purchased by so-called “patent trolls” – firms that do not commercialize the technology but rather profit by suing other companies for patent infringement.

A second additional problem with using patents as proxies for innovation is that many innovations are never patented. Patenting levels vary from industry to industry (Cockburn and Griliches, 1988; Arundel and Kabla, 1998). Using European patents, Arundel and Kabla, (1998) found that a large percentage of innovations in the food, petroleum and primary metals sectors were never patented.

2.5 Recent Policy Literature

Although basic concepts of spatial agglomeration that underpin cluster approaches may be traced back at least as far as Marshall's analysis of industrial districts (Marshall, 1932), contemporary U.S. Economic Development Administration (EDA) policy and the research that shapes it have tended not to look back beyond the initial writings of Porter and Florida until recently (see for example Muro & Katz, 2010; or Mills, Reynolds & Reamer, 2008). Policymakers have only recently begun turning to the rich body of European research and literature that focuses more on the relationships and systems involved in supporting emergent network – cluster structures (Helper, 2012). The broader body of cluster research and other cluster examples beyond Silicon Valley and Route 128 are slowly making their way into policy shaping documents and events (Brookings, 2012). This bodes well for future cluster-based economic development policies which may finally move beyond their narrow focus on a few popular ideas.

This is not to say that existing policies are entirely wrong, or that they do not represent movement in a positive direction. However those policies embody a lingering commitment to assumptions about the necessity and importance of density and research universities that do not necessarily hold outside of major metropolitan regions (Mayer, 2011). This may be changing, as there appears to be some new receptiveness to network approaches, particularly as they relate to improving U.S. innovation performance (Brookings, 2012; Cowhey, 2012; Whitford & Shrank, 2012). With its funding of the University of Maryland – Morgan State University Center in 2011 the EDA demonstrated an interest in network analytical approaches

(Tickner, 2011). At the same time the Kansas State University Center has been experimenting with facilitating regional innovation clusters across a rural state using network strategies (Sani, 2011).

Given this recent receptiveness to SNA approaches and their usefulness in planning applications (discussed further in Chapter 3) the rationale for a network – based approach to evaluating the relationship between innovation and economic growth is clear. Network research on innovation as well as brokerage suggests that specific measures of innovation network structure may influence certain economic outcomes (Burt, 1995; 2005; Borgatti, 2008).

2.6 Literature Summary

This research contributes to the economic development literature by weaving these three strands of thought together into a new conceptual framework of innovation and economic development. The three strands of research – economic, management / sociology, and economic geography - are merged in the following way. From the economic strand one observes that after decades of research by some of the finest economists *we are still faced with a concept and process of innovation that defies measurement using actor attributes*. The conclusion that is evident from the evolving literature on social networks is that *innovation is to some extent relational, not solely dependent on the attributes of individuals, firm, and other actors*. Both the management and sociology fields contribute to this strand of theory and provide good evidence that entrepreneurial opportunity emerges out of the structure of social networks. The specific arrangement of relationships and actors in the network creates structural patterns that either expand or constrain each actor's opportunity to advance their own interests. *In the context of innovation, this means that the opportunity for growth emerges out of the structure of the innovation network.* Taken together, these two strands of the literature suggest that combining conventional social science analysis which focuses on actor attributes with Social Network Analysis focused on relational structure may provide a more complete picture of how innovation affects economic growth.

The economic geography strand and particularly the agglomeration vs. network effects debate frames this combined approach in a spatial, theoretical and economic development policy context. Agglomeration effects have dominated economic development policies, in part because they are easier to measure and easier to understand, and in part because policy-makers tend to favor place-based economic development strategies as noted by Bolton (1993). Network effects and agglomeration effects may also be conflated as they were in Bettencourt, Lobo and Strumsky (2004), for example, where network size was used as a measure of spatial agglomeration. While this summary suggests that the three papers reviewed in section 2.4 suffer from limitations associated with trying to analyze networks within a geospatial frame of reference, it should be noted that <u>within</u> that frame of reference the research is well structured and makes multiple empirical and methodological contributions. Specifically, the use of Herfindahl and Shannon Entropy indexes are introduced in the context of innovation research and these metrics are adapted for this research as will be discussed later in the methodology section.

Weaving these three strands of research together suggests the need for a new conceptual framework of innovation and growth and a new model that includes measurement and analysis of both actor attributes and relational structure. This new framework is built on the notion that innovation-related growth emerges out of the relational structure of the innovation network, and that this outcome is at least partially independent of the spatial and resource density associated with agglomeration economies. This new framework also proposes that technology is a significant organizing feature of innovation networks and that it influences economic growth by organizing and expanding the number of weak ties within the network. This increases the level of opportunity available in the network structure, which leads to economic growth. This framework is incorporated into a network model of innovation networks in Pennsylvania between 1990 and 2007 in chapter 4. The network models are used to generate independent variables for an economic model also discussed in chapter 4.

This economic model measures the relationships between the structure of innovation networks, the flows of resources and activity undertaken by certain actors within those networks, and the spatial distribution of manufacturing employment and value added measured at the county level in subsequent years. This research builds on the recent body of literature that uses social network analysis and patent data discussed in section 2.4. However it departs from those studies in several important ways, mostly in how the network models are constructed. Another important departure from the prior research is in the way network structure and spatial agglomerations are modeled. Rather than using a network variable to represent agglomeration influences, this research uses different measures of agglomeration that are independent from the network measures. For example, prior research used measures of network size to model "agglomeration effects" and measures of network density to model "network effects" (Bettencourt, Lobo and Strumsky, 2004; Strumsky, Lobo and Fleming, 2005). In contrast, this research considers both network size and network density to be important *network* variables that work together to help define and influence network structure. Agglomeration is viewed as a *spatial* phenomenon rather than a network one, and is modeled through a pair of dummy variables representing two important thresholds of *spatial* size and density.

Although the network proposed in this research is still based on the same basic patent data as previous studies, the differences in the way the network is constructed and measured allow this basic approach to be used in a more sophisticated way. The open structure of the network allows other relationships to be added, for example funding relationships with federal and state agencies and support from universities and intermediaries. Invention remains central; however the structure modeled here clearly begins to capture the broader process of innovation. This in turn allows the focus to shift from the spatial organization of invention to the question of how innovation influences economic growth across different spatial contexts.

The potential impact of this research on economic development policy and practice is significant. This research challenges some basic assumptions of current policy and practice. It proposes a critical rethinking of the use of capital-intensive strategies, –for example building technology parks or incubators, or offering large grants or tax incentives for business attraction or retention, in favor of more cost effective strategies designed to expand innovation networks in relational space rather than physical space. It also proposes a critical rethinking of the mechanisms by which technology influences economic growth and contributes to the spatial organization of regions in a global economy. This new approach is likely to create more supportive regional environments for entrepreneurs and emergent industry clusters, leading to stronger, more sustained growth over time, especially in second tier manufacturing regions.

Chapter 3: The Uses of Social Network Analysis in Planning

The use of social network analysis (SNA) in many social science disciplines has increased exponentially over the past two decades. Although documented applications of SNA in planning research and practice are still quite rare, instances of its use in planning's allied disciples of sociology, management, economic geography and political science are increasingly common. Journals including the Annals of Regional Science (2009); American Politics Research (2009); Methodological Innovations Online (2009); and Innovation: Management Policy and Practice (2010) have published special issues focused on the use of SNA within their respective disciplines. Individual papers – many of which are reviewed or cited herein – have demonstrated the applicability of SNA to a wide variety of social science problems relevant to planning, from studies concerning the nature of "community" (Wellman, 1979, 2001b) ; to collective action in estuarine management (Scholz, Berado, and Kile 2008); to public participation in the redevelopment process (Holman, 2008; Rydin & Holman, 2004); to innovation studies (Fagerberg & Verspagen, 2006); to environmental management (Davies, 2002); and supply chain management (Borgatti and Li, 2009). Social network analysts themselves have addressed the broader use of network analysis in the social sciences and increasingly, the physical sciences (Borgatti, Mehra, Brass, & Labianca, 2008). With rapidly growing interest in the potential uses of SNA it is both appropriate and timely to review its applications and potential within the field of urban planning.

Within the discipline of planning itself, planning theorists have wrestled with whether networks represent a new paradigm for planning; how they relate to and organize space and time; and their potential to influence the process of governance (Albrechts & Mandelbaum, 2005). Growing out of the 2003 Joint Conference of the Association of Collegiate Schools of Planning and the Association of European Schools of Planning, *The Network Society: a New Context for Planning* is a compilation of 18 papers on the subject with commentaries by several leading planning theorists. Within this volume two essays, one by Innes and the other by Fainstein, represent both the divergence of opinion among planners with respect to networks, and the common conclusion that more information is needed (Innes, 2005; Fainstein, 2005). This paper responds to Innes' call to review the base of knowledge in related disciplines (Innes, 2005 p60), and to the common observation of the lack of empirical research. By introducing the field of Social Network Analysis proper, as opposed to the generic term "network analysis," this paper also seek to address Fainstein's critique of network analysis as a "fuzzy concept" (Fainstein, 2005 p223). One unavoidable observation from this volume is the complete lack of reference to the specific field or methods of Social Network Analysis that are described in this paper. The fact that just five years ago a volume of 347 pages with 26 highly esteemed contributing authors from the field of planning could present a coherent, balanced and comprehensive discussion of the role of networks in planning without a single reference to the field or methods of Social Network Analysis is itself worthy of reflection. Is this simply an indicator of how rapidly the field of Social Network Analysis has emerged, or does it reveal some insular tendencies within the planning academy? We do not answer this question, but offer it along with the research that follows as reflective practitioners in an effort to advance the debate initiated in Th*e* Networ*k* Society.

More than 40 years ago, planning scholars and practitioners argued that the traditional, top-down, expert-driven and often unrepresentative, 'rational' planning process was not effective in addressing the types of problems we might now refer to as 'wicked problems' and 'social dilemmas' (Arnstein 1969, Davidoff 1965, Jacobs 1961, Rittel and Webber 1973, Ostrom 1998.)[6] A wide range of 'alternative' participatory theories and approaches evolved over the last half century to address problems arising from limited or ineffective involvement of key actors and the general public in planning processes, including advocacy, equity, consensus building, and communicative planning (Davidoff 1965, Krumholz and Forester 1990 , Innes 2004, Forester 1989). Although theoretical and practical debate about how to plan in the face of uncertainty and competing interests continues to be lively, the inherently embedded nature of actors in networks is a cross-cutting and consistent theme. The eighteen papers in Albrechts & Mandelbaum, 2005) explore five variations of that theme: 1) whether a network view of society is a new paradigm for planning; 2) the impact of physical networks; 3) the organization of space and time; 4) local networks and capital building; and 5) governance capacity and policy networks. Despite the lack of reference to Social Network Analysis or citations of some of its core texts (Wasserman & Faust, 1994; Scott, 1991; or Granovetter, 1973, for example), the five variations resonate in the network analysis literature reviewed below.

[6] References suggested by Lyles.

Innes and Booher present a useful conceptual model of 'network power' as part of their body of work over the last fifteen years on collaborative planning (Booher and Innes 2002 and Innes and Booher 2010). They argue that the diversity and interdependence of actors are tremendous assets in planning processes that can be leveraged to produce better outcomes of the particular planning process in question as well as adaptations to the ongoing system of actors and interests over time. Yet, understanding and harnessing those assets in a constructive way is a tremendous challenge because of the complexity associated with the diversity and interdependence of actors. In our view, although the planning literature has begun to engage network issues from multiple angles, empirical knowledge of how actors in planning processes are embedded within networks and how the structure of those networks serves to enable or inhibit individual and joint action to address wicked problems and social dilemmas is under-developed. We review the empirical work that does exist and argue that SNA is a promising approach for exploring questions along these lines[7].

This paper seeks to answer five questions concerning the use of social network analysis in urban planning research and practice. 1) What is social network analysis? 2) What unique value does SNA offer compared to other approaches and methods commonly used in planning? 3) What bodies of social science literature can planners turn to for ideas on how SNA might be applicable to planning? 4) For what types of planning problems and processes does the use of social network analysis

[7] This paragraph contributed by Lyles.

offer significant benefits? 5) How has social network analysis been applied in planning research or practice and what contributions have these applications made?

The answers to the first two questions provide an overview of key SNA concepts and place social network analysis as a methodology within the broader toolbox of methods commonly used in planning research. The answer to the third question relates social network analysis to the concerns of planning theory, particularly those of communicative action and equity planning as advocated by Forester, Krumholz, and Friedmann, among others (Forester, 1989; Friedmann, 1987; Krumholz & Forester, 1990). Social network analysis does not replace the relationship building and political savvy that these works describe. We argue that it does, however, provide a useful approach for visualizing, analyzing, understanding and remembering complex networks of actors in support of the judgment and relationship building they advocate. For answers to the fourth question we draw on and adapt research on the use of SNA in the field of political science (Heaney & McClurg, 2009). The answer to the final question draws from a relatively small number of documented applications of SNA that fall within the domain of planning and urban studies. Planners often draw on the concepts and literature of related disciplines, and determining which papers belong to "planning" and which belong to "related disciplines" is not always clear. Drawing on a broad literature review we identify three types of planning-oriented papers using SNA. These include 1) papers focusing on issues of community and social capital and 2) papers focusing on issues of collective action and governance, both of which can grounded in any sub-field of planning (i.e. economic development, land use, transportation, etc.); and 3) papers primarily focusing on substantive issues in planning sub-fields. We review these three clusters of literature and conclude with a brief discussion of potential applications of SNA in areas of planning that have yet to be undertaken.

3.1 What is Social Network Analysis?

Social network analysis is both a theoretical perspective on how the interactions of individual autonomous actors form the social structures of community, and a set of analytical tools to analyze those interactions and social structures as networks of nodes (actors) and ties (relationships). Some earlier scholars questioned the claim that SNA represents a distinct body of theory (Scott, 1991; Watts, 2008). Others have offered compelling evidence that SNA has emerged as a body of theory in its own right and not just a set of methods. (Borgatti, Mehra, Brass, & Labianca 2008). Several papers apply social network concepts without using the analytical methods. This would tend to support the latter position of an emerging theoretical discipline.

Social networks are one among multiple domains in which network analysis approaches are considered useful. Drawing from these domains we place SNA in a useful context for understanding what is both familiar and unique about SNA. Newman identifies four 'loose categories' of network analysis, including: 1) social networks, such as forms of contact or interaction between individuals, 2) information networks, such as links in the world wide web and academic citation networks, 3) technological networks, such as water, transportation and energy systems, and 4) biological networks, such as food webs with predators, prey and decomposers (2003, p. 5)[8]. All four categories of approaches share a common empirical focus on relational structure and a similar set of mathematical analyses. Although the evolution of each type of network approach has varied, empirical analysis has historically been limited to smaller, dense networks and the visualization of those networks (Newman 2003). This is especially true of social networks drawn from costly-to-collect data sources such as interviews and surveys. More recently, development of improved statistical models and a shift towards using data from available affiliation networks (for example company directors serving on the same boards of directors and co-authorship among scholars) have enabled increasingly systematic analysis of larger and more complex networks of all kinds (Newman 2003). Rapid growth in the study of networks has been described as a "dramatic surge" crossing a wide range of disciplines (Butts 2009, p. 325). What is unique about SNA as compared to the other three types of network analyses is its utility in theorizing about and systematically analyzing the competing forces of individual agency and structural social forces. This notion frames several critical debates regarding SNA and should be of interest to planners[9][10].

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[8] Environmental planners trained in environmental sciences and ecology will see connections between biological network analysis and their own efforts to conserve and manage lands to promote such goals as ecosystem health and creation of green infrastructure that provide ecosystem services. Transportation and infrastructure planners will be very familiar with technological network analysis and tasks such as bus route planning and transmission line siting. A wide range of planners will be familiar with information network analysis, including for example those involved in developing and updating comprehensive plans that must account for information in transportation plans, utility plans, housing plans, hazard mitigation plans, etc., as well as the plans of adjacent and overlapping jurisdictions.

[9] This paragraph developed primarily by Lyles.

Social network analysis has been criticized and defended as both a conceptual approach and analytic methodology. One of the debates concerns SNA's status and validity as a theoretical discipline that encompasses more than a set of analytical methods. A second, somewhat related criticism focuses on the issue of *agency* among actors in the network. Social network theory suggests that an actor's behavior and outcomes are determined to some extent by network structure, and this contention has been criticized by scholars who view actors' behavior and outcomes as the result of choices made by the actors themselves[4]. Some authors take a more nuanced approach. Rather than viewing network structure and agency as mutually exclusive, they contend that actors exhibit agency, but network structure constrains the choices available to them. In turn, the actors' choices influence the structure of the network over time (see for example Safford, 2009).

Additional debate focuses on how actors' awareness and understanding (or misunderstanding) of the structure of the network in which they are embedded shapes their behavior, and whether this in turn affects network structure. This debate in particular is reflected in the communicative planning literature. For example, Innes and Booher have categorized four types of results that typically arise from collaborative planning processes, each of which relate to how planning networks can change over time: 1) increased awareness of reciprocal interests among stakeholders, 2) new relationships, 3) single and double-loop learning that can reframe understandings of problems and interests, and 4) adaptations to the network itself as

[10] For a more detailed review of these debates see Borgatti (2008). Readers interested in a thorough treatment of social network analysis methods are encouraged to consult Wasserman & Faust (1994) and the selected SNA resources listed at the end of this paper.

perceptions and practices change and new partnerships and institutions arise (Innes and Booher 2010; Innes and Booher 1999)[11].

Returning to the agency-environment debate, the reflexive response is to position SNA on the side of environment. However this position is less clear in our reading of the literature, as the forgoing discussion illustrates. Perhaps networks and network analysis belong neither to agency nor environment, but instead represent a mediating concept *between* agency and environment. Thus networks may represent one of the mechanisms by which environments constrain the choices of individual agents at any given moment, but also one the mechanisms by which agents alter their environment over time. Because network analysis considers and measures both the influence of individual agents on the entire network and the influence of the entire network on individual agents, the nature of the debate changes significantly. The *either-or* debate between agency and environment not only presents a false choice, it presents a meaningless one; replaced instead by a much richer discussion of the dynamic interplay *between* agency and environment. While the *tools* of network analysis make this dynamic interplay apparent, it is the *theory* of social networks that allow us to interpret it.

3.1.1 A Brief History of Social Network Analysis

While all forms of network analysis may be traced back to Euler's development of Graph Theory (mathematics) in 1736, the antecedents of social network analysis in particular extend to Comte's notion of "social physics" in the early 1800's. Durkheim's comparison of societies to biological systems 50 years after

[11] This paragraph contributed by Lyles.

Comte suggested that the reasons for social irregularities were to be found in the structure of social environments in which actors were embedded. The development of Field Theory and Gestalt psychology are also widely credited antecedents (Borgatti, Mehra, Brass, & Labianca, 2008; Crossley, Prell, & Scott, 2009; O'Kane, McGinley, & Kelly, 2009; Scott, 1991). Accounts of SNA's historical development diverge between European and U.S. perspectives, but they merge in the 1930's with Sociometry and Jacob Moreno's study of teenage runaways from the Hudson School in upstate New York. Moreno and his colleague, Helen Jennings measured and mapped the friendship ties between girls at the school as a social network in what Moreno called a "sociogram." Noting that these friendship ties depict a structure of influence that even the girls themselves were unaware of, Moreno argued that the position of the girls within the network structure determined whether they ran away, and if so, when (Borgatti, Mehra, Brass, & Labianca, 2008; Moreno, 1934).

The 1940's, 50's and 60's saw continued development of "structural" approaches involving the mapping of actors and relationships as networks, and the use of matrix algebra and graph theory to manipulate and analyze those structures mathematically. Influential studies include Davis, Gardner and Gardner's 1941 study of social status among women in the Deep South(Davis, Gardner, & Gardner, 1941); the work of Bavelas and the Group Networks Lab at MIT on the effect of communication network structures on problem solving (Borgatti, Mehra, Brass, and Labianca, 2008); and Bott's 1957 study of kinship and social networks (Bott, 1957). Davis, Gardner and Gardner were able to identify cliques and social status among a group of women based on their attendance patterns at a series of social events (Davis, Gardner, & Gardner, 1941; Wasserman & Faust, 1994). Bavelas and his team at MIT quantified the importance of coordination in the efficient functioning of human networks (Borgatti, Mehra, Brass, and Labianca, 2008). Bott's anthropological study examined the influence of social networks on spousal roles among British families, finding that the types of network ties indeed influenced whether spouses shared responsibilities or held to a traditional division of responsibilities between husband and wife (Bott, 1957).

Sociologists during this period also began applying social network analysis techniques to studies that have shaped our current understanding of community structure and urbanism. For example, Fischer's 1948 study of social networks in California found that urbanization decreases network density, and a 1949 study by Hollingshead documented the influence of cliques on adolescent behavior (Borgatti, Mehra, Brass, and Labianca, 2008).

By the 1970's an influential group of sociologists had adopted social network analysis. Led by Lorraine & White, who were focused on issues related to roles, network position and structural equivalence, several students emerged as influential scholars in the field. Mark Granovetter's *The Strength of Weak Ties* (1983) has been widely cited, shaping our understanding of network interactions in a number of disciplines. Barry Wellman's work has shaped our understanding of what "community" means, and has influenced the study of social capital in multiple disciplines (Wellman, 1979; Borgatti, Mehra, Brass, and Labianca, 2008). The strong influence of sociology has continued since the 1970's.

3.1.2 Modeling and Measuring a Social Network

Networks may be modeled using dots or "nodes" to represent actors in the network, and lines between the dots to represent the relationships or "ties" between actors. Actor attributes are measures associated with the nodes and the full set of actor attributes is the network composition (Wasserman and Faust 1994). The pattern of all the ties between actors is the network structure (Wasserman and Faust 1994). Two actors (nodes) and the relationship (tie) between them form the simplest possible network known as a dyad. It is possible to measure the structure of a network from the perspective of a single actor, and this perspective is called an eg*o* network. The actor at the center of this perspective is called the "ego", while all the actors he or she is connected to are referred to as "alters." Ego networks may also be referred to as "personal communities" (Wellman, 1999). A subtle but important point is that while network measures of ego networks produce values that may be analyzed in combination with actor attributes (for example in econometric models), the*y* hav*e* no*t* becom*e* acto*r* attributes. Rather, they remain descriptions or "snapshots" of the network from the perspective of each individual actor.

Moving from picturing a social network as a graph made up of nodes and lines to relational data that can be analyzed using matrix algebra techniques requires the construction of an adjacency matrix. The row and column headings for an adjacency matrix are identical, listing the names of the actors involved in the network. In the simplest case, the cells of the matrix are coded with a "1" if a tie exists between the actors or "0" if no tie exists.

Ties may also be "valued". Values indicate a characteristic of the relationship that the research has quantified, for example measurements of the intensity of interaction. Ties may also be "directed". For example, the relationship "lends money to" is a directed relationship. Graphically, this would be depicted using arrowheads on the lines connecting nodes. In matrix form, row actors "send" ties to column actors. Thus if Jill lends money to Jen, the (Jill, Jen) cell would be set to "1" while the (Jen, Jill) cell would be set to "0".

Social networks analysis tends to follow two different models of organization (Borgatti, Mehra, Brass, & Labianca, 2008) depending on the goal of the analysis. *Architectural models* tend to focus on the structure of the network, seeking to discern whether specific structures lead to similar outcomes, or whether actors in similar network positions behave in similar ways. Planning applications related to the social and spatial structure of "community" tend to be organized and analyzed as architectural models.

Flow models view the network as a system of pathways along which things flow between actors. Analysis of flow models can, for example, identify which actors in the network are more active, or which ones are more powerful. Flow models are good for evaluating processes, as will be shown in the review of public participation in the planning process.

Numerous analytical measures of social networks have been developed to help evaluate network structure and flow[12]. These measures can be applied at the node level and at the network level, and some measures can be applied to both. Some are intuitive and easy to calculate, such as degree, which is measured as the number of actors directly connected to any given actor. Others are more complicated and computationally intensive, such as 'betweenness' centrality, which measures the centrality of an actor in the network based on how much others depend on that actor for connectivity. Wasserman and Faust (1994), Scott (1991) and Jackson (2008) are recommended references for descriptions of the theory and uses, as well as the formal calculation, of these measures.

3.2 What Distinct Value Does SNA Offer for Planning?

Social Network Analysis is both a conceptual approach to social science research and a set of methods to model and measure the relationships between actors. There are four key points that will help readers new to SNA understand 1) how it differs from traditional approaches to social science research; 2) how it relates to those traditional approaches; 3) how networks are constructed, manipulated and measured; and 4) what value SNA offers beyond traditional approaches.

The first point is illustrated nicely by the well□known saying "it's not *what* you know, but *who* you know" that matters when it comes to access and opportunity.

[12] An abbreviated list appears at the end of this paper. For a more detailed discussion of social network analysis measures see for example Borgatti, 2008; Wasserman & Faust, 1994; Scott, 1991.

We distinguish two types of knowledge – technical (what you know) and relational (who you know). Abstracting this notion to the realm of social science research it becomes clear that these two types of knowledge utilize two types of data. The first is data about the actors being studied – what we refer to as *attributes.* Attributes describe characteristics of individual actors, for example their race, income or physical location, and are the primary variables considered in traditional social science research. The second type of data is *relational data* – that is, data about the relationships between individual actors.

Relationships are also referred to as *ties* in SNA. Ties exist *between* actors. This leads to the second point about SNA -that it requires a different conceptual approach. Because ties only exist *between* actors, it is useful to think of ties existing in a separate dimension from actors, who are anchored in physical space. This dimension is sometimes referred to as *relational space.* To visualize the difference, think of someone far away with whom you correspond regularly, say using a phone, email, or Facebook. Even though the two of you are not physically close, you have a strong relationship. The two of you are distant in physical space but close in relational space. This notion of relational space is in part what Castells means when he refers to *the space of flows* as something distinct from *the space of places* (Castells, 2001). Wellman also takes up the distinctions between communities as networks of personal relationships and neighborhoods as spatially bounded places. These two ideas have become conflated in popular and political dialogue since the 1950's, and much of Wellman's work has been focused on disentangling the two (Wellman, 1999).

The third point that distinguishes SNA from other social science approaches is that it involves different methods of analysis. Because traditional research methods consider actor attributes as variables in a wide variety of statistical analyses, these methods are sometimes referred to as variabl*e* analysi*s* (Scott, 1991). Social networks use networ*k* analysi*s* methods to model relational data and to measure various characteristics of network structure. A fundamental concern and challenge of network analysis is that the relationships between actors are treated as being dependent on each other. That is, when actor A has a relationship with actor B that relationship is not considered to be independent of actor A's relationship with actor C.

The idea that network structure may be correlated with actor attributes and behaviors is the fourth point to consider in comparing SNA to other approaches. Planners may recognize a parallel concept in the idea that the arrangement of actors in *physical space* – what we will refer to as the *spatial structure* of the network – is often correlated with the behavior or attributes of those actors. This is the basis for cluster analysis and spatial autocorrelation methods. For example, these methods have been used to identify the spatial distribution of industry and occupational clusters (Feser, 2003; Feser, Sweeney & Renski, 2005). In SNA, the arrangement of the network in *relational space* – what we will refer to simply as the *network structure* – may also be correlated with the behavior and attributes of those actors. For example, employees of the same firm may share similar attributes such as location or department, and actors in similar roles (jobs) within that network may share similar behaviors. Conventional social science analysis measures various attributes of actors (the nodes in a network) and attempts to discern something about the relationships between actors (the ties or lines in a network) based on those attributes. When the network structure is simple and the differences in node attributes are clear, the conventional analytic approach is sufficient. However when relationships are complex or node attributes are more nuanced, clear answers using conventional analysis may prove elusive. SNA offers a tool to help researchers disentangle some of the relational complexities, just as cluster analysis and methods for dealing with spatial autocorrelation help researchers disentangle the complexities of spatial organization.

3.3 What Literature shows how SNA Applies to Planning?

Two themes in the SNA literature relevant to planners have exhibited strong growth recently. The first theme investigates questions related to the nature and influence of social capital and community and tends to extend from sociology, business, and management. The second theme investigates questions related to collective action and governance and tends to extend from political science and public policy. In general, these two themes converge in the realm of planning theory. However with respect to convergence of the two themes specifically in regards to *networks and network analysis*, we have found limited integration to date[13]. Here we

[13] One anecdotal example of this observation is that the co-authors of this paper both read extensively on network related issues in their respective subfields of innovation, industrial economic development and, more broadly, social capital (Dempwolf) and land use, hazard mitigation, and, more broadly, public policy (Lyles) but until they met each other, their reading lists barely overlapped.

briefly review these two themes and identify a few studies that have begun to integrate them.

The idea of social capital is that there is value embedded in the relationships between people and thus in the networks that they form. The theoretical foundations of social capital and community lie predominantly within sociology, however the applications of this concept in planning were well documented in a special symposium section in an issue of the Journal of the American Planning Association (Putnam, et.al., 2004). Definitions of social capital vary, and perhaps the three most often cited are Bourdieu, Coleman and Putnam. Writing from a Marxist perspective, Pierre Bourdieu attributed social capital to the elite class, connecting it with the ability to access other forms of capital (economic or cultural.) (Bourdieu, 1986) James Coleman approached social capital from a structural – functional perspective. He connected social capital and social structure more broadly, but rather than attributing social capital to specific structures, Coleman offered a more contextual definition that included how individuals use their positions within the social structure to achieve their goals (Coleman, 1988). Robert Putnam's definition is focused more specifically on the characteristics of the ties or relationships between individuals in a network. Putnam focuses specifically on social capital accumulating from the value of trust and reciprocity characterizing relationships between individuals (Putnam, 1995).

Interpretations of the relationship between social capital and community differ sharply, often depending on how rigidly "community" is defined and whether it is spatially bounded. For example Putnam's 1995 paper *Bowling Alone: America's Declining Social Capital* and his 2001 book of similar title both document and decry the loss of social capital and “civic community.” Putnam’s work has fueled a vigorous debate, however one could argue that much of the debate has less to do with social capital than with the definition of community. Putnam’s two “Bowling Alone” pieces bracket the 1999 publication of Networks in the Global Village in which Barry Wellman argues that “community” is in fact alive and well if you know where, how and what to look for. In framing “community” from the perspective of individual networks of “personal communities” Wellman addresses some of the key criticisms of Putnam’s work without ever mentioning Putnam or “Bowling Alone” directly. Wellman’s “communities as personal networks” approach avoids problems that arise as a result of spatially bounded definitions that assume networks are neatly contained within discrete spatial boundaries. It also avoids *a priori* normative assumptions about the attributes of community members vs. nonmembers. (Wellman, 1999)

Manuel Castells both extends Wellman’s notion of personal communities, accounting for the effects of technological enhancements, and rejects Putnam’s claims of social isolation. For Castells, technology has extended the reach of individuals beyond the confines of physical location, allowing them to easily develop and maintain long distance ties (Castells, 2001; Foth, 2006)[14]. Rounding out the discussion of social capital and community we will briefly mention the contributions of Mark Granovetter (1983) and Ron Burt (1992) in quantifying the idea of social capital in network analysis. We will return to them in a later section. Finally, any planning related discussion of social capital would be incomplete without at least

[14] The work of Castells was specifically noted by Albrechts & Mandelbaum as being of significant influence in many of the papers published in *The Network Society* (2005).

mentioning Jane Jacobs and her observations of how urban design contributes to building and maintaining social capital (Jacobs, 1961).

Just as there have been a variety of approaches to defining and investigating social capital, many theoretical lenses have been used to understand social dilemmas and wicked problems in public policy and planning arenas. We focus on two – Ostrom's Institutional Analysis and Design (IAD) and Sabatier and Jenkins-Smith's Advocacy Coalition Framework (ACF) -because of their relevance to planning, the considerable empirical testing that has been used to update the frameworks over time, and the natural fit they provide for network analysis (Ostrom 2005, 2007; Sabatier and Jenkins-Smith 1993; Sabatier and Weible 2007). The IAD has been applied to a wide array of collective action situations domestically and internationally, including provision of public services and natural resource management, while the ACF has been applied extensively to understanding environmental policy action, including coastal planning and management (Norton 2005 and Salvesen 2005) and regional land use and transportation planning in California (Henry, Lubell and McCoy, 2010). Both frameworks focus on factors that influence policy action that occurs within a realm where a diverse array of interdependent actors engage issues of policy and shared governance. This realm is termed the *action arena* in the IAD and the policy subsystem in the ACF. One manifestation of this realm is the set of communicative processes for developing, implementing, monitoring and evaluating plans. The IAD and ACF focus on complementary sets of drivers of action of interest to planners with the IAD focused on institutions (formal and informal rules) and the ACF focused on the beliefs of individual actors. Particularly relevant to the study of networks in planning is the shared emphasis on the patterns of interactions among actors that lead to policy coalition formation, policy outputs, and policy outcomes.

These two complementary and planning-relevant frameworks are supplemented by a growing policy networks literature. Echoing other criticism of social network analysis Adam and Kreisi argue that “the policy network approach is more an analytical toolbox than a theory” and caution researchers “not to overreach its possibilities” (2007, p. 146 and 131). They also argue that it will provide the greatest contribution when linked with factors drawn from other theoretical systems for explaining policy change, such as the institutions of the IAD and the beliefs of the ACF, by addressing actor diversity and interdependence in a structural way (2007, p. 146). Two other key points to take from their review of the policy networks literature is the under-utilization to date of its mathematical capabilities in the policy context and the need for clearer demonstration not only that policy networks exist, but that they matter in influencing policy outcomes[15].

Weaving these two broad literatures of social capital and collective action/governance together in a network context, Scholz and colleagues seek to explain the influence of network structure on collaborative and agreement among actor in estuarine management (Scholz, Berado and Kile 2008). They draw on the works of Putnam, Burt, Granovetter, Ostrom and Sabatier among others to frame competing network theories for overcoming obstacles to collective action. Their findings indicate that large, boundary-spanning networks facilitate collaboration while smaller, denser networks are associated with greater perceptions of agreement.

[15] This paragraph and the preceding one contributed by Lyles.

These findings are consistent with Burt's study of the influence of network structure on innovation (Burt, 2004). Henry, Lubell, and McCoy also draw on these two literatures to examine the comparative influences of ideology, power and social capital as drivers of the structure of policy networks in regional land use and transportation in California (2010).

3.4 Types of Planning Problems where SNA Might Add Value

A broad expansion in the use of social network analysis has occurred across many disciplines over the past decade and several researchers have evaluated the impact and potential of this approach on their respective disciplines. Three of these works from related disciplines are particularly relevant to planning and provide a logical framework for organizing the types of problems where SNA has been used or has significant potential to augment traditional analysis methods. Ter Wal and Boschma (2009) frame the use of SNA from the perspective of economic geography. Chan and Liebowitz (2006) explore the use of SNA from the management perspective, introducing its use as a tool to facilitate organizational knowledge mapping. They present a case study using SNA to map knowledge networks within a large foundation in Washington DC. More broadly, asset mapping as a generalized case of knowledge mapping is a technique promoted within various planning disciplines. Chan & Liebowitz provide a good example of upgrading that process with SNA. Liebowitz expands the discussion of such applications in a later volume (Liebowitz, 2007). In *Social Networks and American Politics: Introduction to the Special Issue,* Michael Heaney and Scott McClurg provide insightful analysis of the reasons why network analysis is useful in the study of politics. They highlight four types of problems where network analysis yields unique and valuable insights that are not possible through the use of traditional methods alone (Heaney & McClurg, 2009). The political nature of both planning theory and planning practice makes the framework suggested by Heaney and McClurg a natural entrée into a discussion of the use of SNA in planning. This section will introduce and elaborate on that framework, augmenting it with insights from Ter Wal and Boschma (2009) and Chan and Liebowitz (2006).

Planners routinely face six types of problems where social network analysis may prove especially useful. These include problems that involve a) coordination, cooperation, or trust; b) the sources and uses of power and influence; c) multiple levels of organization; d) informal organization; e) flows of information and/or transaction costs; and f) problems involving the dynamics of community (network) development (modified from Heaney and McClurg 2009). Each type of problem is discussed separately in this section.

3.4.1 Problems involving coordination, cooperation and trust

Planning is a social undertaking and almost always involves issues of coordination, cooperation and trust. These are essential elements of communicative planning that are "reproduced" in a communicative planning process as the actors work together to produce substantive plans and outcomes (Forester, 1989). Similarly, the practice-oriented consensus building and dispute resolution approaches often applied to planning problems also emphasize the importance of these elements in resolving conflicts and achieving satisfactory agreements (Innes 1996, Innes and

Booher 1999, Fisher, Ury, and Patton 1991). At a more general theoretical level, Nobel laureate Elinor Ostrom has developed a behavioral approach to the rational choice theory of collective action supported by empirical evidence (1998). Her model explains social benefits, akin to those planners seek to foster through planning processes, as a function of the level of cooperation among actors, which in turn varies as a function of interactions between trust, reputation and reciprocity (1998)[16].

In addition to the practical and theoretical recognition of the importance of coordination, cooperation and trust, another key observation we wish to make is that these three elements are each relational or dyadic in nature. That is, they are characteristics of the relationship*s* between people. Further, they have no specific meaning as actor attributes. If one considers only a single actor, then there is no one else to coordinate with, to cooperate with, or to trust. If one considers two unrelated actors, the same condition holds. It is only in the relationship*s* between actors that coordination, cooperation, and trust are meaningful. When planners evaluate conditions of coordination, cooperation and trust within a group of actors involved in a planning process, social network analysis offers a unique set of measures and methods. For example, problems involving insufficient coordination, cooperation and trust between two competing interest groups (i.e. a development firm and a neighborhood group) may be improved by establishing or strengthening ties between a few key actors – a process known as "bridging." SNA enables the identification of actors and relationships that need to be bridged to overcome problems of coordination, cooperation and trust.

[16] This section was developed jointly with the input of Lyles.

3.4.2 Problems involving the sources, uses and exercise of power

Power and influence are central to politics and planning. Power and influence contribute to control of decision-making, and agenda setting and even the awareness and framing of underlying problems (Lukes 1974.) Altshuler's (1967) study of comprehensive planning in the Twin Cities laid bare the challenge that planners face in defining and achieving the 'public interest' in a political landscape by demonstrating planners' relative powerlessness. Arguments have been made that consensus building techniques developed and honed over the decades since Althsuler's work address many of his critiques by fostering dialogue and shared decision-making among actors (Innes 1996). By extension, planners who employ such techniques increase their relevance, legitimacy and power. This line of argument aligns with the foundational principle of communicative planning that a key source of planners' power is their ability to shape attention (Forester 1989.) In what Castells has labeled the informational age or network society, attention shaping is becoming increasingly important (Booher and Innes 2002), suggesting an increasingly important role for planners who understand how to shape attention. Booher and Innes draw on an extensive literature on conceptions of power, including the works of Altshuler, Flyvberg, Forester, Bryson and Crosby and Gidden in defining networ*k* powe*r* as "a shared ability of linked agents to alter their environment in ways advantageous to these agents individually and collectively" (2002, p. 225). They posit that higher amounts of network power arise through relationships amongst a diverse set of actors with interdependent interests[17].

Social network analysis can contribute to our understanding of the formal and informal exercise of power and influence by analyzing the diversity (network composition) and interdependent relationships (network structure) of actors in planning processes. Granted, SNA is not needed for simple assessments of network composition; that is, to measure the relative levels of key assets actors bring to a planning process. However, what it does offer is the ability to identify and compare the structural positions of individuals or organizations in information sharing, trust, and other relationship networks. Systematically and simultaneously analyzing network composition and structure provides much deeper insights into how *what you know* and *who you know* combine into the ability to affect problem framing and decision-making. Practically speaking, such information can be useful to planners in regards to how they seek to position themselves in a network and, especially, the types of connections they seek to foster for actors whose interests are under-represented in planning processes. SNA also includes models developed specifically to answer questions related to formal and informal flows of information and other forms of influence through networks. Tracing information flows through a planning network can expose critical gaps or inefficiencies that may contribute to communicative distortions as classified by Forester (1989 and 1993).

[17] This paragraph contributed by Lyles.

3.4.3 Problems involving multiple levels of organization

Contemporary planning requires coordinating multiple organizations, both formal and informal. Planning processes may for example involve multiple political jurisdictions across local, regional, state and federal levels. Hazard mitigation planning requires this under the Disaster Mitigation Act of 2000, which has been characterized as a reflexive law devolving federal power and requiring intergovernmental collaboration (Nolan 2009, Berke, Smith and Lyles, 2010). The Federal Emergency Management Agency provides guidance for and formal review of state and local plans, state agencies provide their own guidance for local plans, develop their own plans, provide support for local planning, and provide intermediate review of plans, while local governments often participate in multi-jurisdictional plans that can involve dozens of municipalities and counties. This complicated set of guidance, support, review and collaboration relationships fits the collaborative governance model that Innes and Booher contrast with the top-down, hierarchical method of traditional governance network (Innes and Booher, 2010). They highlight that these forms of governance consist of an inter-dependent network of clusters[18].

Informal organizations may also span multiple "levels" including ad-hoc groups of residents; neighborhood-based community organizations including community development corporations; issues-based advocacy organizations, for example housing councils; or community foundations and business groups. Quite often, each group claims to speak for the "community." How do planners sort it all out? As with problems involving informal organization, no analytical tool can replace

[18] This section was developed jointly with the input of Lyles.

political instincts. Proponents of communicative action and equity planning including Forester, Krumholz and Friedmann have devoted significant attention to this issue.

SNA offers tools to visualize the myriad relationships, organizations and factions, along with analysis methods that can augment political instincts. These can be especially useful for planners attempting to design and manage participatory planning processes. For researchers, who often are not immersed in any one community enough to develop an appreciation of the local politics, SNA offers a systematic method for modeling and understanding the interactions of multiple groups and organizations in the abstract. Key players, cliques and cohesive subgroups may be identified and their relative qualities assessed. Structural holes and opportunities for bridging may be identified and remediation strategies devised. Analysis of structura*l* equivalenc*e* may help researchers sort out which factors are unique to specific networks and which factors are common to all networks. These may be especially helpful, for example, in multi-jurisdictional and environmental planning efforts.

3.4.4 Problems involving informal organization

For planners, problems involving informal organization are generally of two distinct types. The first involves informal networks within an established organizational structure. Specifically, these problems deal with the informal networks of influence and power that coexist and interact with existing political structures. Understanding and using these informal networks are often key to a planner's survival within a political environment (Hoch, 1994) or their ability to pursue an activist agenda (Krumholz & Forester, 1990). While no analytical tool can replace the instincts necessary to navigate such environments and activities, SNA offers a systematic framework for thinking about such informal structures and analytical methods that may remove some of the guesswork.

The second type of informal organization that planners must work with is the community itself. For any given plan there will be a host of individual and group stakeholders, each with their own agenda. Understanding how these actors are connected to each other and what they bring to the process is a central task of communicative action (Forester, 1989). SNA offers an obvious tool for collecting, organizing and understanding informal structures that influence both planning processes and planning outcomes. Mapping and analyzing such informal structures using SNA can provide insight into planning problems related to communicative distortions; coordination, cooperation and trust; the sources and uses of power; the aggregation of preferences; and network dynamics that may signal shifts in perception or co-opting of the planning process. Such problems often go unnoticed or undocumented because they occur within informal or poorly understood organizational structures. SNA helps make these structures visible, and thus can help to identify and pinpoint the sources of problems in the planning process. Maintaining network graphs and analyses over time may also provide a metric to evaluate planning activity and progress towards process goals.

3.4.5 Problems involving flows of information and / or transaction costs

Much of the process of planning involves flows of multiple forms of information between diverse groups of people. In practice the transaction costs associated with those flows vary dramatically. Flows among planners and between planners and elected officials often follow established channels and formal structures and are therefore relatively efficient (low transaction cost). Flows between planners and citizens and community groups are not routine, and often no formal structure or mechanism exists to convey such information. Knowledge gaps may hinder comprehension of the information being conveyed. Information flows between planners and the public are likely to have higher transaction costs. For example, Hanna has shown that participation alone is not enough for measuring the success of a planning process because participation is not the same as access to information (2000).

From a theoretical perspective, communicative planning theories recognize the central importance of establishing and maintaining good flows of information between planners, elected officials and the public (Forester, 1989; Friedmann, 1987; Hoch, 1994). Forester pays particular attention to building and maintaining a network of relationships with particular emphasis on groups that are typically disenfranchised (1989). His typology of four sources of disinformation that constrain rationality categorizes the distortions based on whether they are inevitable or socially unnecessary and whether they are socially ad hoc or socially systematic-structural (1989, 1993). Additionally, there are a multitude of forms of knowledge and the importance of local, or non-expert, knowledge needs to be better incorporated into planning processes (Innes and Booher 2010), By providing a tool to map and measure relationships and information flows, social network analysis can provide planners with new insights into the sources of communicative distortions, especially those that are socially systematic-structural. It also holds the potential to help elucidate how multiple forms of knowledge, originating from both 'experts' and 'lay' actors can be distributed throughout a network. These forms of analysis may identify specific practices planners can use to reduce the transaction costs associated with information flows and produce better planning outcomes[19].

3.4.6 Problems involving the dynamics of community (network) development

Network dynamics refers to the changing nature of networks *over time*. Within the broader context of community, some networks persist for long periods of time relatively unchanged. Other networks represent ad-hoc associations that exist for a specific purpose and then disappear, although the residual relationships may lead to other, more permanent networks. Wellman characterized personal networks as "unstable," not in the sense that they were disintegrating but rather that they were in a constant state of flux (1999, p25). Without explicitly focusing on the static vs. dynamic issue in network analysis, Wellman nevertheless does so succinctly in stating that "People are not wrapped up in traditional, densely knit, tightly bounded communities, but are maneuvering in sparsely knit, loosely bounded frequently changing networks" (1999, p24). Although most established SNA methods are typically static in nature, dynamic SNA tools do exist. *SIENA* software for example, is designed to work with longitudinal data[20]. Dynamic network analysis is an active area of research within the field of social network analysis.

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[19] This section was developed jointly with the input of Lyles.

[20] (http://www.stats.ox.ac.uk/~snijders/siena/)

3.5 SNA Applications in Planning Research and Practice

Relatively few uses of SNA in planning related applications have been documented. The majority of documented uses fall into three broad types of applications. The first type of planning application in which the use of SNA has been documented is in understanding the spatial and social dimensions of "community" and social capital. The second type of application involves using SNA concepts and methods to understand and improve public participation and equitable outcomes in the planning process. In both of these applications the literature shows a progression from theoretical to empirical approaches over time. As noted previously, public participation applications tend to be more flo*w* oriented, while network structur*e* tends to be emphasized more in the community studies. These first two types of applications can be used across many sub-fields of planning to understand participation and community, for instance in economic development, environmental planning and natural resource management, and land use planning. We categorize sub-field specific applications as the third type of planning for which SNA has been used and focus on economic development as an example.

3.5.1 The Spatial and Social Dimensions of "Community" and Social Capital

The first group of studies that apply social network analysis to planning issues is focused on understanding the spatial and social dimensions of community, to what extent social "distance" depends on spatial distance, and what the implications are for planning policy and practice. Within this group the work of Barry Wellman is central in defining community and establishing the context for most of the other studies. In considering the relationships between spatial and social distance and their affect on the social bonds associated with "community" and "social capital" Wellman provides an easy transition from the discipline of sociology to that of planning (Wellman, 1979, 2001a, 2001b).

Hajer & Zonneveld (2000) frame a critique of the Dutch planning process in terms of what greater personal connectivity and the "coming network society" is likely to mean for a wide spectrum of planning issues. While largely editorial, the analysis is thoughtful, driving home the compelling message that planners must be increasingly aware of rapidly changing social dynamics when planning physical spaces and other systems that are subject to spatial and social distances.

Assessing the effect of social networks among residents of clustered vs. scattered public housing units on the job search process, Kleit (2001) found that public housing residents in scattered suburban housing relied on their neighbors less than those in clustered public housing when searching for a job. Her findings contrast with Granovetter's findings for executives on getting a job, which showed that weak ties were more important, but they are consistent with Granovetter's later study on the influence of weak ties among low income individuals in getting a job (Kleit, 2001). Moreover, the findings are consistent with other studies on different perceptions of social capital in low income neighborhoods compared to middle and upper income neighborhoods (see for example Hutchinson & Vidal, 2004 and related papers in that issue). The implication is that the tradeoffs between spatial and social distance are different depending on the income / social status of the individual and the prevailing income / social status of their surroundings.

So to what extent are social networks neighborhood based, and how do residents' conceptions of social networks and social capital relate to their perceptions of what a neighborhood is? These questions were taken up by Gary Bridge (2002). His study utilized social network analysis to answer these questions, finding that most neighborhood residents had many more total ties and many more strong ties outside the neighborhood than within. Ties within the neighborhood were important to residents, but were generally weak in nature. Bridge concludes that the findings suggest planners should eschew preconceived notions of neighborhood "solidarity" and focus instead on designing neighborhoods with greater "porosity" and connectivity. While Bridge suggests that neighborhood interventions should be designed from the perspective that residents have city-wide networks, it does not appear that the influence of income / class discussed in the previous paragraph was considered. Thus the interpretation of Bridge's research may be different between, say a new urbanist neighborhood and the redevelopment of a low-income neighborhood.

Applying a new urbanist perspective at the scale of the city and region, Stanley (2005) examines the prospects of applying social network measures including centrality, density, and structural holes to evaluate the sizes, locations and activity (flows) in and through systems of cities in the Middle East. The author does not attempt such empirical measurements, but makes a compelling case for doing so. One particularly interesting idea evaluates "black holes" – places that should be thriving and much larger based on the network structure, but which have not developed according to their potential. Such an analysis sets the stage for comparative policy studies to determine the causes of differential development.

The book *Why the Garden Club Couldn't Save Youngstown* (Safford, 2009) evaluates the role of social networks among elite members of Allentown Pennsylvania and Youngstown Ohio societies in shaping the capacity of these two cities to respond to the impacts of industrial globalization. This exceptional work stands in a class by itself. Safford traces the histories of these two cities and shows how similar they appeared in 1975 using the demographic and economic metrics common in planning studies. After demonstrating that none of the traditional explanations could account for the subsequent economic divergence of the two cities, he presents key differences in the structure of business and social networks between them. In the case of Allentown, business and social networks only partially overlapped, while in Youngstown the overlap was far more extensive. When deindustrialization swept over the two communities, business networks were hit hard. Leaders in Allentown were able to fall back on their social networks to rebuild. In Youngstown, the high degree of overlap meant that deindustrialization decimated both business and social networks, leaving little structure upon which to rebuild the community's leadership.

Clark (2007) offers a thorough review of the literature covering the "shifting terrain of 'community' research", identifying a growing need to move beyond the spatial / social dichotomy to an interactive view of how spatial and social aspects combine to shape emergent forms of community. Clark evaluates the "death of distance" and the compression of space and time afforded actors connected in relational or social space rather than physical space. One important aspect of these concepts is that they tend to exclude low-income individuals and communities. One wonders whether these concepts are related to the apparent polarization of society along class and income lines.

Piselli (2007) approaches the study of community from a network analysis perspective, arguing that while the spatial and social dimensions of community "condition and reinforce each other", community must ultimately be considered as a network, not a place. Central to Piselli's argument is the notion that relationships involve exchanges or flows of many different kinds, one of the most important being communication. Historically these exchanges have involved face-to-face contact and spatial proximity. However there are an increasing number of examples where community is created and maintained, even over great distances. These include the continuity of community among groups of emigrants, and the creation of virtual online communities. While making a compelling case for defining community as a network rather than a place, the author does not discount the importance of place in shaping and supporting many communities. For example the relationship between geographically bounded industrial districts and the community of establishments, workers and institutions that define industry clusters has endured and even intensified with the globalization if industry.

Mandarano's case study of a multi-jurisdictional environmental planning process demonstrates the use of SNA in evaluating social capital as a necessary intermediate outcome in an ongoing collaborative planning process (2009). Her study focuses on a regional collaborative environmental partnership formed through the

National Estuary Program, finding that SNA was a useful tool for measuring the creation of social capital in terms of the formation and structure of new relationships built through the collaborative planning process. The study also shows that both internal and external factors influenced the participants' capacity to build dense social networks (Mandarano, 2009).

Taken together, these papers challenge planners working at multiple scales to engage a more precise and nuanced definition of community in their work. Terms like "place making" and "community building" which in the world of practice could easily be understood as synonymous, take on very different and distinct meanings. A widespread re-conception of *place* and c*ommunity* as separate but related phenomenon that condition and reinforce each other would have enormous implications for the planning profession, the *places* we create and the *communities* we work with. The conflation of these terms in the past is understandable. Places are easy to visualize and represent with great precision. Community in the strict sense is more of a fuzzy concept that is difficult to picture or represent but it is nevertheless powerfully emotive. The combination is a marketer's dream. Disentangling the two concepts in the minds of planners, let alone the public, will be no easy task. The value of social network analysis in facilitating such a re-conception is that it provides a conceptual framework and methods to visualize and analyze community as a relational network, separate and distinct from the geography of place. As planners de-couple their conceptions of place and community, these papers also caution us that class differences – predominantly income and education – have a strong influence on social and spatial dimensions of community and perceptions of social capital (See for example Hutchinson & Vidal, 2004 and related papers in the special section on social capital). Safford's work on Youngstown and Allentown in particular shows how communities have many "layers" of networks that interact and overlap in different ways that can have significant implications for community resilience at times of stress.

3.5.2 Using SNA to Understanding and Improving Planning Processes

The second group of studies focuses on understanding and improving public participation in the planning process. Focusing on the role higher-level government interventions can have on fostering stronger local networks, Schneider and colleagues (2003)[21] frame management of estuaries as a policy domain where top-down, government driven approaches may be less suited than network-oriented approaches that are community-based and inclusive. This type of policy domain describes many, if not most, planning situations, from reducing risks to people and property from natural hazards to ensuring affordable housing availability to integrating multiple modes of transportation within a region. This paper identifies a typology of four classes of networks that can help address barriers to cooperation: 1) vertical boundary-spanning networks (i.e. involving multiple levels of government; 2) horizontal boundary-spanning networks (i.e. coordinating across jurisdictions in the same geographic area); 3) expertise boundary-spanning (i.e. accessing academic, private sector and other experts) and ideological boundary-spanning networks (i.e. providing less confrontational settings for airing and negotiating conflicts). It also

[21] Schneider et al. (2003) is one of a set of studies focusing on estuary program management networks, including the Scholz et al. (2003) and Mandarano (2009) papers cited earlier.

categorizes a variety of supports the federal National Estuary Program (NEP) used to increase collaboration and span these boundaries in the estuarine management policy domain. Schneider and his colleagues' results suggest the NEP supports have made progress in spanning these boundaries and increasing cooperation, a finding that should be of interest to planning scholars on both theoretical and applied levels[22].

Beginning with the critique of communicative planning that it does not translate easily into practice, Doak and Parker (2002) present a detailed and highly theoretical argument for a "pre-plan mapping" of the network of actors and capitals (economic, environmental, social, human and cultural). Their arguments focus on the value of visualizing the "planning network topology" as a precursor to enhancing network and capital interactions for those with limited access to the planning process. Such a visualization also includes an assessment of what they refer to as the "power geometry" of the network (e.g. cliques, subgroups, positions, brokerage roles), with particular attention to the position and role of the planner within the network. While Doak and Parker include conceptual diagrams of what is to be included in "pre-plan maps" and discuss how these would be useful in the context of a specific project, they do not undertake the process themselves.

Moving from a highly theoretical approach to a more practical grass-roots presentation, three different "how-to" approaches are presented by Provan, Veazie & Staten (2005), Krebs & Holley (2006), and Prell, Hubacek, and Reed (2009). Provan, Veazie & Staten focus on the use of SNA in helping communities build and sustain functioning networks of social service providers and community action groups. The

[22] This section developed jointly with input from Lyles.

authors provide a sample questionnaire (as an appendix) that may be used to gather data to populate the network. Most of the paper is focused on a presentation and analysis of eight strategic questions that communities may then ask about the network analysis results that may help them build stronger, more sustainable networks. As was the case with Doak & Parker, the authors do not actually undertake a case study. Krebs & Holley also offer a "hands-on" approach that focuses on building community economic networks or clusters in Appalachia. The paper offers an extensive discussion of what they term "network weaving" – the process of building and facilitating relationships strategically over time to transition a region through increasingly ordered and stable network structures. While they do not present the detailed empirical analyses one would find in peer reviewed journals, they take a step in that direction, relating examples of how they have used the various methods they describe in practice.

The third "how-to" paper, Prell, Hubacek and Reed (2009), demonstrates the utility of social network analysis in conducting a stakeholder analysis in a natural resource management process in the United Kingdom. Although the article does not reference the dispute resolution or consensus building literatures discussed earlier, the authors' conception of a stakeholder analysis designed to identify and target stakeholders for inclusion in a planning process aligns closely with these literatures. Prell and her colleagues use Social Network Analysis techniques to determine which stakeholders are already most heavily involved in the network, which of those stakeholders are most central, and which categories of stakeholders are currently underrepresented. In turn, the results of these analyses can be used in practice to ensure that a planning process network includes those stakeholders that are already highly central, those that have been underrepresented previously, and, importantly, those that bring preexisting bridging contacts to the process.

Nancy Holman's case study of community participation in planning for a large-scale redevelopment in Portsmouth, England uses social network analysis to examine the effects of network structure on "due process" participation, social-developmental[9] and instrumental outcomes (Holman, 2008). The case is well documented and analyzed, focusing on the effects of network structure on flows of information, and the use of power to control instrumental outcomes. Holman finds that network structure does in fact influence the planning process, as well as both developmental and instrumental outcomes. Participants and planners alike were largely unaware of these structural influences. In light of her findings, Holman discusses what the outcomes might have been had the network structure been explicitly known or accurately perceived at the outset of the project. She concludes that the use of social network analysis as a tool in planning practice is likely to lead to an improved process with better developmental and instrumental outcomes.

A provocative dissertation proposal by Genevieve Borich (2008) rounds out the literature focused primarily on understanding and improving participation in the public process. Borich proposes the use of social network analysis to develop empirical evidence about participation in both formal and informal planning networks and how formal and informal planning processes relate to each other. She argues that formal planning networks are fully contained within informal planning networks, and that the two types of networks are both structurally and functionally different. The results of her research could present some valuable new insights into planning practice, and provide the grist for further refinements of communicative planning theories.

In summary, the literature documenting the use of SNA in understanding and improving public participation and outcomes in the planning process suggests that further use of SNA's concepts and methods are likely to have a positive influence on both planning practice and planning research. These applications typically involve all five types of problems for which SNA is especially well suited. The potential for improving the implementation of communicative planning theories is apparent. So too are the possibilities for new approaches to empirical research into the relational processes that planners care about and that influence much of their work.

3.6 Substantive Applications of SNA in Planning

Many of the studies reviewed thus far present substantive as well as procedural examples of SNA in planning. This section reviews several substantive examples that have *not* been discussed previously in this paper. These studies fall into three categories. The first pair of studies examines social activity-travel behavior from a social network approach. The second group of studies uses SNA to understand the organization and interaction of economic development and policy networks. The third group of studies uses SNA to understand the social and spatial dimensions of innovation as an economic development driver.

3.6.1 Using SNA to Understand Social Activity-Travel Behavior

Two related papers document the use of SNA in understanding social activity-travel behavior and the data collection methodology necessary for such an analysis (Carrasco & Miller, 2006; Carrasco, Hogan, Wellman & Miller, 2008). These papers begin with the hypothesis that "individuals' travel behavior is conditional upon their social networks; that is, a key cause of travel behavior is the social dimension represented by social networks." (Carrasco, Hogan, Wellman & Miller, 2008, p 961)

3.6.2 Using SNA in Economic Development and Policy Networks

Social network analysis has been used in economic development to help understand networks of policy and practice and to facilitate complex projects involving multiple jurisdictions and actors from the public and private sectors. For example, Eraydin, Koroglu, Ozturk, & Yasar, (2008) used social network analysis in conjunction with econometric methods to model and evaluate the development of "policy networks" consisting of both governmental and non-governmental actors among various cities and towns within the Izmir region of Turkey. Such networks were considered important in augmenting existing government infrastructure or in some cases providing that infrastructure when government institutions did not. The study found that even in the absence of effective institutional structures, the networks had a positive effect on economic performance. The authors conclude that the expansion of policy networks would be an effective way to boost innovation and economic performance throughout the region.

From a methodological perspective, the Eraydin study also illustrates a critical issue related to the use of SNA as a "new" and relatively unfamiliar method in planning studies. Because SNA is not yet widely understood there is the potential that it will not be used correctly. In this case, although the researchers were able to construct the networks from survey data and other sources, their study could have been much more robust with a few changes to the survey and the use of additional network measures that would have allowed them to evaluate several issues they regarded as qualitative, including trust, reciprocity, power relations and ideological divisions. Their use of SNA was not "wrong" in terms of their technical execution. The precise reasons for the weak application of SNA are not entirely clear, and as this is the only known example of its kind to date, any criticism is tempered by a greater respect of the researchers for having tried it.

In a practitioner-oriented paper, Reid, Carroll and Smith (2007) advocate and illustrate the use of SNA in the cluster building process, using it to map key actors in the Ohio greenhouse industry. The authors are effective in placing SNA within an integrated group of analytical methods that include spatial clustering / spatial autocorrelation, and input / output analysis, and SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis. However, the article does not fully explain or document their SNA methodology. They identify three survey questions and the software package used in the analysis, and then move on to discuss the findings and interpretation of the network analysis. The authors found it particularly helpful in identifying influential network members and in identifying where network connections should be established or strengthened. A second practitioner-oriented paper by DeSantis (2006) discusses the use of SNA and networking more generally as "purposeful" economic development tools.

In a relatively early use of SNA, Hagen, Killinger & Streeter (1997) mapped and analyzed economic development organizations (EDO's) in the Tampa Bay, Florida region. The analysis was undertaken to help facilitate the re-use of a decommissioned federal facility with substantial technological assets[23]. A primary goal of the study was to determine an appropriate (new) role within the network for the University of South Florida with respect to the Pinellas STAR Center and regional engagement with the dozens of EDO's in the Tampa Bay area. Additional goals of the study were to assess levels of communication, interaction and leadership among the region's 37 EDO's, as well as specific development capacities and specializations. The study used SNA measures of centrality, equivalence, centralization, and density to evaluate the network. As a whole, the study suggests and demonstrates that SNA may be viewed as a rapid assessment, research and planning tool for evaluating regional economic development in a multijurisdictional context.

Shifting the focus from mapping and assessing EDO's in multiple jurisdictions to identifying the conditions necessary for them to actually work together, Hawkins (2010) examines the affects of network structure and social capital on multi-jurisdictional collaboration on regional economic development projects. The paper makes several important and timely contributions to the field, combining a lucid assessment of the theoretical literature with empirical analysis to advance a critical understanding of the roles of social capital and governance (network) structure in determining whether multi-jurisdictional collaboration on economic

[23] The Pinellas STAR center in Largo FL, was a U.S. Department of Energy complex engaged in the engineering, prototyping and manufacturing of special components for the U.S. nuclear weapons program for 30 years prior to the 1997 study.

development projects is likely to occur. Policy implications are also discussed. Interestingly, competition and collaboration are presented as an interactive policy dynamic rather than mutually exclusive policy choices. From a methodological perspective the author provides a clear example of how SNA may be combined with other methods to facilitate insights that would otherwise not be possible[24].

3.6.3 Facilitating Innovation as a Regional Economic Development Strategy

As an example of how SNA can be used to inform substantive issues in planning sub-fields, the third area we review concerns the spatial and social dimensions of innovation, which is thought to be a key contributor to economic growth. Economic developers in particular are interested in the social, spatial and technological characteristics associated with innovation and how to create regional environments that foster innovation and growth. Within the innovation studies literature there have been multiple studies concerning the use of social network analysis. Many of the published studies identified during this review emerge out of

[24] In reviewing this paper it was unclear whether the regression analysis was carried out using the UCINET software or another software package. Efforts to contact the author for clarification were unsuccessful. In general terms, typical regression models are based on the assumption that the observations (i.e. actors) are independent. If the network measures are "ego network" measures, this assumption holds true. However, if "whole network" measures are used, then the assumption of independence does not hold, and the regression model should be modified. UCINET, along with other SNA software packages provide this functionality. This question is raised here not as a criticism of Hawkins, for it is entirely possible and even probable that this issue was addressed in his research. Rather, it is raised to illustrate a generic caution for readers on the use of SNA in a mixed-methods approach. Even if such an error occurred in this study the effect is likely to be minor and related to the *degree* of certainty. The logic of this study and the conclusions draw would remain unaffected. We offer our respect to the author for a fine piece of research and beg his indulgence as a straw man in making this important point about mixed methods.

related disciplines other than planning although *European Planning Studies* has published several papers within the past year addressing the role of networks and network analysis in innovation and economic development from the planning perspective[25]. Most recently, several papers were published together in a special issue of Innovation Management: Policy and Practice (Kastelle & Steen, 2010)[26]. Other noteworthy volumes include *Clusters, Networks and Innovation* (Breschi & Malerba, 2005); and *The Economic Geography of Innovation* (Polenske, 2007). Many of these studies focus on the agglomeration vs. network effects debate within the field of economic geography. Others are drawn from management and sociology. Given the timeliness of the focus on innovation to economic development policy in the U.S., what follows is a brief review of this large volume of multi-disciplinary research under the banner of innovation studies.

One strand of literature shaping innovation studies emerges from a debate within economic geography over the effects of spatial agglomeration vs. network effects on the spatial distribution of innovation activity. Those advocating agglomeration and knowledge spillover effects have held the high ground in the argument for some time, and have had significant influence on economic development policies and practice (for example Florida, 2002, 2005; Porter, 1998a, 1998b, 1998c, 1998d). While acknowledging the underlying importance of networks,

[25] Online access to the most recent 12 months of *European Planning Studies* is restricted, making timely access for this paper difficult. Interested readers are encouraged to explore the journal's 2010 issues at http://www.tandf.co.uk/journals/ceps.

[26] This special issue of Innovation Management: policy & Practice was not yet accessible when this paper was submitted, and thus the papers within it are not reviewed herein.

agglomeration-based analyses have nevertheless focused almost exclusively on spatial structure and the attributes of place. Little attention is paid to relationships or network structure.

Those advocating network effects of innovation have suggested that the co-location of firms that leads to agglomeration effects are actually spatial manifestations of underlying network dynamics (i.e. interactions and changes over time), and that network growth is a catalyst for spatial agglomeration (Prevezer, Opsahl, & Panzarasa, 2008; Sorenson, 2003). They also suggest that within spatial agglomerations, innovation and cluster growth results from the interaction of multiple overlapping networks (Granovetter, 1983; Powell, Koput, & Smith-Doerr, 1996; Sorenson, 2003; Whittington, Owen-Smith, & Powell, 2008). Differences in cluster performance have been linked to the effectiveness of such networks (Saxenian, 1996). More recently, researchers have begun to consider the effects that industry sector (i.e. technological) differences may have in network development and co-location (Breschi & Malerba, 2005). Sectoral differences are believed to influence communication styles and methods (Cowan, 2005; Okamura & Vonortas, 2006), labor mobility, and communities of practice (Saxenian & Hsu, 2001).

The dominance of agglomeration arguments in this debate may be interpreted in several ways. For example, Wellman points out that popular literature and political rhetoric often conflate the social concept of “community” with the spatial concept of “neighborhood” (1999). This conflation, while likely not intentional, nevertheless tends to serve political predilections towards place-based rather than people based economic development (Bolton, 1993). Whatever the reason, the focus on agglomeration has led to an economic development policy environment that is heavily skewed towards an interpretation that spatial density and concentrated institutional resources are the only factors that influence innovation. Such policies have been based in large measure on cluste*r* concepts advanced by Michael Porter, and creativ*e* clas*s* concepts advanced by Richard Florida (Florida, 2002, 2005; Porter, 1998a, 1998b, 1998c, 1998d). Widespread implementation of strategies based on these concepts has yielded mixed results (see, for example Feldman, 2007), but one clear observation can be made. Both concepts are manifestations of agglomeration theory and are therefore based on certain assumptions about population and institutional resource density. For example, it is widely believed that spatial density and depth in both talent and institutional resources are necessary to drive the knowledge spillovers that are fundamental to the growth of innovation clusters under these theories (see for example, Muro & Katz, 2010). The central role of research universities in such strategies exemplifies this assumption.

In terms of the empirical use of SNA related to the forgoing, Okamura & Vonortas (2006) offer an exploratory analysis of knowledge networks based on patent citations and technology alliance networks based on strategic partnerships, predominantly within the European context. These two types of networks are modeled and compared for five industrial subsectors: pharmaceuticals, plastics, computers, electronics and instruments. The analysis revealed apparent differences in the networking behavior in the pharmaceuticals subsector vis-à-vis networking behavior in computers, electronics and instruments; a difference in effectiveness between knowledge and alliance networks across all examined sectors in terms of knowledge communication; and apparent differences in the competitive positioning of European firms compared to U.S. and Japanese firms in the examined sectoral knowledge networks suggest significant differences in inter-continental business strategy (Okamura & Vonortas 2006). While the findings themselves are interesting, this paper demonstrates SNA's graphical and analytical power in helping to identify and frame future research using more traditional social science methods. This approach to using SNA contrasts nicely with the mixed-method approach demonstrated in Hawkins (2010).

A handful of studies within economic geography have applied social network analysis to patent data in order to study the spatial distribution of inventors (Bettencourt, Lobo, & Strumsky, 2007); the effects of inventor networks on the spatial distribution of patents (Strumsky, Lobo, & Fleming, 2005); and the effects of state policies on inventor mobility (Marx, Strumsky, & Fleming, 2007).

Overall the literature covering the spatial and social dimensions of innovation and economic development presents planning professionals and academics with some broad challenges. The first of these is that widely held and taught concepts of spatial agglomeration may be incomplete and the policies they inspire may need to be revisited. The issue is not that current conceptions are wrong but rather that they may be incomplete, especially in "non-agglomeration" regions. This in turn leads to the creation of policies and programs that yield inconsistent results and a lack of policies and programs that address critical network-building needs like those identified in the Izmir region (Eraydin, Koroglu, Ozturk, & Yasar, 2008). Further empirical studies on the spatial and social dimensions of innovation and economic activity using social network analysis represent a critical need in advancing a more complete understanding of regional economies and improving the policies and practices of regional economic development.

A second challenge to both planning practitioners and academics concerns the training of planners in the concepts and methods of social network analysis. As illustrated in the discussion of Eraydin, Koroglu, Ozturk, & Yasar, (2008) SNA is more than simply a method to be applied after the data is collected. A full appreciation of the SNA perspective will help shape the research design and data collection activities as well. The Eraydin study illustrates the more benign case of missed opportunity in the research. A more serious potential problem is the misapplication of social network analysis methods and/or a misinterpretation of the results due to inadequate training in SNA. This problem may be compounded by a lack of critical readers or researchers with sufficient understanding to catch and correct errors. Such problems are not unique to SNA but rather accompany the rapid growth of any new concept or method.

3.7 Summary and Conclusions

This paper has presented a brief introduction to the history, concepts and methods of social network analysis. It has attempted to position SNA as both a unique perspective and unique methodology with respect to analytical approaches and methods commonly used in planning. Building on this foundation the paper then identified five types of problems for which social network analysis has been identified as particularly useful, and examined these types of problems in terms of their relevance to planning theory and practice. We conclude that social network analysis has the potential to advance and operationalize certain aspects of communicative planning theory that have been criticized due to their reliance on tacit knowledge in the form of judgment and experience. In particular, SNA has the potential to help planners visualize, measure and document sources of communicative distortion and to identify specific steps to address these situations.

Having developed a basic understanding of SNA and its relationship to planning from both methodological and theoretical perspectives the paper proceeds to review and evaluate documented examples of the use of SNA concepts and methods in planning related applications. The applications found in the literature tended to focus on three broad planning issues. On the issue of understanding the spatial and social dimensions of community and, by extension, social capital, the literature challenges planners working at multiple spatial scales to engage more precise and nuanced definitions of "community" and "place" in their work. Disentangling the two concepts in the minds of planners, let alone the public, will be no easy task. The value of social network analysis in facilitating such a re-conception is that it provides a conceptual framework and methods to visualize and analyze community as a relational network, separate and distinct from the geography of place. As planners de-couple their conceptions of place and community, these papers also caution us that class differences – predominantly income and education – have a strong influence on social and spatial dimensions of community and perceptions of social capital.

On the issue of understanding and improving public participation in the planning process the literature suggests that further use of SNA's concepts and methods are likely to have a positive influence on both planning practice and planning research. These applications typically involve all five types of problems for which SNA is especially well suited. The potential for improving the implementation of communicative planning theory is apparent. So too are the possibilities for new empirical research into the relational processes that comprise so much of what planners do and care about.

The literature on the spatial and social dimensions of innovation and economic development offers two additional challenges for both planning practitioners and academics. The first challenge presented by the literature suggests that widely held and widely taught concepts of spatial agglomeration may be incomplete if they do not include a basic understanding of network influences and dynamics. This is not simply an academic question since agglomeration theories have a strong influence on economic development policy and practice. As Safford (2009) demonstrated, network structures may be critical to regional resilience. More empirical research is needed to clarify the relationship between spatial agglomeration and social network effects and to design more effective economic development policies, particularly for “non agglomeration” regions. The second challenge suggested by the literature is the need for training among planning researchers and practitioners on the concepts and methods of social network analysis.

Some broad conclusions may be drawn from this body of literature as a whole. First, the issues around which the literature has concentrated are all characterized by “elusiveness” when researchers have approached them using traditional methods. This elusiveness stems in part from the fact that all three issues tend to wrestle with all or most of the problems for which SNA is ideally suited and which, conversely, traditional methods are poorly suited. All three issues are characterized by the presence of a complex set of formal and informal relationships involving a wide array of actors with highly variable attributes. These actors and relationships form social networks that may be modeled and visualized with SNA. Emergent structural influences on behaviors and outcomes may be identified, measured and analyzed along with actor attributes to yield better explanations of the phenomena being observed.

While documented empirical planning studies using SNA remain quite rare, the literature evaluated in this paper nevertheless presents a clear and compelling case for planning practitioners and academics to expand the understanding, use and teaching of social network analysis concepts and methods. These concepts and methods augment existing approaches and provide tools for exploring the relational dimension, which has been widely acknowledged as influential but difficult to measure using traditional methods. The research potential related to the issues discussed in this paper is substantial. Other research possibilities related to, say, issues at the intersection of planning and public health; or those related to fundamental debates concerning the claims for and against New Urbanism are equally enticing. Addressing the challenges identified in this paper represent first steps in a strategy to take advantage of these new opportunities.

Chapter 4: Methodology

Within the field of economic development the relationships between global networks and regional clusters are becoming increasingly apparent. Many economic development policies and practices in the U.S. focus on regional clusters of industry, for example the U.S. Economic Development Administration's Regional Innovation Clusters (Singerman, 2010). Despite a large and diverse literature covering the intersection of clusters, networks, and innovation; regional innovation cluster policy and practices tend to be narrowly based on Michael Porter's work on industrial clusters; and Richard Florida's clusters of creative talent or the so-called creative class (Muro & Katz, 2010; Mills, Reynolds & Reamer, 2008). These approaches routinely acknowledge that firms and individuals within such clusters maintain global relationships through supply chains and knowledge networks. Yet they maintain an overwhelmingly geographic perspective that insists such relationships be interpreted in terms of spatial attributes. Within this perspective, social and spatial characteristics are often conflated under fuzzy interpretations of agglomeration (Whitford, 2007). Spatial distance and density may, for example, be interpreted as interchangeable with social distance and density. This perspective tends to value relationships with actors who are geographically close more than ties with distant actors, which in turn tends to favor major metropolitan areas where large populations increase the statistical likelihood of ties. Research and policies that incorporate this perspective internalize and reinforce such biases.

Social Network Analysis (SNA) offers an alternative approach with the potential to analyze social and spatial relationships simultaneously (Chapter 3). The models that emerge from this network analysis present both visual and empirical evidence that clustering of similar and related firms is a social phenomenon as well as a spatial one. Additionally, these new network models reveal relationships with distant actors and places that locate regional clusters within global networks of commerce and knowledge. Where industry cluster and creative class models tend to focus on and promote competitive differences between places, the network models described in this paper focus on how places are connected by identifying collaborative relationships that were previously invisible. They suggest clusters of talent and industry are far more interconnected and less exclusive than creative class or cluster theories acknowledge.

Recently, the U.S. Economic Development Administration (EDA) has funded initiatives that are exploring new network approaches to regional innovation[27]. New publications and dialogue by influential policy advocates have engaged the broader base of literature and have connected manufacturing employment to both innovation and networks[28]. Both will be discussed shortly, but taken together they appear to signal an emerging opportunity to influence economic development policy. By incorporating provisions for strengthening collaborative networks, U.S. economic development policy would provide more support for second-tier and rural communities while maintaining an appropriate focus on major metro regions as significant economic drivers.

[27] For example, EDA has provided funding for a Regional Innovation Acceleration Network (RIAN) (http://www.regionalinnovation.org/index.cfm); also network based approaches have been approved and funded for at least two University Centers at Kansas State (http://innovatekansas.org/) and University of Maryland (http://www.arch.umd.edu/research/).
[28] See Brookings Institution, 2012.

This chapter builds on the introduction to social network analysis in chapter 3 to develop network models of regional innovation, and test the influence of network structure on county level economic growth. Chapter 3 introduced many network concepts and examples from the literature. It revisited an open question within planning theory as to whether networks represent a new paradigm for planning, and in so doing it establishes the rationale for the application of a network-based approach to the study of innovation and economic growth. The first half of this chapter defines the methodology used to construct network models for Pennsylvania's 67 counties over the period 1990 – 2007. Chapter 2 briefly reviewed relevant literature that situates this new approach within both methodological and policy contexts, and discusses findings and conclusions that can be drawn directly from the models themselves relative to the literature and policy context. Finally, the second half of this chapter develops an econometric model that measures the influence of network structure on economic growth using data describing network structure generated from social network analysis of the innovation network models.

Taken together, these three papers demonstrate that social network analysis is a valuable empirical approach to complex planning problems; they reveal new perspectives on the interaction between the social and spatial dimensions of innovation, clusters and agglomeration; they show that the structure of innovation networks and what flows through them have a significant influences on subsequent economic growth; and they establish the basis for new economic development tools, policies and practices that offer significant enhancements to industry cluster and creative class based approaches.

4.1 What are Innovation Networks?

Innovation networks are simply networks comprised of all of the actors involved in the innovation process and the ties or relationships that connect them. These actors and relationships will be identified and discussed in more detail shortly. Chapter 3 provided an introduction to networks and Social Network Analysis (SNA), and readers new to SNA are advised to consult that chapter and the references cited therein for a broader treatment of basic concepts. Certain key concepts are briefly reviewed throughout this paper; however basic knowledge of SNA from these or other sources will enhance the reader's understanding.

One of the first lessons of SNA concerns vocabulary. Certain terms have very precise meanings in network analysis that may not be interchangeable with their meanings in other disciplines or common parlance. For example, ***nodes*** in network analysis refer vertices, agents or actors within the network. Planners who are accustomed to using the term *node* in other ways should take a moment to recognize that any preconceptions they may have regarding this term should be set aside in the context of a discussion on social networks. ***Nodes, vertices, agents****, and* ***actors*** are typically used interchangeably. When we talk about a specific node and the nodes that it is connected to, we refer to the node in question as the ***ego*** and the nodes that are connected to it as ***alters. Relation*** is a term in SNA that refers to a collection of similar *relationships* or *ties* between nodes in the network. ***Relationships*** **or** ***Ties*** refer to individual connections between two nodes. Ties may also be referred to as *edges, links, lines, or arcs*, although these terms are not used in this paper. Ties may also be valued, meaning that the value, strength, or multiplicity of the relation -

measured by the count of ties between a pair of nodes - is variable and this may affect the analysis.

In SNA a ***Dyad*** **is** the smallest network consists of two nodes and a single tie between them. Three actors and the ties between them form a ***Triad.*** Larger groups of connected nodes within the network may be referred to as ***connected components, sub-graphs, subgroups, sub-networks, cliques, k-plexes, k-cores or m-slices***. Each of these terms has a specific meaning and differs from the others in important respects. The only one used in this paper is *m-slice,* which is defined as a "maximal sub-network containing the lines with multiplicity equal to or greater than *m*, and the vertices incident with these lines" (deNooy, Mrvar & Batagelj, 2005). This will be discussed in greater detail in the methodology section. Briefly, a "maximal sub-network containing the lines with multiplicity equal to or greater than *m*" means that it is a sub-network in which all of the lines have values greater than or equal to *m*, where the value of *m* is selected by the analyst.

Collectively, ***agents, dyads, triads sub-networks*** and ***whole networks*** may be referred to as network ***levels***. Different theories of social interaction and network behavior focus on different levels of interaction, For example transaction theories may focus more heavily on dyads, while theories of balance and transitivity in relationships focus on triads. Since real networks tend to include relationships at multiple levels, explaining network behavior often involves multiple theories. This gives rise to the ***multi-level multi-theoretical (MTML)*** network model (Monge & Contractor, 2003). This model will be discussed in greater detail shortly.

Innovation networks include a variety of actors involved in multiple relations. Often the there are multiple ties and / or valued ties between pairs of actors (dyads), which we refer to as multiplicity. This notion of multiplicity and the value or specifically the sum of the values of these multiple ties between actors becomes important in the analysis, as will be discussed in the methodology section. The fact that there are multiple types of ties is also significant in network analysis, creating what is referred to as a ***multiplex*** network. Finally, the innovation networks involve multiple levels of organization and this invokes multiple theories of social interaction to help explain why and how network structure influences particular behaviors or why particular behaviors result in specific network structures. ***Network structure*** refers to the patterns of nodes and ties, specifically the presence or absence of ties between actors. The strength of existing ties may also be considered in some cases. Network structure may also be referred to as ***network topology***. This section has reviewed and defined the key terms and concepts used throughout the rest of this paper. Readers who are unfamiliar with social network analysis are again directed to the references mentioned at the beginning of this section, and are cautioned that the terms discussed in this section will be used as defined herein throughout the rest of this paper without further clarification unless noted otherwise.

4.2 Multi-Relational and Multi-Level Multi-Theoretical Network Models

The vast majority of network studies have focused on networks comprised on a single relation, and network methods and measurements have generally developed based on such networks. While the methodological literature on social network analysis discusses the extension of various methods to multi-relational or multi-modal networks, actual examples are still fairly limited[29] (Wasserman & Faust, 1994; Koehly & Pattison, 2005). Both Wasserman & Faust (1994), and Koehly & Pattison (2005) offer detailed discussions of the theoretical and methodological issues involved in the analysis of multi-relational (or multiplex) networks. Readers interested in expanding on the work presented in this paper are advised to consult these and other sources regarding multi-relational networks. The network model described later in this paper is a multi-relational network; however the analyses described are egocentric – that is they consider each node's network independently – rather than considering the network as a whole. Therefore multi-relational influences are minimized[30]. The impact of incomplete data is also more limited with an egocentric approach (Valente, 2005).

As this discussion points out, networks may be considered from a number of perspectives, including both egocentric and whole-network perspectives. In fact, social network analysis involves implicit or explicit assumptions about the *level* of the network being analyzed. The term *level* refers to basic unit of analysis being considered – actor, dyad, triad, subgroup or whole network (Monge & Contractor, 2003). As researchers begin using SNA for more empirical rather than exploratory research, and as the relations being analyzed become more complex, the level of analysis becomes more significant because different theories of social interaction may be operating on different network levels. Monge and Contractor note that much of

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[29] Such examples often include (1987); Galaskiewicz' study of board interlocks (1985); or Davis Gardner & Gardner's study of influence among southern women based on which events they attended (1941), for example.

[30] See Wasserman & Faust (1994) for a full discussion of social network analysis methodology.

the literature on SNA applications does not explicitly consider the level of analysis or the multiple theories of social interaction which may be influencing observed network structures. They therefore develop a multi-theoretical, multi-level (MTML) approach to network modeling. From this perspective the network model and analyses proposed in the methodology section are among the most basic, focusing on actor-level measures and theories of social capital developed by Burt (1995) and Granovetter (1973). Nevertheless, framing this research within the MTML framework introduces the broader theoretical context for modeling complex networks and invokes a more disciplined approach that permits higher level analyses in the future (Monge & Contractor, 2003; Contractor, 2011).

4.3 Methodological Literature Summary

Recent actions by EDA as well as publications by policy advocates suggest that while clusters will continue to influence economic development policy, there is a growing recognition among policymakers that a new array of approaches to understanding and promoting clusters and innovation may be possible and more effective in smaller regions and rural areas (see for example Brookings, 2012; Mayer, 2011; Helper & Wial, 2012). Innovation networks represent a new way of understanding the interplay between social and spatial proximity and their influence on both innovation and economic growth.

Prior innovation network models have focused on innovation diffusion (Bettencourt, Lobo and Strumsky, 2004) or on the spatial distribution of inventors (Strumsky, Lobo and Fleming, 2005). However, while they sought to connect the social and spatial dimensions of innovation they experienced some difficulty in trying to get networks to fit within spatial boundaries. It is possible that the steps taken to fit the networks within spatial boundaries distorted the network structure sufficiently to weaken their results. An alternative approach that interprets geography through the network lens may resolve many of the issues faced by these studies.

Finally, framing the social network model within the multi-theoretical, multi-level network framework establishes the broader theoretical context and establishes a sound basis for connecting network structure to economic growth through concepts of social capital. While generating the necessary egocentric measures to support the economic analysis model later in this chapter, the methodology described below creates network models that may be used for further analysis in future studies of multi-level networks.

This research uses two distinct methodologies and data sets. The first methodology and data set is focused on generating a multi-relational model of selected innovation networks in Pennsylvania between 1990 and 2007. The second methodology and data set is focused on the analysis of economic growth measures in Pennsylvania between 1990 and 2007. The network model generates measures of constraint that become key independent variables in the economic analysis model. The network model also generates images and data that may be analyzed both independently and in conjunction with the results of the economic analysis model.

4.35 Research Questions

The following models are designed to answer the main research question: ***Are innovation networks drivers of economic development in regions that lack the institutions and density present in agglomeration economies?*** In order to answer this question three intermediate questions are posed.

1. ***Does network structure affect economic growth?*** Network influence is a function of network structure, thus if innovation networks are drivers of economic growth we should see a relationship between network structure and economic growth.
2. ***Do the spatial density and arrangement of networks affect economic growth?*** Untangling the interplay between network influence and spatial agglomeration influence has remained elusive in the literature, prompting the need for a new approach and new tools as noted by Ed Glaeser and his colleagues (2002; see passage on page 10 of this document).
3. ***Does technological alignment affect economic growth?*** The literature clearly shows that what inventors are inventing matters. The relationship between productive capacity and economic growth is foundational in economic analysis. If innovation networks are drivers of economic growth then we should see some alignment between the technologies being invented and the products that local industries are able to produce.

4.4 The Innovation Network Model

Innovation networks are extensive and complex. This research focuses on a subset of innovation networks that allow for the integration of multiple relations and data sources, and which also permit a focused economic analysis. Rather than trying to engage the full spectrum and debate over what constitutes innovation, this research will focus on product innovation revealed in patent and other data records (discussed shortly) and its influence on manufacturing jobs. Due to the scale of network data, the study is limited to patents with at least one inventor residing in Pennsylvania. This geography was chosen because it has a major concentration of manufacturing activity and a range of urban and rural community sizes dispersed throughout and because the author's familiarity with economic development in Pennsylvania.

The innovation network model includes six different relations: patents, related patents, technology, SBIR/STTR, PA DCED, and inter-county commuting, each of which will be fully defined in turn below. As discussed previously in this paper, relations refer to different types of relationships between actors. As the relation descriptions will make clear, together these relations create a useful model that includes the major elements necessary for innovation, specifically invention, entrepreneurship, technology, capital and labor markets. In total the network is comprised of 48,176 actors, connected by 894,418 ties among six different relations. These are summarized in table 4.1, followed by a detailed discussion of each relation.

4.4.1 Patent Relation

Node Type	Description	Count
1	PA State Agencies	18
2	Federal Agencies	22
3	Firms	5,877
4	Intermediaries	304
5	Inventors	38,374
9	Universities	183
10	PA Places	35
11	Philadelphia Metro Counties	5
12	Pittsburgh Metro Counties	7
13	PA Rural 0 Counties	23
14	PA Rural 1 Counties	19
15	PA Tier 2 Counties	14
17	Countries (non-US)	170
18	States	50
19	non PA Counties	3,075
	Total Nodes	**48,176**
Relation	**Description**	**Count**
1	Commute Relation	9,782
2	Patent Relation	259,737
3	Tech Relation	432,285
4	SBIR Relation	5,916
5	DCED Relation	9,378
6	Related Patents Relation	177,320
	Total Ties	**894,418**

Table 4.1: Summary of Nodes, Relations and Ties

Disaggregated patent data is used to identify innovation network fragments. Patent data is inherently "noisy" and there are several valid criticisms concerning the use of patent counts as indicators of innovation (Griliches, 1990; see also discussion in chapter 2 of this paper). However, this research is focused on the effects of innovation networks, not patents themselves or patent counts, and this distinction avoids the problems identified in those criticisms. With these considerations in mind some selection criteria are introduced to filter the patent data and reconstruct the network fragments.

All patents must be filed with the U.S. Patent and Trademark Office (USPTO) under the name(s) of the inventors. However many patents are assigned to another party, often a firm. Assignment permanently conveys the rights of ownership to the assignee. Individual patent records contain the names of all inventors and their locations; the name of the assignee; patent classification; dates of application and much more[31, 32]. From the full patent database several filters were applied.

1. Only product patents with two or more inventors, with at least one inventor residing in Pennsylvania have been selected.
2. From that subset, only patents assigned to corporate entities (not individuals) have been selected.
3. Patents with Pennsylvania inventors who could not be geo-coded by county due to missing or erroneous data (after the application of data cleaning algorithms) were excluded.

The resulting sample includes 28,215 patents, 3,704 assignees and 38,374 inventors. Patents connect inventors to each other, and inventors to assignees. In addition, each inventor is connected to a specific place through residence at the time of the patent application. Locations for many assignees may also be determined through additional patent documentation although locations for 29% of the 3,704 assignees could not be determined from the data.

Ties between inventors and their locations and from assignees to their locations are included in the patent relation. All ties are non-directional and have a value of "1". The ties are considered active from one year prior to one year after the patent application year. This is done to help account for the fact that the relationships existed prior to the patent application event, and that they persist for some time after that event. Locations within the State of Pennsylvania have been converted to counties wherever possible. This permits the calculation of county level network statistics that may be used later in the economic analysis model, and for the linking of

[31] For example, see the record for patent # 7352075 (http://patft1.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PALL&p=1&u=%2Fnetahtml%2FPTO%2Fsrchnum.htm&r=1&f=G&l=50&s1=7352075.PN.&OS=PN/7352075&RS=PN/7352075).

[32] Readers may familiarize themselves with the details of the patent system and patent data at http://www.uspto.gov/patents/index.jsp.

location data between different relations. The data source for this relation is the USPTO.

4.4.2 Related Patents Relation

Within the patent database some patents are explicitly related to other patents by the applicants. This relation differs from patent citations (references to other work or prior art), which may be added by the inventor, patent attorneys, or patent examiners. Since patent citations may be added by multiple people involve in the patent application and approval process they may or may not imply an actual relation between inventors and assignees of each patent to those of the other. This relation however includes the inventors and assignees of patents where a direct relation has been explicitly stated. All ties are non-directional and have a value of "1". The ties are considered active from one year prior to the first patent application to one year after the second patent application. This is done to help account for the fact that the relationships existed prior to the patent application event, and that they persist for some time after that event. The data source for this relation is the USPTO.

4.4.3 Technology Relation

Whereas the ties in other relations are considered *strong ties* meaning they represent actual connections identified in the data, ties in the technology relation are considered *weak ties.* In this model, weak ties represent potential or *likely* relationships between actors based on similarities in patent class *and* subclass. For example, ties between inventors who worked on the same patent are considered strong ties because the patent provides evidence of a relationship and the sharing of knowledge. Weak ties refer to more indirect relationships, often through a mutual contact or membership in the same organization. Weak ties often have the potential for strong ties. The sample includes 13,607 unique patent class/subclass[33] combinations which characterize the technology field. The top ten patent class/subclass combinations for the sample are shown in table 4.2. Statistically, the probability of two patents having the same class/subclass is 7.35×10^{-5}. I define these as weak ties because it is unlikely that inventors and firms within Pennsylvania that are patenting in a specific class/subclass would be unfamiliar with other firms and inventors in the same state who are patenting in that same class/subclass. It does not necessarily imply a strong relationship. The actors are likely to know *of* each other. They may belong to the same professional organizations or attend the same conferences or trade shows. There are many different possibilities for weak ties. Another possible type of weak tie is identified between firms that have patented with the same inventor. Weak ties also exist between locations that have inventors and

Class	Subclass	Count		Class Name
435	069100	181		Chemistry: Molecular Biology And Microbiology
435	006000	169		Chemistry: Molecular Biology And Microbiology
530	350000	67		Chemistry: Natural Resins Or Derivatives; Peptides Or Proteins; Lignins Or Reaction Products Thereof
439	079000	58		Electrical Connectors
514	044000	58		Drug, Bio-Affecting And Body Treating Compositions
435	007100	50		Chemistry: Molecular Biology And Microbiology
514	221000	50		Drug, Bio-Affecting And Body Treating Compositions
514	291000	49		Drug, Bio-Affecting And Body Treating Compositions
514	012000	45		Drug, Bio-Affecting And Body Treating Compositions
439	607000	40		Electrical Connectors

Table 4.2: Top 10 Patent Class/Subclass Combinations

[33] According to the USPTO "A Patent Classification is a code which provides a method for categorizing the invention. Classification is typically expressed as "482/1". The first number, 482, represents the class of invention. The number following the slash is the subclass of invention within the class. There are about 450 Classes of invention and about 150,000 subclasses of invention in the USPC." These are technological categories. See http://www.uspto.gov/patents/resources/classification/index.jsp for detailed information on patent classification.

firms that share weak ties. Weak ties are non-directional and I assign them a value of .5[34]. The ties are considered active from one year prior to the first patent application to one year after the second patent application. This is done to help account for the fact that the relationships existed prior to the patent application event, and that they persist for some time after that event. The data source for this relation is the USPTO.

4.4.4 SBIR / STTR Relation

Capital for research and development is often noted as a critical part of the innovation process. The federal Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) Programs provide grant funding to firms and university researchers to advance the development and commercialization of specific technologies. The SBIR / STTR relation connects federal agencies to firms. Firms are also connected to the counties where they are located. Funding amounts are scaled to produce tie values of between 1.2 and 1.5. These numbers are somewhat arbitrary, but they are intended to capture the variation in funding amounts while remaining comparable to patent relations. SBIR relations are considered active from one year prior to the award year to one year after the award year. This is done to help account for the fact that the relationships existed prior to the award event, and that they persist for some time after that event. Award data is provided for each year between 1990 and 2007. The data source for this relation is the SBA TechNet.

[34] One might estimate the strength of the weak ties relative to the strong ties based on independent information, and this is a possible subject for future research.

4.4.5 PA DCED Relation

The Commonwealth of Pennsylvania's Department of Community and Economic Development (PA DCED) also provides capital for research and development, as well as capital for the provision of infrastructure that is deemed critical to new innovation. In many cases the connection to innovation is clear. In some cases the inclusion of certain programs was made on the basis of the author's familiarity with the intent and uses of those programs. These programs have been aggregated into three groups here. The first is DCED-TIO (Department of Community and Economic Development – Technology Innovation Office) which includes several programs including those that fund Pennsylvania's Ben Franklin Technology Partnerships. The second group includes more general capital projects that provide critical infrastructure under the Commonwealth Financing Authority (CFA). The third group is the largest and includes all other funding programs that provide direct or indirect support for innovation through the Department of Community and Economic development (DCED). In some cases funding is provided directly to firms. In other cases it is provided to intermediaries such as economic development corporations or municipal authorities. The DCED relation connects state agencies to firms and intermediaries; intermediaries to firms; and both firms and intermediaries to their locations. Funding amounts are scaled to produce tie values of between 1 and 1.7. These numbers are somewhat arbitrary and thus a subject for future research, but they are intended to capture the variation in funding amounts while remaining comparable to patent relations and SBIR relations. DCED relations are considered active from one year prior to the award year to one year after the award year. This is done to help account for the fact that the relationships existed prior to the award event, and that they persist for some time after that event. Award data is provided for each year between 2000 and 2007. The data source for this relation is the PA DCED.

4.4.6 Commute Relation

The commute relation is intended to provide the model with a sense of regional labor market dynamics through inter-county commuting patterns. Although not directly related to innovation the labor market nonetheless helps to shape the conditions that make innovation more or less likely. Ties are directional and scaled to values between 0 and 1. These values are somewhat arbitrary but are intended to reflect the fact that these relationships are of lesser value than any of the other relations based on patens or funding and more comparable to the weak ties of the technology relation. Commuting patterns are taken for the year 2000 only and extended to all years as a persistent background relation. The data source for this relation is the U.S. Census.   Counties are also classified according to urban intensity based on a modified version of the Beale 2003 scale (see table 4.3). These values help determine the “node type” classification in table 1.

beale03	Description
1	County in metro area with 1 million pop+
2	County in metro area of 250,000 to 1 million pop
3	County in metro area of fewer than 250,000 pop
4	Nonmetro county with urban pop of 20,000+, adjacent to a metro area
5	Nonmetro county with urban pop of 20,000+, not adjacent to a metro area
6	Nonmetro county with urban pop of 2,500-19,999, adjacent to a metro area
7	Nonmetro county with urban pop of 2,500-19,999, not adjacent to a metro area
8	Nonmetro county completely rural or less than 2,500 urban pop, adj. to metro area
9	Nonmetro county completely rural or less than 2,500 urban pop, not adj. to metro area
	Source: MABLE / Geocorr

Table 4.3: Beale 2003 urban classification

4.4.7 Modeling the Network

I use the Pajek software (http://pajek.imfm.si/doku.php?id=pajek) to model the network with the following steps. This is a technical procedure and basic knowledge of social network analysis methods is recommended.

1. Data for the entire network (1990 – 2007) is imported into Pajek.

2. Ties are imputed: Loops (self ties) are removed. Multiple ties are combined by summation of tie values. For example if two actors share a patent tie (value=1) and a weak tie (value = .5) these would be converted to a single line with a value of 1.5.

3. The networks are computed for each year between 1990 and 2007. The network for each year contains ties from three years – the year in question plus one before and one after. The notion is that the networks were in place before the triggering event (e.g. patent app, SBIR grant) and that they have some persistence after the event. While the actual duration is unknown, one year on either side seems to be

a reasonable starting point. Future research may evaluate this assumption in greater detail.

4. For each yearly network, I calculate constraint (which will be defined shortly) and then take the inverse of the constraint, creating the variable I refer to as "opportunity". Opportunity values for county nodes are exported for use in the economic model (discussed later in this chapter). Opportunity is also used as the node-size variable in visual representations of the network. The inverse of constraint or "opportunity" represents the level of opportunity a particular actor in the network has to broker relationships between the other actors it is connected to. If they are already interconnected, constraint will be high and the actor's opportunity for brokerage will be low (i.e. the size of the node will be small). If the ego's alters are not connected, constraint is low and the opportunity for brokerage is high (i.e. the imputed size of the node is large).

5. For each yearly network, I then determine the *m-slices* or cohesive subgroups determined by the multiplicity of lines between actors. As defined previously in this paper, an *m-slice* is a maximal sub-network containing the lines with multiplicity equal to or greater than *m*, and the vertices incident with these lines. Determining the *m-slices* allows us to extract and view those portions of the whole network where interaction between nodes is most intense – revealing high concentrations of innovative activity. The step-by-step procedure for determining *m-slices* in Pajek is detailed in deNooy, Mrvar & Batagelj, (2005, pp 109-117). I use this method to extract the core network where actors are highly interconnected and highly interactive, and the peripheral network where the number and intensity

of ties between actors is lower[35]. The core network is graphed independently. The core and peripheral networks are also recombined for graphing. This is an effective means of displaying the essence of the network without all of the noise[36, 37].

6. The network graphic is generated in Pajek using the Fruchterman-Reingold 3-D algorithm[38]. Node size is determined by the "opportunity" vector described in #4 above. The graphing option in the Pajek program "values of lines: similarities" is selected. This option captures the degree to which nodes share high-value ties and visual draws them closer to one another. Those nodes with lower-value ties are drawn further apart. Since the values of the ties generally represent the intensity of interaction or value of flows between nodes, the interpretation is that the most highly connected nodes are drawn towards the center and nodes with high frequency / high value interactions are drawn close to one another.

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[35] Affiliation networks like the innovation networks created here generate a large number of low value ties. This method is specifically recommended by deNooy, Mrvar & Batagelj for finding cohesive subgroups in affiliation networks.

[36] This method actually splits the network in two, and some ties between core and periphery are lost. Therefore the new network is used only for visualization. Any calculations are done on the complete network.

[37] The resulting core networks include roughly between 900 and 1,400 nodes, and the core-periphery networks contain between 1,800 and 3,400 nodes. These are extracted from yearly networks of between 9,800 and 16,000 nodes, so the actual periphery is much "thicker" than what is portrayed in the models. See for example the core-periphery network for 1991, which contains roughly 3,400 nodes. The added complexity of roughly 1,000 more nodes compared to 1990 or 1992 can easily be seen. These simplifications only affect the visualizations. Network calculations include the full network with all nodes and ties.

[38] The Fruchterman-Reingold algorithm is a force-based graph drawing algorithm that is common in most SNA software packages that considers the value of ties between nodes to determine how far apart the nodes should be drawn in a network visualization. See Fruchterman & Reingold (1991) for a detailed discussion.

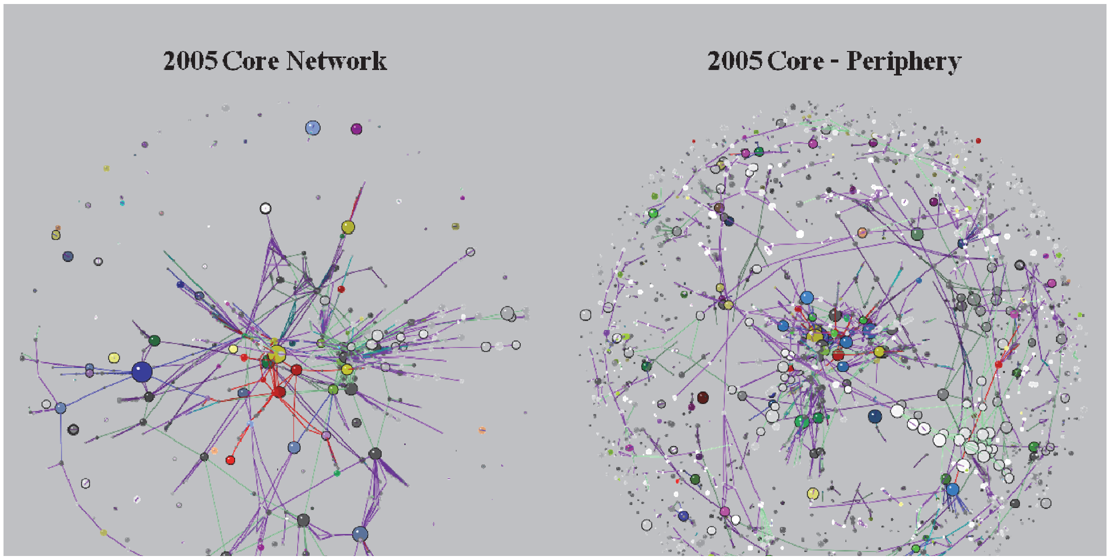

Figure 4.1: Core (left) and Core - Periphery (right) images for Pennsylvania networks 2005

7. The resulting graphic is then exported as 3-D Kinemages which may then be explored using the King viewer[39]. King is used to generate multiple series of still images that are then assembled into a video using Corel Video Studio Pro or similar programs.

The results of this process include 36 interactive network models - one core network and one core/periphery network for each year from 1990 – 2007 (see example, figure 4.1). These interactive models[40] allow for visual exploration and qualitative analysis of the networks. The actual results will be discussed in chapter 5, but a brief discussion of the importance of the core-periphery structure and why we expect to find such structure is useful at this point.

As discussed in Chapter 2 the literature on clusters and agglomeration has tended to suggest that innovation is highly concentrated in a few large metropolitan

[39] Available open source from http://pibs.duke.edu/software/king.php.
[40] accessible through www.terpconnect.umd.edu/~dempy

areas, especially the San Francisco bay area and the Boston / Route 128 area. Network literature focusing on innovation has also tended to suggest a core-periphery structure (for example Borgatti, 2008; Borgatti & Everett, 1999; Borgatti & Li, 2009). Thus there is a strong base of literature suggesting the existence of a core-periphery structure. If the networks created here are good representations of innovation then we should see some type of core-periphery structure. Equally important for this thesis is the composition of the core. Much of the literature suggests that we should find major metro (Philadelphia and Pittsburgh) actors in the core, and everyone else in the periphery. However, if innovation networks are able to overcome physical distance to connect metro, tier 2 and rural actors effectively, then the core-periphery picture will be much more complex. While we may not see metros in the periphery, we should see some tier 2 and rural actors participating in core innovation networks.

4.4.8 Generating Network Measures for the Econometric Model

The network model is used to generate values for two independent variables used in the economic model, which will be discussed shortly. The first variable is the "entrepreneurial opportunity" variable, which reflects the level of opportunity each actor in the network has to broker relationships between other actors based on network topology (structure). The second variable "degree" which is simply the number of lines incident with each node, and is a measure of the level of activity associated with that node[41]. Taken together the opportunity and degree variables

[41] The calculation generated by the network model is the sum of the line values, whereas "degree" in the strict sense ignores line values. However in the course of the network analysis multiple ties – each representing a separate transaction – were consolidated into a single valued tie. Thus the sum

provide relevant measures of the topological structure of the network and the flow of activity through that network.

Entrepreneurial Opportunity (*O*): I define *Entrepreneurial Opportunity* as the reciprocal of Burt's Constraint[42] (1 / constraint). This independent variable provides a measure of each county innovation network's capacity to respond to the new opportunities arising from invention and patenting. Burt's constraint may be calculated using Social Network Analysis software or other matrix methods[43]. Let *i* represent a specific actor (which we call the "ego"), and *j and q* represent other actors connected to the ego (which we call "alters"). Let p_{ij} be the proportional strength of *i's* relationship to *j,* and p_{qj} be the proportional strength of *q's* relationship with *j*. The constraint for *i's* ego network (the network that includes *i* and all nodes *j* that share ties with *i*) is defined as:

$$Constraint_i = \sum_j \left(p_{ij} + \sum_q p_{iq} p_{qj} \right), i \neq j$$

From the perspective of a single actor (the *ego*), constraint measures the extent to which the actors to whom the ego is connected (the "alters), are connected to each other. The more the members of the ego's network are connected to each other, the higher the ego's constraint. Higher constraint means fewer structural holes exist between alters, thus the ego's opportunity for brokerage (his entrepreneurial opportunity) is lower. Taking the reciprocal of constraint provides a measure that is

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of the line values in this case gives a close approximation of degree from the "level of activity" perspective, which is what is of interest here. This is a loose application of the term "degree" in the metric. See for example Wasserman and Faust, 1994 pp 100-107 for a full discussion of degree.

[42] See Burt, 1992 for a full discussion of constraint and its relationship to brokerage.

[43] Calculations for this research were performed using Pajek software.

intuitively oriented towards more or entrepreneurial opportunity present in the network. The data source for this variable is the network model, discussed at the beginning of this chapter.

Degree $(\boldsymbol{D_{k,t_1}})$ is simply a measure of the number of ties incident with county k, and represents the level of network activity for each county. The basic relationship suggested in the production function is that *manufacturing employment* in county *k* is a function of the level of *network activity* in the county and the level of *opportunity present in that county's innovation network* to translate new inventions into commercial innovations.[44] The data source for this variable is the network model. Consult the discussion of that model for additional information.

4.5 The Economic Analysis Model

The economic analysis model is designed to elucidate the relationships between the structure of innovation networks, the inventive activities undertaken by certain actors within those networks, and the spatial distribution of manufacturing employment measured at the county level[45]. I therefore model manufacturing employment and value added as a function of innovation network structure and activity (or flow); the level of technological alignment between industries, patents and the market; and agglomeration-related measures including average establishment size,

[44] Clearly, manufacturing employment is also a function of several other factors. This research is concerned only with the marginal employment related to innovation, holding all other factors constant. In the final regression form of the model the influence of all other factors will show up as the intercept, β_0.

[45] This research also models manufacturing value added as a dependent variable. The functional form of the model is the same and is therefore not repeated or discussed separately.

and simple indicators of urbanization and localization economies[46]. The production function that models this relationship is as follows:

$$ME_{k,t_2} = \boldsymbol{A}\, O_{k,t_1}^{\beta_{n+1}}\, Deg_{k,t_1}^{\beta_{n+2}} \quad \text{(EQ 1a)}$$

$$VA_{k,t_2} = \boldsymbol{A}\, O_{k,t_1}^{\beta_{n+1}}\, Deg_{k,t_1}^{\beta_{n+2}} \quad \text{(EQ 1b)}$$

Where $\boldsymbol{ME_{k,t_2}}$ is the ***manufacturing employment*** in county *k* at time t_2; $\boldsymbol{VA_{k,t_2}}$ is the ***manufacturing value added*** in county *k* at time t_2 $\boldsymbol{O_{k,t_1}}$ is a measure of the ***entrepreneurial opportunity*** present in the innovation network for county *k* at time t_1; and

$$\boldsymbol{A} = \prod_{j=1}^{n} x_{j,k,t_1}^{\beta_j} \quad \text{(EQ 2)}$$

where $\boldsymbol{A}$ is a matrix of additional variables x_{j,k,t_1} such that

$x_{j,k,t_1} \in$

$[Degree, SBIR, DCED, IndHerf, PatHerf, JointEntropy, EstSize, Local, Urban]$

for county *k* at time t_1. These variables are discussed in the next section.

Transitioning from the basic production function to a log-linear form suitable for econometric analysis is straightforward, yielding the following form of the equation.

$$\ln ME_{k,t_2} = \beta_0 + \sum_{j=1}^{n} \beta_j \ln x_{j,k,t_1} + \beta_{n+1} \ln O_{k,t_1} + \beta_{n+2} \ln Deg_{k,t_1} + \varepsilon_k$$

(EQ 3a)

$$\ln VA_{k,t_2} = \beta_0 + \sum_{j=1}^{n} \beta_j \ln x_{j,k,t_1} + \beta_{n+1} \ln O_{k,t_1} + \beta_{n+2} \ln Deg_{k,t_1} + \varepsilon_k$$

(EQ 3b)

[46] Consult Greene (2008) or similar text for a detailed discussion of econometric methods.

4.5.1 Discussion of Variables

Variables for the model are summarized in table 3. This section discusses the dependent variables (4.5.1); independent variables generated by the network model (4.4.2); independent variables modeling technological alignment (4.5.3); and independent variables modeling agglomeration (4.5.4).

Variables	Abbreviation	What it Measures	Why Included	How Calculated
Dependent				
Manufacturing Employment	lnME	Growth rate of manufacturing employment for each county for years 1 - n	Mfg employment is a principle goal and key metric of economic development	ln(ME) where ME is mfg employment for each county at time t_2
Value Added	lnVA	Growth rate of manufacturing value added for each county for years 1 - n	mfg value added is a principle goal and key metric of economic development	ln(VA) where VA is mfg value added for each county at time t_2
Independent				
Opportunity / Constraint	lnOP	The opportunity or brokerage embedded in the structure of each county's ego network. Opportunity is the inverse of Burt's Constriant. (ln transformation applied)	Contraint (opportunity) is a measure of network structure associated with opportunities for growth	$Constraint_i = \sum_j \left(p_{ij} + \sum_q p_{iq} m_{qj} \right), i \neq j$ lnOP = ln(1 / constraint)
Control (Network)				
Network Size	lnDeg	The degree of a network node measures the number of ties incident with that node and is an indication of network size. (ln transformation applied)	Constraint is influenced by network size and density (see note 2). Inventor and patent counts are higher in metro regions; network size should be as well.	Sum of nodes incident with the county
SBIR / STTR	lnSBIR	The total amount of SBIR funding awarded to firms in each county in dollars (000) with ln transformation applied.	Capital flows are critical to the innovation process. While most private capital data are unavailable, these public sources improve the network model and offer at least a partial control measure for capital flows.	Sum of funding to nodes incident with the county
DCED	lnDCED	The total amount of PA DCED (state) innovation related funding in each county in dollars (000) with ln transformation applied.		Sum of funding to nodes incident with the county
Network Density	see note	The density of a node's ego network is a measure of how connected the other actors are to each other.	see note.	Sum of ties present / maximum possible ties
Control (Agglomeration)				
Localization	local	Agglomeration factors; a dummy variable set to 1 for Philadelphia & Pittsburgh metro counties and tier 2 counties (Beale classes 1 – 5); 0 for all others.	Agglomeration factors are considered to be influential on economic growth. These factors include economies of scale, localization and urbanization. While influences of each factor may be seen at different geographic scales relative to the surrounding area, economies of urbanization are most often associated with the kind of spatial density found only in metro areas. Moreover, urbanization economies are most associated with the types of interactions captured in the network model. Setting up the two dummy variables in this way allows the "localization" variable to capture all of the agglomeration effects that are common to both metro and tier 2 counties which the "urbanization" variable captures the agglomeration effects found only in the metro counties.	
Urbanization	urban	Agglomeration factors; a dummy set to 1 for Philadelphia & Pittsburgh metro counties (Beale 1-3); 0 for all others.		
Average Establishment Size	lnFS	Average size of manufacturing establishments by number of employees within each county. (ln transformation applied)	While not an agglomeration measure per se, average establishment size controls for differential effects of establishment size between counties.	mfg employment / # of mfg establishments
Control (Technology Alignment)				
Industry Herfindahl	lnIH	A measure of each county's national market share in manufacturing industries based on employment in four-digit NAICS / SIC industries. (ln transformation applied)	Having production capacity in technologies that are aligned with the market is important to being able to translate innovation into job growth.	$IndHerf = \sum_{i=1}^{n} \left(\frac{e_{i,t}}{E_{i,t}} \right)^2$
Patent Herfindahl	lnPH	A measure of each county's national "market share" in patent technologies based on the local share of patents for each patent class. (ln transformation applied)	Commercial success in innovation requires being innovative in technologies with market demand.	$PatHerf = \sum_{i=1}^{n} \left(\frac{p_{c,t}}{P_{c,t}} \right)^2$
Joint Entropy	lnJE	A measure of how clustered or concentrated manufacturing industries and patent technologies are within each county (although the technologies are not necessarily the same). (ln transformation applied)	Entropy is a scientific term for order. Systems (county economies) that are highly ordered or concentrated in a few industries and paatent technologies will have low entropy. Those that are less structured or more diverse will have higher entropy. This variable provides an indicator of the importance of concentration vs. diversity of economic activity.	$H(X,Y) = -\sum_{i=1}^{n} \sum_{j=1}^{m} p(x_i y_j) \log p(x_i y_j)$

Figure 4.3 Table of Variables (continued on next page)

Variables	Abbreviation	Expected Sign of regression coefficients	Explaination of sign	Data Source	Notes
Dependent					
Manufacturing Employment	lnME	N/A		County Business Patterns	
Value Added	lnVA	N/A		Economic Census	Data only available for 1997, 2002, 2005
Independent					
Opportunity / Constraint	lnOP	(-)	If a county has high opportunity that means that its firms and inventors are not connected to each other. Both agglomeration and cluster theory suggests that connected firms, inventors and institutions are what lead to growth. Thus we expect the sign to be negative: decreasing county opportunity results in more connected firms, inventors and istitutions and therefore higher growth.	Network Model	Note 1; See Burt (1992).
Control (Network)					
Network Size	lnDeg	(-)	Intuitively one expects this to be positive, but as note 2 suggests, increasing size alone decreases constraint. Burt's theory and empirical work suggest that the expected sign in this case will be negative. See Burt (1992), Figure 2.3 (Figure 4.2 this document).	Network Model	Note 2
SBIR / STTR	lnSBIR	(+)	The investment of capitl in the innovation process is expected to have a positive effect on employment growth.	Network Model; SBA TechNet	
DCED	lnDCED	(+)	The investment of capitl in the innovation process is expected to have a positive effect on employment growth.	Network Model; PA DCED	
Network Density	see note	(+)	See Burt (1992) Figure 2.3 (Figure 4.2 this document). Increasing density increases constraint. Thus in the case of counties, increasing density means connecting firms, inventors and institutions within the county. Cluster theory suggests that more connections lead to economic growth. Therefore, increasing density is expected to have a positive effect on economic growth.	Network model	See Note 2. This variable was excluded from the model due to multicolinearity. However the relationship between network size, density and constraint is central to explaining the findings and the recommendations for economic development policy.
Control (Agglomeration)					
Localization	local	(+)	Agglomeration is generally expected to have a positive effect on employment growth.	Missouri State Data Center	These are control variables and ultimately are not intended as precise indicators of localization and urbanization economies. Nevertheless they do offer rough estimates of the geographic scales over which these two factors of agglomeration are thought to
Urbanization	urban	(+)			
Average Establishment Size	lnFS	(+)	Increasing the county's average mfg establishment size is expected to have a positive effect on mfg job growth while decreasing average size is expected to have a negative impact. See Haltiwanger and Jarmin (2011).	County Business Patterns	
Control (Technology Alignment)					
Industry Herfindahl	lnIH	(+)	Higher market share of productive capacity is expected to have a positive effect on mfg job growth.	County Business Patterns	
Patent Herfindahl	lnPH	unknown	Different arguments suggest different signs. Refer to the discussion.	USPTO	
Joint Entropy	lnJE	unknown	Different arguments suggest different signs. Several cluster theories suggest that greater concentration and order in targeted industry clusters should lead to growth. Theories of lock-in and path dependence suggest that especially in older areas and declining industries greater diversity is associated with growth.	County Business Patterns; USPTO	
		Notes			
		Note 1: Burt's original measure is constraint and this is the measure derived from network analysis. Opportunity is a variable used exclusively in this research and is intended to provide a more intuitive grasp of what constraint means. Opportunity is defined as the mathematical inverse of constraint.			
		Note 2: According to Burt, "Size and density work together. Density increases constraint (the difference between the dashed and solid lines) Less in large networks than in small networks. Size decreases constraint, More in dense networks than in sparse networks." (Burt, 1992)			

Figure 4.3 Table of Variables (continued)

4.5.2 Dependent Variables

Dependent variables in this model include manufacturing employment and manufacturing value added measured at the county level. Both employment and value added are widely recognized metrics of economic growth. Positive changes in the level of these variables from one period to the next reflect economic growth, while negative changes reflect economic decline. The econometric models in this research narrow the range of industries for which employment and value added are measured, limiting them to the manufacturing sector (NAICS 31-33 / SIC 20-39). Limiting these variables to manufacturing in this research provides a more accurate picture of the influence of innovation networks based on ***product*** patents and product development funding since they minimize distortions that may be caused by changes in employment or value added in unrelated industry sectors such as services. This research is limited to ***product*** innovation[47] which results in the ***manufacturing*** of new or differentiated products.

Manufacturing Employment (*ME*): Manufacturing employment is a dependent variable and consists of employment in all manufacturing industries (NAICS 31-33 / SIC 20-39) measured at the county level. Positive employment growth is one of the principle goals of economic development, especially in higher-wage jobs typically found in manufacturing industries. Manufacturing employment is likely to be more sensitive to product innovation than general employment figures.

[47] See page 87 for a full discussion of filtering methods designed to limit patents used in this network to product patents. Briefly, only utility patents are included. While this does not absolutely exclude process innovation, within a network comprised of 48,176 actors in 15 different classes, connected by 894,418 ties among six different relations, the preponderance of patent ties are product patents.

The data source for this measure is the U.S. Census Bureau's county business patterns, annual data from 1990 – 2007[48].

Manufacturing Value Added (*VA*): Manufacturing value added is a dependent variable and consists of value added for all manufacturing industries (NAICS 31-33 / SIC 20-39) measured at the county level. Growth in value added (or "output" more generally) is one of the principle goals of economic development, especially in manufacturing industries. Manufacturing value added is likely to be more sensitive to product innovation than value added for the broader economy which may include services and agriculture. The data source for this measure is the U.S. Census Bureau's economic census for 1997, 2002 and 2007.

4.5.3 Independent Variables Generated by the Network Model

A detailed discussion of the construction of the network model and the technical steps involved in computing various network measures is presented earlier in this chapter. Each variable is summarized below with a brief discussion of why it is relevant to the model and what results should be expected.

Entrepreneurial Opportunity (*Op*): I define *Entrepreneurial Opportunity* as the mathematical inverse of Burt's Constraint[49] (1 / constraint). This independent variable provides a measure of each county's opportunity for brokerage among other actors in its network. Burt's constraint may be calculated using Social Network Analysis software or other matrix methods[50].

$$Constraint_i = \sum_j \left(p_{ij} + \sum_q p_{iq} m_{qj} \right) , i \neq j \qquad \text{(EQ 3)}$$

[48] Links to all data sources are provided in the References section and are summarized in table 3.
[49] See Burt, 1992 for a full discussion of constraint and its relationship to brokerage.
[50] Calculations for this research are performed using Pajek software.

From the perspective of a single actor (the *ego*), constraint measures the extent to which the actors to whom the ego is connected (the "alters), are connected to each other. The more the members of the ego's network are connected to each other, the higher the ego's constraint. Higher constraint means fewer structural holes exist between alters, thus the ego's opportunity for brokerage (his entrepreneurial opportunity) is lower. Taking the mathematical inverse of constraint simply provides a measure that is intuitively more straightforward and which directly reflects the level of entrepreneurial opportunity present in the network. Importantly, Constraint (and therefore Opportunity) is considered to be purely a network structural metric (Burt, 1992; Wasserman and Faust, 1994; Scott, 1999).

If a county has high opportunity that means that its firms and inventors are not connected to each other. Both agglomeration and cluster theory suggests that connected firms, inventors and institutions are what lead to growth (see Porter, 1998, or Muro and Katz, 2010, for example). Thus we expect the sign to be negative: decreasing county opportunity results in more connected firms, inventors and institutions, and therefore higher growth. The data source for this variable is the network model described earlier in this chapter.

Network Size is measured by degree **($\boldsymbol{Deg_{k,t_1}}$).** **Degree** is simply a measure of the number of ties incident with county *k*, at time t_1. If multiple ties between actors are counted as they are in this case, degree provides a simple measure of both network structure (which nodes are connected) and network activity (flows of information or resources between actors) given by the total value of all ties between each pair of actors. The basic relationship suggested in the production function is that *manufacturing employment* in county *k* is a function of the level of *network activity* in the county and the level of *opportunity present in that county's innovation network* to translate new inventions into commercial innovations.[51] The data source for this variable is the network model described earlier in this chapter.

Network Density is an important variable that is excluded from the regression analysis due to multicolinearity when it is included with both Opportunity and Network Size (degree). This is because Network Size and Network Density both influence Opportunity (or Constraint). According to Burt, "Size and density work together. Density increases constraint (the difference between the dashed and solid lines in figure 4.2) less in large networks than in small networks. Size decreases constraint, more in dense networks than in sparse networks" (Burt, 1992).

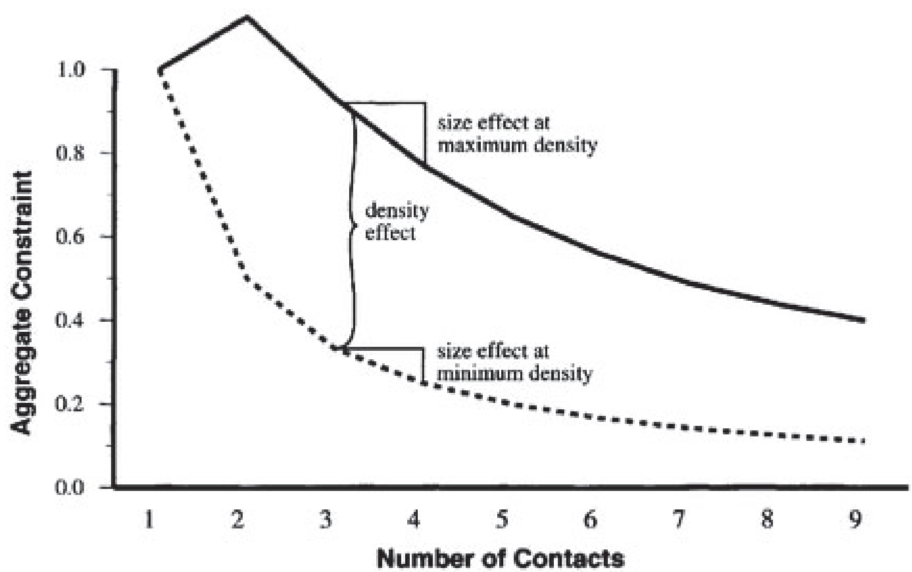

Figure 4.2: Network size and density effects on constraint (from Burt, 1992)

[51] Clearly, manufacturing employment is also a function of several other factors. This research is concerned only with the marginal employment related to innovation, holding all other factors constant. In the final regression form of the model the influence of all other factors will show up as the intercept, β_0.

SBIR *and* ***DCED*** are flow variables that reflect the fact that innovation involves more than just patents. These two variables indicate the total amount of funding to firms in county *k at* time t_1 from federal Small Business Innovation Research / Small Business Technology Transfer (SBIR / STTR) programs and Pennsylvania Department of Community and Economic Development (DCED) innovation-related programs respectively.

SBIR/STTR funding is provided jointly through the US Department of Commerce and other federal agencies depending on the nature of the innovation being supported. For example, health related innovation may be supported by Health and Human Services, while a wide array of product innovations may be supported by various agencies or branches within the Department of Defense. Phase I SBIR grants support initial feasibility and prototyping efforts and are typically in the \$50,000 - \$100,000 range. Phase II grants support commercialization activities and generally range between \$500,000 and \$750,000. Funding is provided directly to firms. Aggregate totals for each county are derived by summing the funding amounts for all recipient firms located within each county for each year between 1990 and 2007 through the network model. The source for SBIR/STTR funding data is the US Small Business Administration TechNet database.

DCED funding from the Commonwealth of Pennsylvania typically flows either directly to counties or to intermediaries including the Ben Franklin Technology Partners and regional economic development organizations. Depending on the specific program the funds are either invested directly by the county or intermediary on innovation related projects (technology incubators, for example), or they are passed through to firms as either debt or equity financing managed by the intermediary. Aggregate totals for each county and year between 2000 and 2007 are computed through the network model. The data source is the PA DCED Investment Tracker database.

One question related to both of these variables is whether the level of funding in year 0 influences economic growth in subsequent years, or if the selection process “picks winners”. It is likely that both influences are at work. In the aggregate, the level of funding for innovation is a widely used indicator of innovation related economic growth at the state and national levels. It is therefore a natural extension to model this relationship at the county level. However it is also true that the potential for commercial success is a consideration in all innovation investment decisions, both private and public. Investors – both private and public – invest limited capital in the development and commercialization of the most promising technologies. Political rhetoric aside, “picking winners” by investing in the most promising technologies is a rational part of the process. We should expect to see funding levels influence economic growth at the local level because they are known to influence growth at the state and national levels. We should expect that influence to be stronger and/or more significant if the selection process is effective.

4.5.4 Independent Variables Modeling Technological Alignment

Three variables are introduced to account for the influence of technology in translating new inventions and innovation into economic growth. The influence of technology is manifested in several ways. First, there is Industry Technology which refers to the technologies within which county manufacturers specialize. To measure the extent to which counties contain specialized manufacturing, a Herfindahl index (***IndHerf***) is calculated for employment in manufacturing industries at the 4-digit NAICS level. As previously noted in section 2.5 this metric has been used in prior research (Bettencourt, Lobo and Strumsky, 2004; Strumsky, Lobo and Fleming; 2005). The Herfindahl index is the sum of the squares of "market share." For the purposes of this research the following equation is used:

$$IndHerf = \sum_{i=1}^{n} \left(\frac{e_{i,t}}{E_{i,t}}\right)^2 \qquad \text{(EQ 4)}$$

Where i = 4 digit NAICS manufacturing industry; $e_{i,t}$ = county employment in industry i at time t; and $E_{i,t}$ = US employment in industry i at time t.

The Herfindahl index returns a value between 0 and 1, with larger values indicating larger industrial market share and greater specialization. Innovations are more likely to lead to job creation in a particular county if that county has some manufacturing specialization related to that industry. For example, pharmaceutical innovations are more likely to lead to job creation in counties where drug manufacturing is already established and competitive. Greater productive capacity within such specializations would be represented by relatively larger Herfindahl indexes since they represent higher market share. The data source is the U.S. Census, County Business Patterns for 1990 through 2007.

The second way that technology influences the path from invention to job creation is through the technology associated with the patent itself, as represented by the patent technology class. (See examples in table 1).

New innovations are more likely to create jobs if they result in new products in growing markets. The variable *Patent Technology (**PatHerf**)* is an annual Herfindahl index for each county, which gives a measure of how connected each county is to "hot" technologies and emerging product markets.

$$PatHerf = \sum_{i=1}^{n} \left(\frac{p_{c,t}}{P_{c,t}}\right)^2 \qquad \text{(EQ 5)}$$

Where c = patent class; p_{ct} = number of local patents in class i at time t; and P_{ct} = number of Patents nationally in class c at time t. The data source is the US Patent and Trademark Office (USPTO) patent data from 1990 through 2007.

The first two technology measures (*IndHerf* and *PatHerf)* provide indicators of how well each county's industries and inventive activities are aligned with the market. A third measure, ***Joint Entropy (JE)***, provides a measure of how "organized and focused" each county's industries and patenting activity are. As previously noted in section 2.5 a similar metric, the Shannon Entropy Index, has been used in prior research (Marx, Strumsky and Fleming, 2009) Entropy refers to the level of disorder in a system. In this case the system is the county economy. Within any given county the level of disorder (or lack of specialization) within its productive industries and inventive activities will vary. Joint entropy is a measure of the extent to which they vary together, and is calculated as follows. For discrete random variables X with n outcomes, $\{X_j := 1, \cdots, n\}$, and Y with m outcomes, $\{Y_j := 1, \cdots, m\}$ the joint entropy denoted by $H(X, Y)$, is defined as:

$$H(X, Y) = -\sum_{i=1}^{n} \sum_{j=1}^{m} p(x_i y_j) \log p(x_i y_j) \qquad \text{(EQ 6)}$$

Where $p(x_i y_j)$ is the probability mass function of outcome $x_i y_j$ .Low joint entropy means that both the county's industries and patenting are highly specialized[52]. High joint entropy means that either one or both lacks order and specialization. Data sources include the U.S. Census, County Business Patterns, and USPTO.

The three technology measures focus on three different aspects of technological alignment, each of which is expected to contribute to the creation of a business climate in which innovation related growth is more effective. See figure 6.6. While it is clear that the Industry Herfindahl index should be positively correlated with growth, the expected signs of the regression coefficients for the other two technology variables are less clear. Descriptive statistics show that patents tend to be more concentrated in metropolitan regions (figure 4). However metropolitan regions have also lost manufacturing jobs at a faster rate than tier 2 or rural areas over the entire period (figure 2). The patent Herfindahl may end up identifying counties that are invention hot spots but which may not have sufficient specialized production capacity to translate those inventions into local economic growth.

The Joint Entropy metric measures provide an indicator of each county's position on a continuum between high specialization / concentration of industries and patent technologies on the one end, and economic diversity on the other. Cluster theories suggest that greater specialization leads to economic growth (see for example Porter 1998; Muro and Katz, 2010). Yet theories concerning economic stagnation and path dependence suggest that highly specialized and concentrated industries may experience "lock-in" and path dependence. Therefore determining the appropriate

[52] This does not indicate that they are highly focused on the same technology. Further investigation is necessary to determine whether productive and inventive technologies are similar.

sign of the regression coefficients *a priori* is unclear. However the signs of the coefficients may provide some indication of whether to pursue strategies aimed at creating higher specialization / concentration, or strategies that promote economic diversity.

4.5.5 Independent Variables Modeling Agglomeration

Variables reflecting the factors of agglomeration – ***localization economies (Local) and urbanization economies (Urban)*** provide measures that control for the effects of spatial agglomeration. Innovation has frequently been linked to agglomeration generally, and the various factors of scale, localization and urbanization are sometimes used to explain why agglomeration matters with respect to innovation, as discussed in the literature review. The control measures discussed below provide some simple proxies for these factors. However this research does not purport to model agglomeration in any kind of complex or sophisticated way since these are simple control variables.

Localization economies are predominantly focused on the benefits that arise from co-location of similar firms, including shared labor pools, infrastructure and customer base. For example, as firms within a regional cluster interact in the marketplace they tend to compete more intensely with local competitors than they do with firms at a great distance. Because producers operate in a real-world environment characterized by imperfect competition, local markets tend to generate *pecuniary externalities* as a byproduct of their market interactions. Since these externalities are based on transactions and imperfect competition rather than the exchange of technological information, they tend to be less sensitive to geographic distance (Fujita and Thisse, 2002).

Pecuniary externalities may therefore be observed within and between regional clusters. While localization economies are seen in urban areas they are also frequently seen in many smaller manufacturing regions, although typically not in rural regions to any great extent. Research has shown that economic opportunity in rural regions is related to both the size of the population and the region's access to major metropolitan regions where they can access both specialized services and global markets (Siegel, Swanson and Shryock, 2004; U.S. Economic Research Service 2002a, 2002b). The Rural-Urban Continuum Codes, also known as Beale Codes, reflect varying levels of economic opportunity across the rural-urban continuum (Siegel, Swanson and Shryock, 2004, Butler and Beale, 1994).

The ***Local*** variable is simply a dummy variable that is set to 1 if the county is classified as metro or tier 2 (corresponding to Beale '03 classifications 1 – 5)[53] and 0 otherwise. Metro and tier 2 counties for Pennsylvania are shown in figure 1. 2003 Beal code descriptions are shown in table 2. The data source for county Beale codes is University of Missouri's Mable / Geocor database.

[53] See table 4.3 and the discussion of the Commute Relation in the network model section. Beale classifications obtained from University of Missouri's Mable / Geocor site.

Urbanization economies are concerned primarily with the variety and specialization that become possible when metropolitan size and density reach sufficient levels. Urbanization economies are characterized primarily by *technological externalities* arising from non-market interactions (Fujita and Thisse, 2002). Knowledge spillovers are a widely recognized example of technological

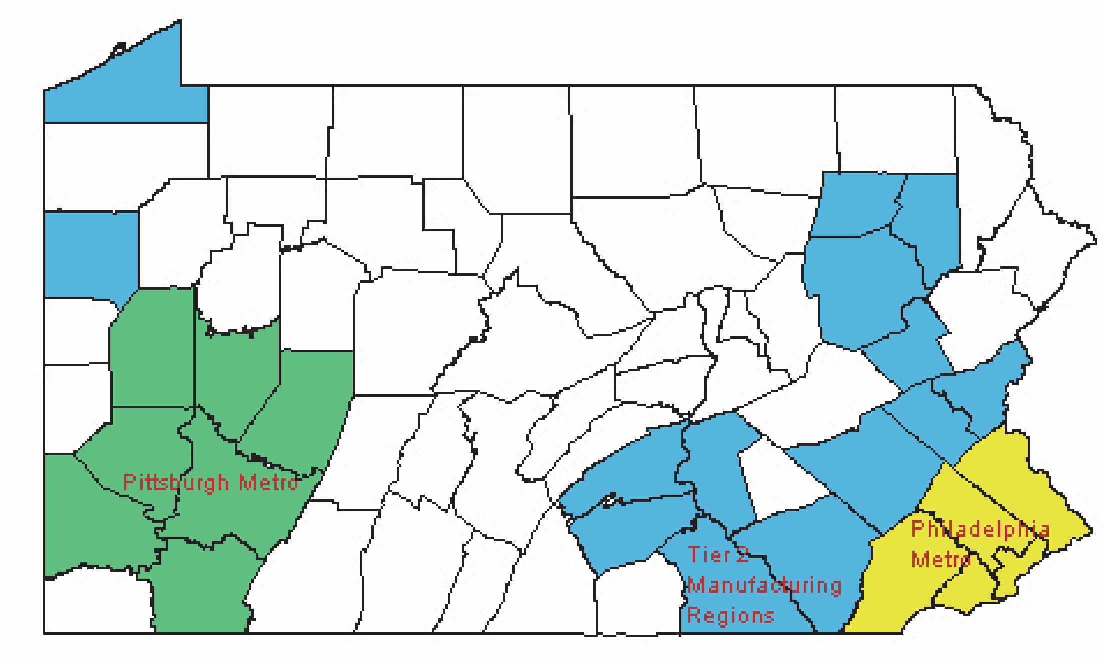

Figure 4.3: Pennsylvania counties with metro and tier 2 regions

externalities related to innovation. The basic premise of knowledge spillovers is that new, innovative knowledge is characterized as *tacit*, necessitating face-to-face interaction – and therefore proximity - to communicate it effectively (Cowan, 2005; Gertler, 2005, 2007; Malerba & Breschi, 2005; Storper & Venables, 2005; Keilbach, 2000). Thus firms and workers that are in close proximity to one another are able to share tacit knowledge more easily than those that are more distant. Spatial distance and density are therefore important factors in urbanization economies, limiting them primarily to major metropolitan areas. The ***Urban*** variable is therefore simple a dummy variable that is set to 1 if the county is part of the Philadelphia or Pittsburgh metro regions (Beale codes 1-3) and 0 otherwise.

It should be stressed again that these agglomeration-related measures are simple control variables and do not represent a detailed or sophisticated analysis of agglomeration. Nevertheless, attempting a simple deconstruction of agglomeration offers a useful entre into a discussion of the fact that agglomeration takes on different characteristics at different geographic scales based on the types of interactions (relationships) between people, generating either pecuniary or technological externalities (Fujita and Thisse, 2002). Inasmuch as the *lack* of such differentiation is an important criticism of much of the research and literature regarding clusters, having multiple control variables takes a preliminary step in addressing that criticism.

Average establishment size (EstSize); while not an agglomeration measure *per se*, average establishment size controls for differential effects of establishment size between counties. Thus the ***EstSize*** variable is simply a measure of average manufacturing establishment size within the county. With the logarithmic transformation applied, the variable in the model is more precisely the rate of change in average manufacturing establishment size. In urban counties the rate of change is expected to be slower because there are already many establishments. Change there is also likely to be negative, given the constant decline of manufacturing employment in metro counties over the period (figure 4.2). In Tier 2 counties and rural counties where development is just beginning, the rate of change is likely to be larger. The sign of the change may be positive for some counties that are gaining establishments and negative for others that are losing. Increasing the county's average mfg establishment size is expected to have a positive effect on mfg job growth while decreasing average size is expected to have a negative impact. Often these dynamics are driven by establishment age (See Haltiwanger and Jarmin, 2011), although this data is much more difficult to come by. The growth rate of average establishment size is likely to pick up some of these age dynamics as younger firms also tend to grow faster than older ones. This control variable thus accounts for differential growth rates between counties due to firm size and to some extent, age. The data source is the U.S. Census Bureau.

4.5.6 Modeling Lagged Dependent Variables

The basic question that this regression analysis seeks to answer is whether there is a correlation between the set of independent variables measured in one year and manufacturing employment or value added in subsequent years. Approaching this relationship from the standpoint of modeling specific years (for example the influence of independent variables measured in 1990 on dependent variables measured in 1991, 1992, 1993, … 2007) may subject the model to unwanted influences caused by the business cycle.

Business cycles are economy-wide patterns of expansion (booms) and contraction (recessions) that occur around the long-run economic growth trend. Cycles tend to last from several months to several years. The National Bureau of Economic Research (NBER) maintains a history of U.S. business cycles (http://www.nber.org/cycles.html). When considering economic data from multiple time periods the business cycle may affect values occurring at different parts of the cycle, as when one measure coincides with the peak of a cycle and the other coincides with the trough of a cycle, for example. To control for this effect economists often select comparison dates that coincide with similar points on the business cycles, say peak-to-peak or trough-to trough.

Another method of controlling for business cycle influences is used in this research. Independent (and control) variables for each year from 1990 - 2006 are in turn set to year 0 and dependent variables for each subsequent year through 2007 are set to years 1 through n, up to a max of 17. For example, modeling a two-year lag between the independent and dependent variables would include the following sets of observations for independent / dependent variables: {1990/1992, 1991/1993, 1992/1994, … 2005/2007}. Separate regressions are run for each lag duration from 1 through 17 years. For the two-year lag example this method generates a set of 1,061 observations over the 17-year period (3 business cycles). Statistically, this counteracts the effects of any one cycle.

The nature of the variables and the relationships being modeled along with the fact that each discrete time lag is a separate regression suggest that temporal autocorrelation is unlikely to play a significant role. Spatial autocorrelation effects are assumed to be present and included in the regression intercept value, or explained to some extent by the independent variables in the regression[54].

4.5.7 Running the Model

As shown in the transition from equation 2 to equation 3 the final log linear form of the model takes the natural logarithm of each of the variables except for dummy variables. Once this is completed the observations are formatted to account

[54] I am grateful to dissertation committee member Peter Meyer for his assistance in structuring this approach to modeling lagged dependent variables.

for lagged dependent variables as noted in section 3.3. Separate regressions are run for each dependent variable (manufacturing employment and value added) and each lag duration (1 – 17 years) representing number of years between the observation of the independent variables and the dependent variables.

Two additional alternative models were run to investigate whether substitution effects were present between agglomeration and network influences. Network effects and agglomeration effects are intertwined by definition[55]. However, since we are comparing network effects measures and agglomeration effects measures from different independent sources we should be able to detect this comingling by selectively removing groups of variables from the regression. Compared to the original model which includes all of the variables:

1. If we remove the agglomeration variables we should see an increase in the size of the coefficients and the level of significance in the network variables. The change should be substantially higher than changes for other variables.
2. If we remove the network variables we should see an increase in the agglomeration variables. Since the network coefficients are small, we should also see a decrease in the difference between the R^2 and adjusted R^2, even though they both decrease slightly, because there is less co-linearity among the variables.

[55] It is possible to define network effects without invoking agglomeration concepts, however agglomeration cannot be defined without explicit or implicit reference to relationships. Thus agglomeration is dependent to some extent on networks *by definition.*

Chapter 5: Innovation Networks in Pennsylvania, 1990-2007

5.1 Results of the Network Model

The results of the network model are presented in three parts. First, the interactive 3-D models are available for inspection on the corresponding web page[56]. These models and the associated video show the evolution of a core-periphery structure over the study period (1990 – 2007). Each model shows the different relationships between individual nodes. Different types or classes of nodes (for example inventors, assignees, universities, counties, etc.) are color coded. Nodes are sized according to the opportunity variable[57]. Node positions and adjacency are as discussed above. Second, images of innovation network clusters have been generated using the NodeXL program with the assistance of PhD Candidate Cody Dunne from the University of Maryland Human Computer Interaction Lab (HCIL). These images provide strong visual evidence of clustering and agglomeration, but also extensive connections to actors in distant locations.

For example, figure 5.1 shows the innovation clusters (each in its own box) for Pennsylvania for 1990, and figure 5.2 shows an enlarged view of the Westinghouse cluster based in the Pittsburgh metro region. In figure 5.1 the large clusters along the top and left edges generally represent

[56] www.terpconnect.umd.edu/~dempy

[57] SNA software allows users to use variable values to determine the relative sizes of nodes as they are drawn by the visualization routines.

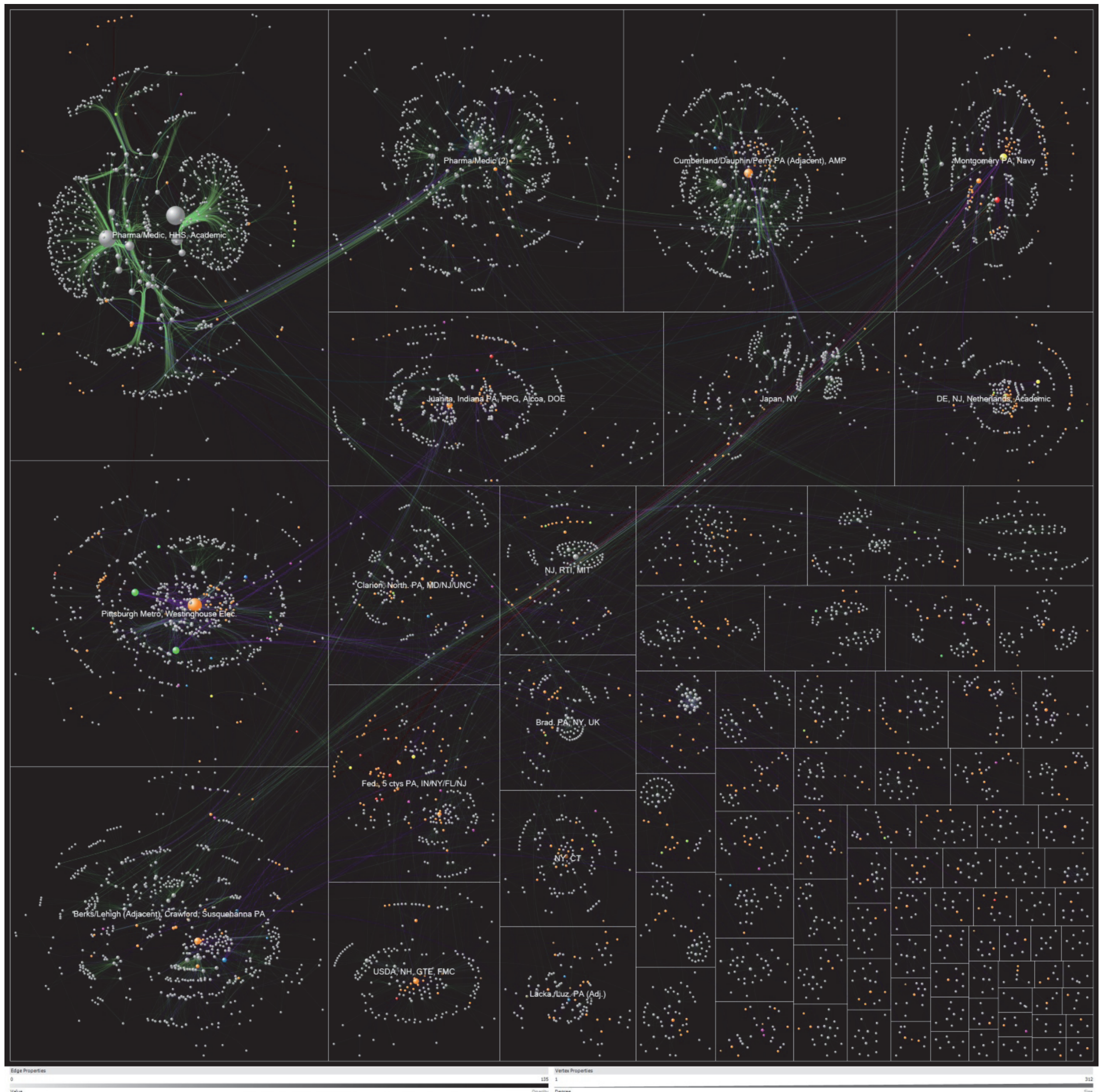

Figure 5.1: Regional Innovation Clusters in Pennsylvania, 1990

major metro-based clusters, of which Westinghouse can be seen on the left-hand side. In general, as one moves towards the lower right corner of figure 5.1 the clusters get progressively smaller and more rural. This general pattern follows what would be expected under theories of agglomeration and clustering. However, within many of the clusters we find distant actors whose social network ties to specific clusters are strong enough to pull them into a cluster in another geographic region. The Westinghouse cluster provides a good illustration. Westinghouse is the world's largest nuclear energy firm and currently has over 60% worldwide market share for nuclear power plants. It is represented by the large orange node in the center of figure 5.2. Other firms are represented by orange nodes; inventors are white nodes;

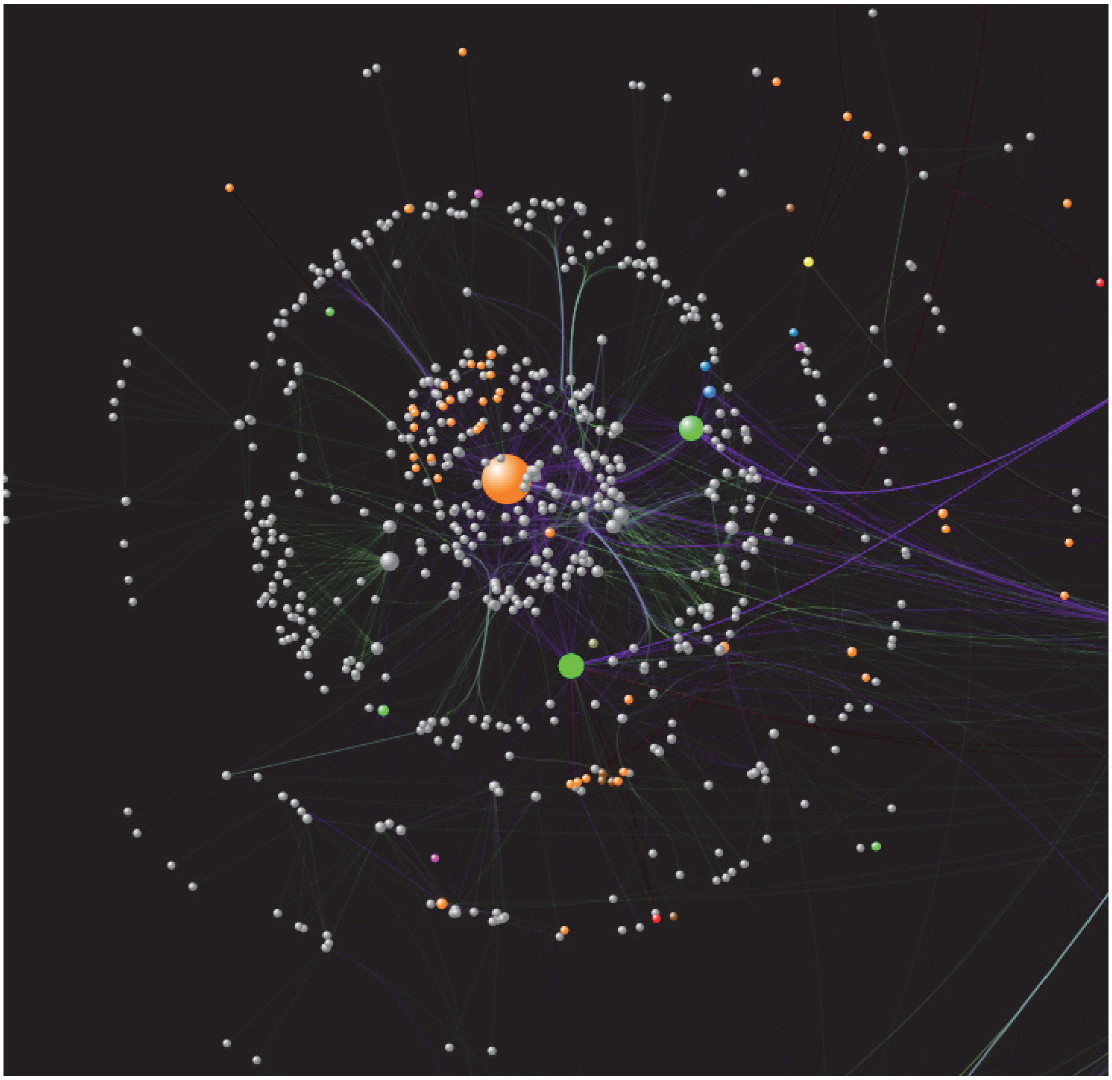

Figure 5.2: Westinghouse cluster / Pittsburgh metro, 1990

and other colors represent counties, universities and other actors. The two large green nodes to the right of Westinghouse at about the 3 o'clock and 5 o'clock positions in figure 5.3 represent Allegheny and Westmoreland counties in the Pittsburgh metro region. This again is consistent with agglomeration. However, just above these two are two smaller blue nodes at about the 2 o'clock position. These nodes represent

Dauphin and York counties that are located in the south-central part of Pennsylvania and are part of a tier 2 region there. This region is home to several Westinghouse contractors. For example, Precision Components Corporation[58] in York County manufactures containment vessels for nuclear reactors. Thus the cluster visualization based on network ties reveals agglomeration influences, particularly in larger metro regions, but also reveals evidence of industry clustering based on strong innovation network ties.

Third, the results of the network analyses are have been exported to the economic analysis model, which is the topic of Chapter 6.

5.2 Discussion of the Network Model

The network models offer a perspective of Regional Innovation Clusters that has not been seen before – one that includes actual firms, inventors, universities, etc. and actual or probable ties that connect them. This contrasts with industry cluster analyses that only show aggregated industries and suspected relationships.

Innovation is visibly dispersed and. While inventors cluster in urban centers, there are intensive networks extending into the second tier and internationally and many disconnected networks in the periphery. These network visualizations provide graphic evidence supporting the hypothesis that tier 2 counties are interconnected via innovation networks and that innovation is not exclusive to urban areas. The video representation of the 3-d network models between 1990 and 2007 clearly shows the emergence of a core-periphery structure. Close inspection of the models reveals that

[58] http://www.pcc-york.com/.

between 1990 and 2001 universities increasingly occupy central positions within the core, consistent with contemporary views on their increasingly important role in the innovation process (see Bowman, J.M. and Darmody, B., 2008; SSTI, 2006; or Franklin, 2011, 2012 for example).

5.3 Preliminary Conclusions Concerning the Network Model

The main purposes for constructing the innovation network models discussed in this paper were to understand visually the innovation network relations between the developers of new technologies; the users of those technologies; the financial infrastructure that supports innovation, such as federal government grants; and universities. The second reason for constructing the innovation network is to calculate independent variables of network structure for use in an economic model that analyzes the relationship between innovation networks and economic growth. The visualizations of the network models have provided several findings that were anticipated. These network visualizations including the 3-d interactive models; the network video and the NodeXL-generated images (figures 1 and 2) reveal the evolution of a core-periphery structure in the innovation networks from 1990 – 2007. They also reveal patterns of spatial agglomeration evidenced by the close proximity of county nodes from the Philadelphia and Pittsburgh regions within the core networks, as well as regional industry and innovation clusters evidenced by the close proximity of physically distant but related nodes within the networks. Examples include the Westinghouse Cluster in the Pittsburgh region, as well as pharmaceuticals and telecommunications in the Philadelphia region. These clusters are visible in the

3-d models as well as the NodeXL cluster image. Visual inspection also reveals some close connections with geographically distant actors, some of whom are in second tier or rural counties or inventors in others countries around the globe. This visualization of regional innovation clusters represents a new perspective that simultaneously shows firms, institutions, government agencies and creative people in the regional and global context.

Yet while we see the emergence of dense clusters within the major metro regions we also see that roughly half of all those involved in innovation are located in the network periphery – in second tier regions, rural counties and distant countries. The visualizations reveal smaller clusters of industry and innovation in these peripheral regions – clusters that are highly interconnected with other firms, inventors and institutions in major metro regions and elsewhere. Far from the portrayal of isolated clusters or enclaves of creative individuals in major cities, these visualizations show that innovation and innovative firms and people are everywhere; and they are highly interconnected in ways that have not been previously visualized.

The network video reveals that the clustering of firms, inventors and universities in the network core is something that has emerged over time throughout the 1990's and into the early 2000's. The network models offer a visual portrayal of the reorganization of business and the growing role of universities in research and development over this time period, particularly in the pharmaceutical cluster. While the patent ties are clearly the strongest and most prevalent, the "strength of weak ties" is also evident. One question for future research is whether these weak ties based on patenting in similar classes or shared personnel serve as precursors to stronger ties in later years.

These new network visualizations present the social and spatial dimensions of innovation in ways that reinforce certain concepts of agglomeration, clustering, regionalization and globalization while challenging other widely held perceptions at the same time. The visual patterns of agglomeration and clustering that are evident in the network images show how agglomeration, clustering and regionalization are social phenomenon as well as spatial ones. The social proximity of spatially distant actors – in some cases from around the globe – provides visual support for the influence and interaction of globalization within local regions and clusters. However these same visual patterns and the sheer volume of ties to tier 2, rural and global places also suggest that the widely held notion that innovation happens only – or even predominantly – in a few major metropolitan regions seems vastly overstated. Tier 2 regions in particular appear to play active roles in the core innovation networks. The network models and visualizations developed in this research provide fresh new perspectives into the social nuances of agglomeration and regional innovation clusters. These new perspectives come at a time when U.S. economic development policies concerned with regional innovation and manufacturing that have been narrowly focused on a few specific cluster models, now appear open to network-based alternatives.

Yet as noted in the earlier discussion in this paper on Multi-Theoretical, Multi-Level (MTML) networks, the network models developed herein make some significant simplifying assumptions. The U.S. Economic Development

Administration has funded efforts to apply an expanded version of this methodology to modeling and analyzing innovation networks in Maryland. These new models will add more data sources, and will be more rigorous in examining potential interaction between different relations and their influence on higher levels of network organization. Addressing these limitations means that the new models will support more extensive analyses of innovation networks throughout Maryland.

Chapter 6: The Influence of Network Structure on Economic Growth

6.1 Results of the Economic Analysis Model

Results reported in this paper focus on the economic model. The results of the network model are discussed extensively in chapter 5 with relevant findings summarized here. The interactive 3-D models are available for inspection at www.terpconnect.umd.edu/~dempy. These models and the associated video show the evolution of a core-periphery structure over the study period (1990 – 2007).

6.1.1 Descriptive Statistics

A few descriptive statistics summarizing manufacturing employment, value added and raw patent counts over the period 1990 – 2007 provide some useful background and context for interpreting the results of the regression analysis. These figures are aggregated according to the three levels of urbanization discussed in section 3.2, namely rural, tier 2, and metro. Manufacturing employment and value added for each of these three areas are shown in figure 6.1 and figure 6.2.

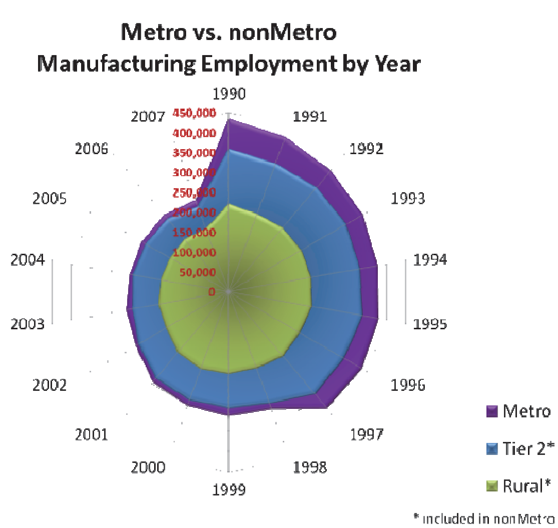

Figure 6.1: Manufacturing Employment by metro, tier 2 and rural counties, 1990 - 2007

Patent counts have frequently been used as indicators in innovation research (For example Nguyen, 2007; Strumsky, Lobo and Fleming, 2005). In the absence of alternative measures,

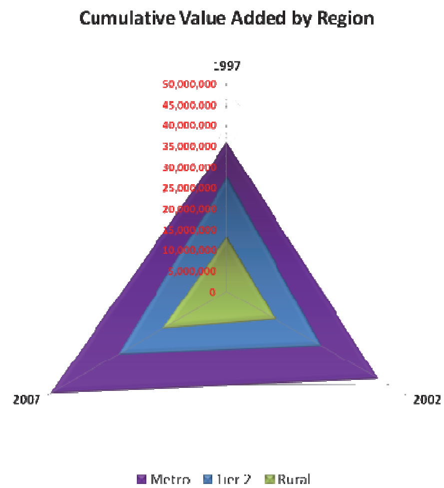

Figure 6.2: Value added for metro, tier 2 and rural, 1996 - 2007

patent counts have facilitated the exploration of certain spatial characteristics of innovation. Most of this previous research has also acknowledged the limitations of raw patent counts as indicators of innovation which were best summarized by Griliches (1990). This research however does not use raw patent data for independent variables. Rather, patent data was used to construct the innovation networks that generated the Opportunity and Degree variables, these variables are quite different from direct patent counts, and they avoid many of the weaknesses attributed to patent counts by Griliches. Patent counts are shown here primarily to illustrate the distinctions between patent counts and the economic outcomes of interest, manufacturing employment and value added (data source US Patent and Trademark Office). This also establishes an empirical connection and point of departure from prior research (for example Bettencourt, Lobo and Strumsky, 2004; Strumsky, Lobo and Fleming; 2005). One observation, for example, is that the distribution of patent counts along the rural – urban spectrum differs significantly from the distribution of both manufacturing employment and value added, and is shown in figure 4.

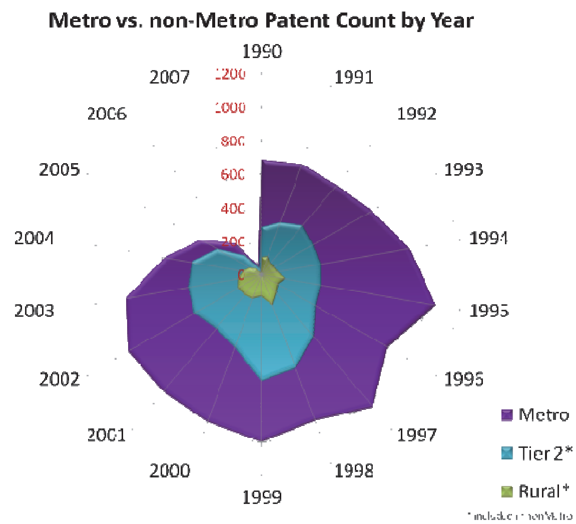

Figure 6.3: Patent counts by year for metro, tier 2 and rural regions, 1990 - 2007

6.1.2 Summary Statistics of Regression Variables and Correlation Matrix

Summary descriptive statistics for year 1 regression variables are shown in table 8. The covariance matrix for the year 1 regression is shown in table 9. Results for the other 16 years are similar and are therefore not reproduced here.

6.1.3 Regression Results

Regression results for manufacturing employment and value added are presented in table 5 and table 6, and are discussed in the next section. Regression results for the two alternative models exploring the interaction between network and agglomeration effects are shown in table 7a and table 7b, and are discussed in the next section. Comparative results are summarized in table 4 and discussed in the next section.

Model					
	1	2	3	4	
Variable	Manufacturing Employment	Manufacturing Employment Alternate 1 (no network variables)	Manufacturing Employment Alternate 2 (no agglom variables)	Value Added	Notes
Agglomeration					
Average Firm Size	Years 1 – 17	Years 1 – 17		Years 1 – 17	Dropping the network variable increses the local and urban coefficients and increses the significance of urban in multiple years.
Localization Economies	Years 1 – 17	Years 1 – 17		Years 1 – 6	
Urbanization Economies	Years 1 - 10	Years 1 - 14		No effect	
Technology					
Industry Herfindahl	Years 1 – 17	Years 1 – 17	Years 1 – 17	Years 1 – 17	Both alternative models reduce the effect of PatHerf and increase the impact of Joint Entropy
Joint Entropy	Years 1 - 7	Years 1 - 13	Years 1,3,9-12	Years 3 - 9; 11 – 13; 17	
Patent Herfindahl	Years 1 - 4	No effect	Years 1-5, 11	No effect	
Network Structure & Flow					
Opportunity	Years 1 – 3; 9 – 10; 13 – 15		Years 1-4; 8,9,12,14	No effect	Dropping the agglomeration variables has a scattered effect with Opportunity showing the most impact.
Degree	Years 1 – 11		Years 1 - 11	No effect	
SBIR Flows	Years 1 – 16		Years 1 - 16	Years 1 – 14	
DCED Flows	Years 1, 2, 4		Years 1 - 4	Years 1 – 7	Only 7 years of data available
Legend	High significant over all or most periods	High significance in early years; none in later years	high significance in early years; fades slowly	Significance emerges in middle years	

Table 6.1: Summary of Results

Regression Results: Manufacturing Employment																		
The Influence of Agglomeration, Technology and Network Variables on Manufacturing Employment in Subsequent Periods from 1 - 17 Years																		
		Number of Years between Independent and Dependent Variable Observations																
	Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intercept	5.82	6.06	6.26	6.13	6.24	6.02	6.30	6.09	6.13	5.72	5.81	6.12	6.31	6.09	5.76	5.89	6.50
Agglomeration	Avg Est. Size	0.94	0.89	0.81	0.84	0.82	0.88	0.83	0.86	0.86	0.91	0.91	0.81	0.83	0.83	0.92	0.90	0.92
	Local	0.71	0.70	0.71	0.74	0.68	0.66	0.61	0.60	0.54	0.59	0.55	0.63	0.59	0.58	0.65	0.67	0.50
	Urban	0.22	0.18	0.24	0.21	0.23	0.26	0.23	0.25	0.24	0.25	0.22	0.19	0.20	0.16	0.22	0.06	0.11
Technology	Industry Herf.	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.12	0.12	0.12	0.11	0.12	0.17
	Joint Entropy	0.22	0.19	0.18	0.16	0.20	0.17	0.16	0.14	0.14	0.15	0.28	0.16	0.18	0.06	0.08	-0.06	0.15
	Patent Herf.	-0.03	-0.02	-0.03	-0.02	-0.01	0.00	0.00	-0.01	-0.01	-0.02	-0.02	-0.03	-0.01	0.01	0.01	0.02	-0.01
Network	Opportunity	-0.02	-0.04	-0.03	-0.02	0.01	0.01	0.00	0.00	-0.02	0.02	0.01	-0.01	-0.03	0.05	0.03	0.01	0.01
	Degree	-0.05	-0.06	-0.06	-0.07	-0.06	-0.06	-0.05	-0.04	-0.05	-0.06	-0.05	-0.05	-0.04	-0.04	-0.04	-0.01	-0.03
	SBIR	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.03	0.05	0.02
	DCED	0.02	0.01	0.01	0.01	0.01	0.01	0.00										
Model Stats	R-Sq	0.71	0.70	0.67	0.66	0.66	0.67	0.67	0.68	0.70	0.69	0.70	0.66	0.65	0.66	0.68	0.74	0.87
	Adj R-Sq	0.71	0.70	0.66	0.66	0.65	0.67	0.67	0.68	0.69	0.68	0.70	0.65	0.64	0.65	0.66	0.73	0.85
	n	1,128	1,061	994	927	860	793	726	660	593	526	459	392	325	258	191	124	57
	F statistic	278.4	249.8	199.8	183.5	166.1	160.6	149.8	156.5	150.7	130.0	120.1	83.8	68.0	56.8	44.6	40.2	41.7
	Significance Levels	.001	.01	.05	(Variable cell values = regression coefficients)													

Table 6.1: Regression Results for Manufacturing Employment

Regression Results: Value Added																		
The Influence of Agglomeration, Technology and Network Variables on Manufacturing Value Added in Subsequent Periods from 1 - 17 Years																		
		Number of Years between Independent and Dependent Variable Observations																
	Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intercept	12.42	12.89	11.54	12.76	10.82	11.09	11.24	11.23	12.33	10.14	9.47	10.15	9.72	10.16	9.05	8.50	8.14
Agglomeration	Avg Est Size	0.74	0.69	1.01	0.77	1.11	1.07	1.06	1.06	0.82	1.23	1.39	1.33	1.42	1.30	1.48	1.67	1.94
	Local	0.62	0.39	0.24	0.26	0.30	0.39	0.28	0.31	0.29	0.31	0.28	0.12	0.16	0.13	0.49	0.07	-0.06
	Urban	-0.07	0.17	0.24	0.15	0.32	0.17	0.29	0.33	0.20	0.37	0.28	0.39	0.48	0.47	0.49	0.52	0.65
Technology	Industry Herf.	0.24	0.23	0.21	0.21	0.17	0.19	0.18	0.15	0.18	0.14	0.16	0.16	0.08	0.16	0.11	0.17	0.14
	Joint Entropy	0.05	0.37	0.58	0.75	0.40	0.41	0.55	0.91	0.89	0.57	0.38	0.43	0.81	0.54	0.54	0.19	0.47
	Patent Herf.	0.01	0.00	-0.01	-0.01	0.02	-0.01	0.00	0.00	-0.02	-0.01	-0.02	0.01	0.04	-0.02	-0.02	-0.04	0.06
Network	Opportunity	0.04	-0.07	0.03	-0.02	0.09	0.04	-0.01	0.02	0.11	0.12	0.15	-0.07	-0.10	0.07	0.04	0.19	0.14
	Degree	-0.01	-0.02	0.05	0.00	-0.08	-0.02	-0.02	0.07	-0.01	-0.09	-0.02	0.05	0.09	-0.11	-0.11	-0.07	-0.09
	SBIR	0.06	0.04	0.05	0.05	0.06	0.04	0.04	0.05	0.05	0.06	0.05	0.05	0.04	0.06	0.05	0.05	0.02
	DCED	0.05	0.04	0.04	0.05	0.06	0.04	0.03										
Model Stats	R-Sq	0.81	0.79	0.83	0.83	0.85	0.82	0.81	0.79	0.79	0.80	0.82	0.83	0.82	0.83	0.78	0.84	0.88
	Adj R-Sq	0.80	0.78	0.82	0.82	0.84	0.81	0.80	0.77	0.76	0.77	0.80	0.81	0.77	0.79	0.73	0.80	0.85
	n	130	130	130	130	130	130	130	84	84	84	84	84	37	37	37	37	37
	F- statistic	56.23	49.75	63.22	65.39	73.40	60.00	55.50	35.22	34.32	36.33	42.81	44.03	18.49	20.20	14.93	20.84	30.73
	Significance Levels	.001	.01	.05	(Variable cell values = regression coefficients)													

Table 6.2: Regression Results for Manufacturing Value Added

Summary Statistics for Year 1 Regression Variables							
Variable*	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
lnME	1139	0	1139	5.01	11.39	8.664	1.341
lnFS	1139	0	1139	0.51	5.14	3.761	0.634
local	1139	0	1139	0	1	0.179	0.384
urban	1139	0	1139	0	1	0.388	0.488
lnIH	1139	0	1139	-23.52	-2.35	-9.928	3.739
lnJE	1139	0	1139	-3.7	-0.24	-0.888	0.526
lnPH	1139	0	1139	-18.08	3.9	-7.131	3.612
lnOp	1139	0	1139	-4.13	8.68	1.164	3.026
lnDeg	1139	0	1139	-2.99	5.9	1.609	1.438
lnSBIR	1139	0	1139	0	13.67	2.869	5.072
lnDCED	1139	0	1139	0	19.05	4.099	5.923
* variable beginning with "ln" indicate that statistics refer to the natural logarithm of the original value.							

Table 6.3: Summary Statistics for Year 1 Regression Variables

Correlation Matrix for Year 1 Regression Variables											
Variables	FirmSize	local	urban	IndHerf	JE	PatHerf	Op	Deg	SBIR	DCED	ME
FirmSize	**1**										
local	-0.064	**1**									
urban	0.079	0.587	**1**								
IndHerf	0.042	0.292	0.356	**1**							
JE	-0.08	0.35	0.386	0.542	**1**						
PatHerf	-0.033	0.265	0.272	0.256	0.432	**1**					
Op	-0.066	-0.118	-0.006	-0.091	-0.05	-0.088	**1**				
Deg	-0.054	0.044	-0.006	-0.02	0.042	-0.062	-0.039	**1**			
SBIR	0.036	0.438	0.481	0.352	0.377	0.302	-0.046	0.006	**1**		
DCED	-0.002	0.082	0.081	-0.009	0.1	0.062	0.018	0.242	0.142	**1**	
ME	0.483	0.395	0.568	0.553	0.401	0.198	-0.125	-0.055	0.523	0.111	**1**

Table 6.4: Correlation Matrix for Year 1 Regression Variables

6.2 Discussion of Economic Analysis Model

This research posed three intermediate questions that may now be answered through a discussion of the research results. 1) Does network structure affect economic growth? 2) Does the spatial density and arrangement of networks affect economic growth? 3) Does technological alignment affect economic growth? This discussion will establish the basis for answering the main research question of whether innovation networks are (or could be) drivers of economic development in the tier 2 regions.

6.2.1 Does network structure affect economic growth?

Detecting network influence is necessary for the answer to the main question to be "yes". The regression analysis is designed to test this relationship, with *Opportunity* as the key network structure variable, with *Network Size (degree)* as a supporting structural variable. Network Density is another important measure of network structure that was excluded from the regression due to multicolinearity, but which shares important relationships with *Network Size* and *Opportunity (constraint)* as discussed in section 3.2.2. The relationship between network size, network density and opportunity are critical to interpreting the regression results. Two additional network variables, *SBIR* and *DCED*, provide measures of network flow or activity that add additional depth to the discussion.

The regression analysis reveals that network structure as represented by *Opportunity* has a significant or highly significant affect on manufacturing employment growth in the short run (1 – 3 years), and mildly significant[59] influence in two additional periods, 9 – 10 years and 13 – 15 years (see results table 5). The significance of these later periods may be associated with medical devices and pharmaceuticals which typically have patent pendency and regulatory approval periods of 8 – 12 years[60].

[59] Throughout this discussion I will use the following convention: "highly significant" means significant at the .001 level; "significant" means the .01 level, and "mildly significant" means the .05 level.

[60] I am grateful to Nancey Green Leigh for identifying this relationship during the 2010 PhD Dissertation Workshop at Georgia Tech. A preliminary analysis during that workshop yielded supporting results for the preliminary data set; however this alternative model was not pursued with the final dataset.

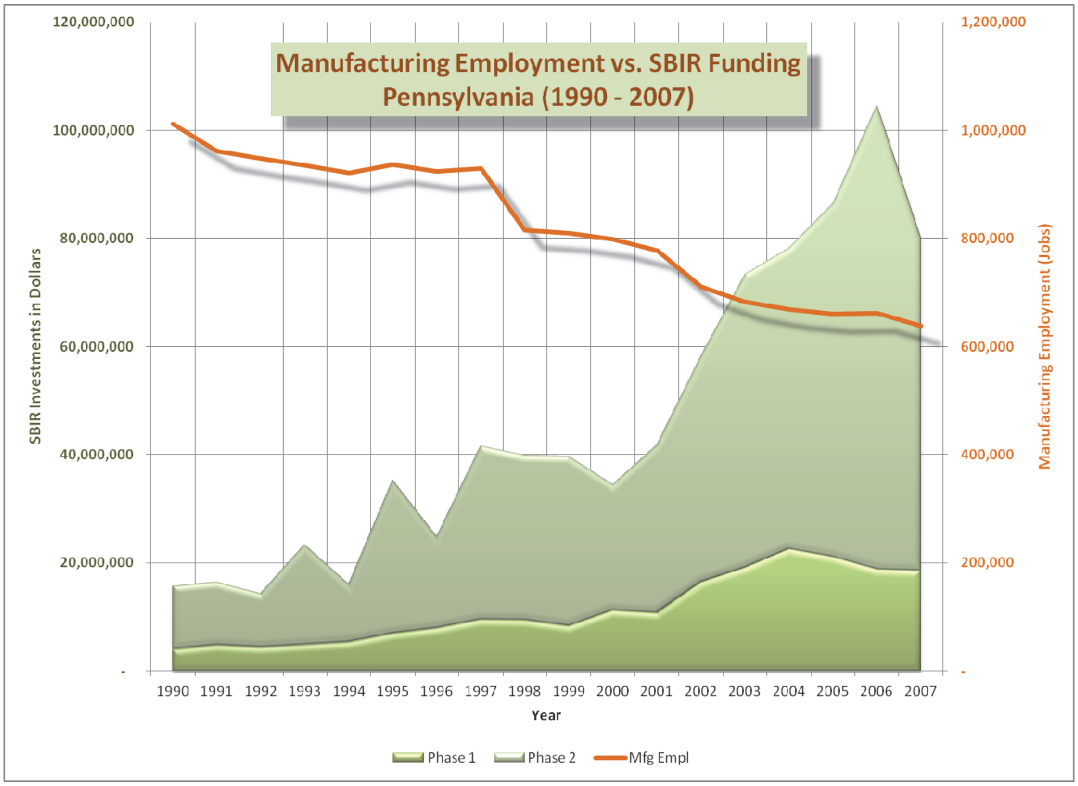

Figure6.4: Comparison of SBIR funding levels to manufacturing employment in Pennsylvania, 1990 - 2007

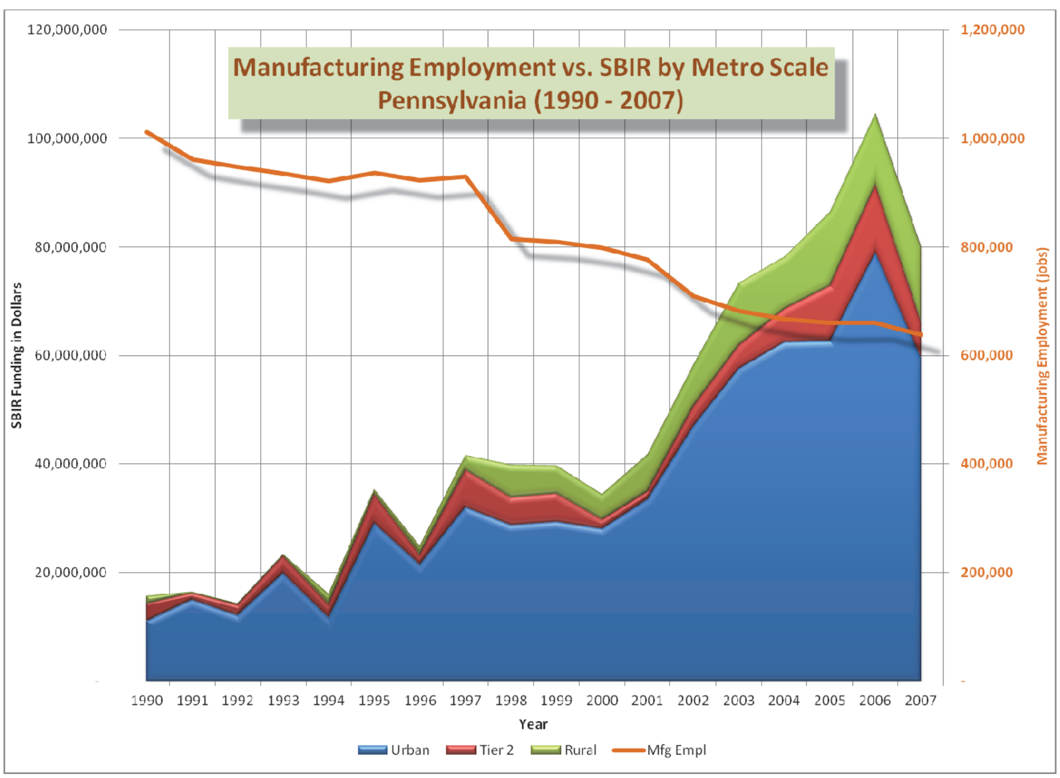

Figure 6.5: Manufacturing Employment vs. SBIR Funding (stacked by metropolitan, tier 2 and rural regions)

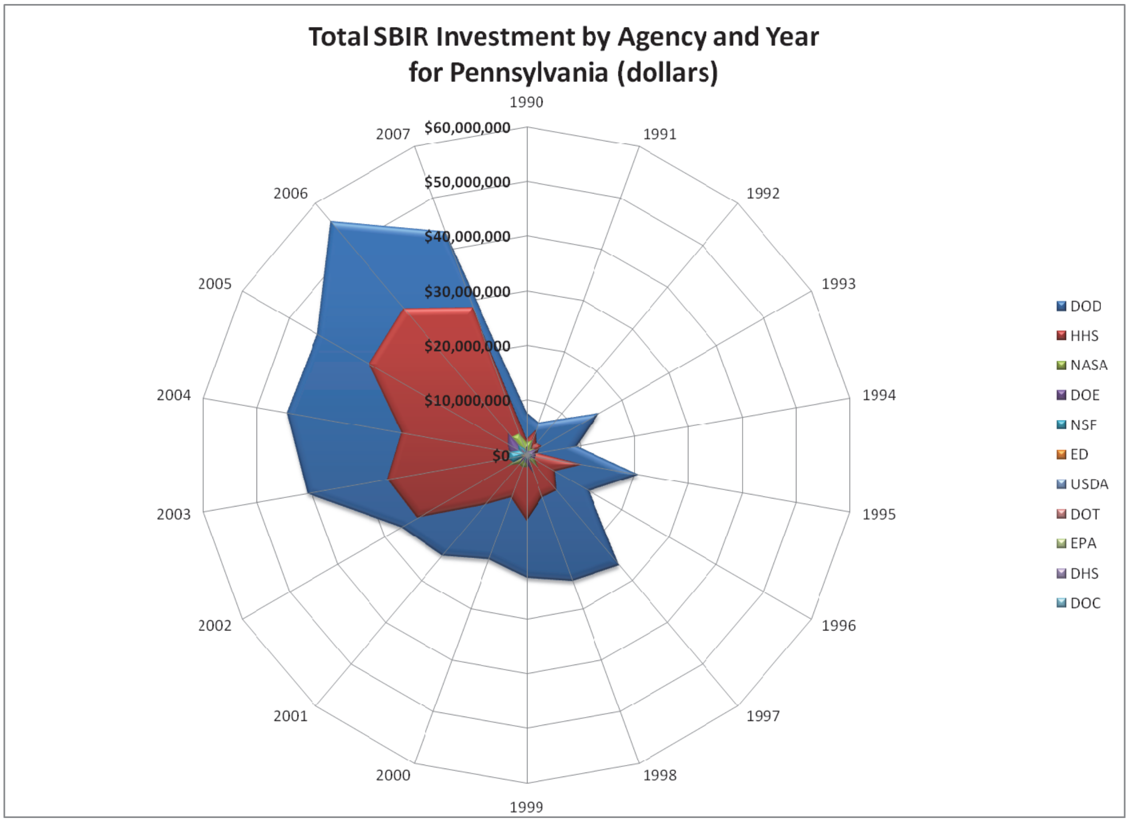

Figure 6.6: Distribution of SBIR funding by Federal Agency and year, 1990 – 2007

As noted in section 3.2.2 and table 3 the expected sign of the regression coefficients is negative because the network nodes being analyzed here (the egos) are counties. In each county's ego network high opportunity means that there are many opportunities to broker new relationships between the firms, inventors and institutions in its network. This means that these other actors are not connected to each other. However research has shown that it is the interconnections between these actors that lead to higher levels of economic activity (Porter, 1998; Muro and Katz, 2010). Therefore high opportunity measures for *counties* should be negatively correlated with economic growth. This is precisely what the regression results show.

The manufacturing employment results also show significant, highly significant and mildly significant influence for the *Network Size (degree)* variable from year 1 through year 11 (table 5). The signs of the regression coefficients are negative, consistent with the expectations discussed in section 3.2.2 and table 3. The negative correlation between network size and manufacturing employment growth seems counterintuitive at first. We tend to expect counties with larger innovation networks to have more growth. The explanation is found in the relationship between network size, network density and network opportunity (figures 9 & 10; Section 3.2.2). In the regression analysis the effect of network size on manufacturing employment is calculated holding all other variables constant. Increasing network size alone has a secondary effect on *Opportunity* (or constraint, in Burt's research). According to Burt (1992), "size decreases constraint [increases *Opportunity*]; more in dense networks than in sparse networks". The negative coefficients do *not* suggest that larger networks are correlated with fewer jobs. Rather, they indicate that increasing county network size *alone* is correlated with declining manufacturing employment in subsequent years due to the influence of *Network Size* on *Opportunity*.

Viewing the results from a social capital perspective we would expect to find higher job growth in counties with higher levels of social capital – that is, in places where people and firms are well connected to each other. From the county perspective, high social capital would mean high constraint (low opportunity) because everyone is interconnected, thus constraining the county's opportunity for brokerage. If we increase the county's opportunity (thus decreasing its constraint) we are effectively decreasing the level of social capital in that county and we would expect this to be negatively correlated with job growth. This is exactly what we see.

When we think of growing the county's network we rarely think of just adding unconnected nodes. County economic developers would like to both add new nodes and connect them to existing ones. This introduces Network Density into the picture. According to Burt (1992), "size and density work together. Density increases constraint [decreases *Opportunity*], less in large networks than in small networks".

There are two implications here for economic development policy and practice. The first is that old fashioned economic development networking – the process of making connections and building relationships among the community's firms, people and institutions – does in fact lead to economic growth by increasing network density and decreasing the county's *Opportunity*. This is an important finding because the networking approach to economic development has fallen out of favor over the past decade because it is hard to measure, and even harder to convert to the "jobs created" metric. It is also an inherently local activity. This finding suggests that perhaps the issue is not that local economic development is ineffective, but rather that it's just not as easy to measure as capital intensive programs like grants, loans and tax incentives that tend to originate at the state and federal levels.

The second implication is that the network models may be used to help target networking activities and make them more effective by identifying gaps or weak ties between specific actors in the network. Those actors may be local or distant. The important factor in making distant connections as a local economic developer is to ensure that as new distant actors are added to the county's network they also become well connected with other actors in the existing county network. That is, be sure to increase network density along with network size to avoid the negative effects of increasing network size alone.

The network structure variables, *Opportunity* and *Network Size (degree)* had no significant affect on manufacturing value added. However the two network flow variables, *SBIR* and *DCED* had significant, highly significant and mildly significant affects in both the manufacturing employment and value added models (tables 5 & 6). The regression coefficients were all positive as expected. These results present some interesting contrasts. First, the network structure variables (*Opportunity*, *Network Size*) measure the presence and configuration of connections among actors in each county. The network flow variables (*SBIR*, *DCED*) provide two measure of the level of activity present in those connections. The notion that the rate of investment in innovation (represented by *SBIR* and *DCED*) is positively correlated with economic growth is widely accepted. Similarly, the idea that such impact on growth is manifested in both manufacturing employment and value added is also widely accepted and represents the basis for public and private investment in innovation.

6.2.2 Do spatial density and arrangement of networks affect economic growth?

This question explores the interaction between agglomeration and networks, and whether those interactions affect economic growth. As noted in the literature review, economic development policy is heavily skewed towards metro regions precisely because there is a belief that agglomeration factors, especially urbanization economies, are essential to innovation and economic growth. At issue is whether innovation networks in tier 2 manufacturing counties can compensate for the lack of urbanization economies found in metro counties.

With respect to agglomeration the model makes a few basic assumptions. First, there is an assumption that at the county level, measurable agglomeration influences would be present in metro and tier 2 counties, but not in rural counties[61]. Within the combined metro and tier-2 regions all three factors of agglomeration (economies of scale, localization and urbanization) are assumed to be present, although distributed differently across the regions. Within this broader regional context urbanization economies are assumed to be restricted to metro counties[62]. Based on these assumptions the two dummy variables *Local* and *Urban* are intended to control for all three factors of agglomeration collectively, while isolating the influences of urbanization economies in a crude but simple way. Thus the *Local* variable controls for agglomeration, but mostly the effects of localization economies. The *Urban* variable controls for agglomeration as well, but mostly the effects of urbanization economies. The influences of economies of scale are most likely split between the two with a heavier portion falling to the *Urban* variable.

The regression results show that agglomeration has significant, highly significant and mildly significant influences on manufacturing employment (table 5). Those factors associated with the *Local* variable were highly significant from years 1 through 16, and the coefficients were roughly three times stronger than those for the

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[61] This does not preclude the possibility of *intra*-county agglomeration, for example where most of the population and activity in a rural county is concentrated in a single town. However this would not necessarily translate to *inter*-county agglomeration.
[62] Again, this does not preclude intra-county urbanization effects. Rather it considers urbanizations from a regional perspective.

Urban variable. All signs were positive as expected in section 2.2.3 and table 3. The results for the value added model were sporadic and did not suggest a significant relationship with the exception of the *Local* variable in years 1 and 2 (table 6).

The Average Establishment Size variable is not an agglomeration variable per se, but rather is an indicator of inter-county employment dynamics. When the logarithmic transformation is applied the variable refers to the direction (sign) and magnitude of change in each county's average manufacturing establishment size in terms of employment. Metro areas, being larger with more establishments and older establishments are more likely to have smaller rates of change, while newly developing counties on the rural fringe are more likely to have high rates of change because they have fewer establishments to begin with so each new firm has a larger impact. The results of the regression analysis indicate that Average Establishment Size (lnFS) has a highly significant and positive influence over the entire 17 year period for manufacturing employment (table 5), and a positive, highly significant or significant influence over the entire 17 year period for manufacturing value added (table 6). While controlling for inter-county growth dynamics related to establishment size, this variable may also be controlling for establishment age to some extent for reasons just discussed. Misconception persists that small firms create more jobs; however Haltiwanger and Jarmin (2011) found that correlations between firm age and firm size cause age effects to be misinterpreted as size effects. Therefore this variable may be controlling for a combination of age and size effects that also tend to vary to some extent over the urban – rural continuum.

To untangle the interplay between agglomeration and network influences a bit, this research ran two alternative models for manufacturing employment. In the first alternative all network variables (*Opportunity*, Degree, *SBIR* and *DCED*) were excluded from the model leaving just the agglomeration and other control variables. In the second alternative the network variables remained in the model but the agglomeration variables (*Local* and *Urban*) and the Average Establishment Size variable were excluded. The purpose was to assess how the significance and relative strength of the agglomeration and network variables changes when the other group was excluded from the model. Changes to the models' R^2 values were also noted. The results are especially interesting given the fact that the correlation table did not reveal any strong correlations between the network variables and agglomeration variables with the exception of *SBIR*, which had correlations of .438 with the *Local* variable, and .481 with the *Urban* variable (table 8).

In the first alternative model (no network variables) the R^2 values barely decreased from an average of .69 to an average of .66, suggesting that the model explained the variances between counties about as well as the model with both agglomeration and network variable included (table 9). The influence that had previously been attributed to network variables was redistributed among the remaining variables, primarily *Urban*, and to a lesser extent *Local* and one of the technology alignment variables, *Joint Entropy* (discussed in the next section). The affected variables became more highly significant and their regression coefficients and increased in magnitude. All signs remained the same.

Regression Results: Manufacturing Employment																		
The Influence of Agglomeration and Technology (no Network) Variables on Manufacturing Employment in Subsequent Periods from 1 - 17 Years																		
		Number of Years between Independent and Dependent Variable Observations																
	Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intercept	5.98	6.07	6.26	6.24	6.35	6.12	6.42	6.21	6.20	5.82	5.89	6.16	6.29	6.21	6.03	6.06	6.65
Agglomeration	Avg Est. Size	0.97	0.94	0.86	0.87	0.86	0.91	0.85	0.89	0.89	0.93	0.94	0.84	0.85	0.88	0.93	0.92	0.93
	Local	0.86	0.87	0.90	0.87	0.84	0.81	0.76	0.73	0.69	0.71	0.65	0.74	0.70	0.69	0.71	0.71	0.50
	Urban	0.40	0.38	0.38	0.38	0.37	0.39	0.37	0.40	0.41	0.44	0.41	0.39	0.37	0.39	0.37	0.31	0.23
Technology	Industry Herf.	0.12	0.12	0.12	0.12	0.12	0.11	0.12	0.12	0.13	0.12	0.11	0.12	0.12	0.14	0.13	0.13	0.18
	Joint Entropy	0.28	0.27	0.23	0.22	0.25	0.22	0.20	0.18	0.19	0.18	0.32	0.20	0.23	0.04	0.07	-0.03	0.16
	Patent Herf.	-0.01	-0.01	-0.01	-0.01	0.00	0.01	0.01	0.00	0.00	-0.01	-0.01	-0.02	0.00	0.01	0.02	0.02	0.00
Model Stats	R-Sq	0.67	0.65	0.62	0.62	0.62	0.63	0.64	0.65	0.66	0.66	0.68	0.63	0.63	0.64	0.66	0.73	0.86
	Adj R-Sq	0.67	0.65	0.62	0.62	0.62	0.63	0.63	0.65	0.66	0.65	0.67	0.63	0.62	0.63	0.65	0.72	0.85
	n	1,128	1,061	994	927	860	793	726	660	593	526	459	392	325	258	191	124	57
	F statistic	378.6	334.2	271.3	255.4	237.7	230.8	218.5	207.2	196.3	167.7	161.6	113.2	92.8	76.0	62.3	57.7	63.0
	Significance Levels	.001	.01	.05	(Variable cell values = regression coefficients)													

Table 6.6: Regression Results First Alternative Model (no network variables)

In the second alternative model (no agglomeration variables) the R^2 values fell substantially from an average of .69 to an average of .43 (table 10). This suggests that the agglomeration variables were able to explain certain variances between the counties that the network variables alone could not. Moreover, while the redistribution of influence among the remaining variables in the first alternative model showed clear patterns (table 9), there are no clear patterns in the second model (table 10). Taken together the two alternative models provide evidence that network influences are in fact a part of what we define as agglomeration, and innovation networks are a significant part of what we consider to be urbanization economies. These findings are consistent with prior research and theory on agglomeration (see for example Fujita and Thisse, 2002, and Keilbach, 2000). However the second alternative model shows that agglomeration and network effects are not entirely interchangeable. When both agglomeration and network effects are included (the original model), the network variables account for marginal influences that would otherwise be attributed to agglomeration by definition (the first alternative). When

Regression Results: Manufacturing Employment																		
The Influence of Network Variables Technology (No Agglomeration) on Manufacturing Employment in Subsequent Periods from 1 - 17 Years																		
		Number of Years between Independent and Dependent Variable Observations																
	Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intercept	9.88	9.93	9.99	9.83	9.87	9.86	9.97	9.76	9.75	9.61	9.60	9.55	9.76	9.25	9.45	9.08	9.85
Network	Opportunity	-0.03	-0.07	-0.05	0.03	0.02	0.02	0.00	0.03	-0.05	0.00	0.02	-0.04	-0.03	0.09	0.01	0.01	0.00
	Degree	-0.07	-0.08	-0.08	-0.09	-0.08	-0.09	-0.07	-0.06	-0.07	-0.08	-0.07	-0.06	-0.06	-0.04	-0.06	-0.06	-0.11
	SBIR	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.10	0.10	0.10	0.09	0.10	0.09	0.10	0.09	0.11	0.06
	DCED	0.02	0.02	0.01	0.02	0.01	0.02	0.00										
Technology	Industry Herf.	0.14	0.13	0.14	0.14	0.14	0.14	0.15	0.15	0.14	0.14	0.14	0.14	0.14	0.13	0.14	0.13	0.20
	Joint Entropy	0.17	0.16	0.21	0.17	0.22	0.16	0.18	0.15	0.12	0.12	0.29	0.23	0.23	0.13	0.07	-0.19	0.29
	Patent Herf.	-0.02	-0.02	-0.02	-0.02	-0.01	0.00	-0.01	-0.02	-0.03	-0.03	-0.04	-0.05	-0.03	-0.01	-0.03	-0.03	-0.09
Model Stats	R-Sq	0.45	0.47	0.47	0.45	0.45	0.43	0.46	0.46	0.47	0.43	0.43	0.43	0.41	0.43	0.34	0.32	0.43
	Adj R-Sq	0.44	0.46	0.47	0.45	0.45	0.43	0.46	0.45	0.46	0.43	0.42	0.42	0.40	0.42	0.32	0.29	0.37
	n	1,128	1,061	994	927	860	793	726	660	593	526	459	392	325	258	191	124	57
	F statistic	130.4	132.6	128.1	110.7	100.9	86.7	90.2	92.3	87.1	67.1	58.6	50.3	38.7	33.1	16.5	10.1	7.6
	Significance Levels		.001	.01	.05	(Variable cell values = regression coefficients)												

Table 6.7: Regression results second alternative model (no agglomeration)

agglomeration influences are excluded the model is less complete as evidenced by the lower R^2 values, however the network variables are still highly significant.

Thus network influences contribute to agglomeration, especially urbanization economies; however they also appear to be independent of it to some extent. It is therefore reasonable to conclude that innovation networks may substitute for certain influences associated with urbanization economies. In terms of the question "does the spatial density and arrangement of networks affect economic growth?" Inspection of the network models clearly show that the spatial arrangement of networks display much more connectivity with distant actors than previously thought. Interpreting these results through Burt's theory, it appears that social distance may be as important as spatial distance when it comes to innovation networks and the growth of manufacturing employment. These findings also suggest that network density may be at least as important if not more so than spatial density.

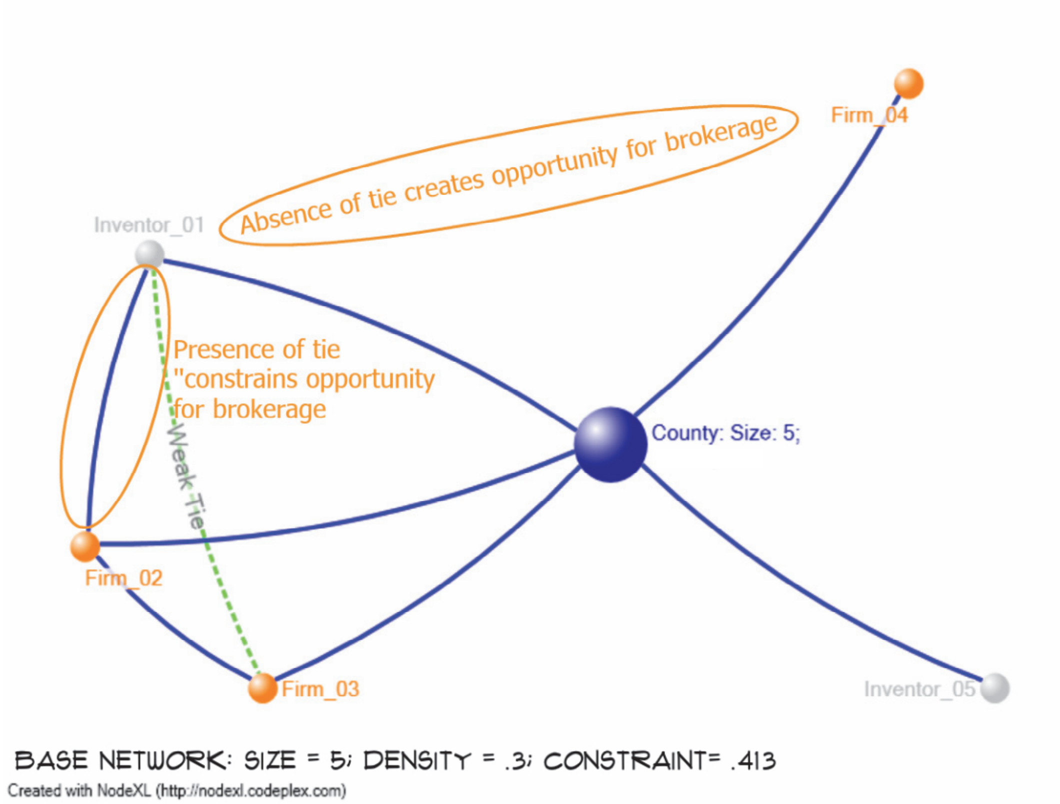

Figure 6.7: Constraint and the opportunity for brokerage

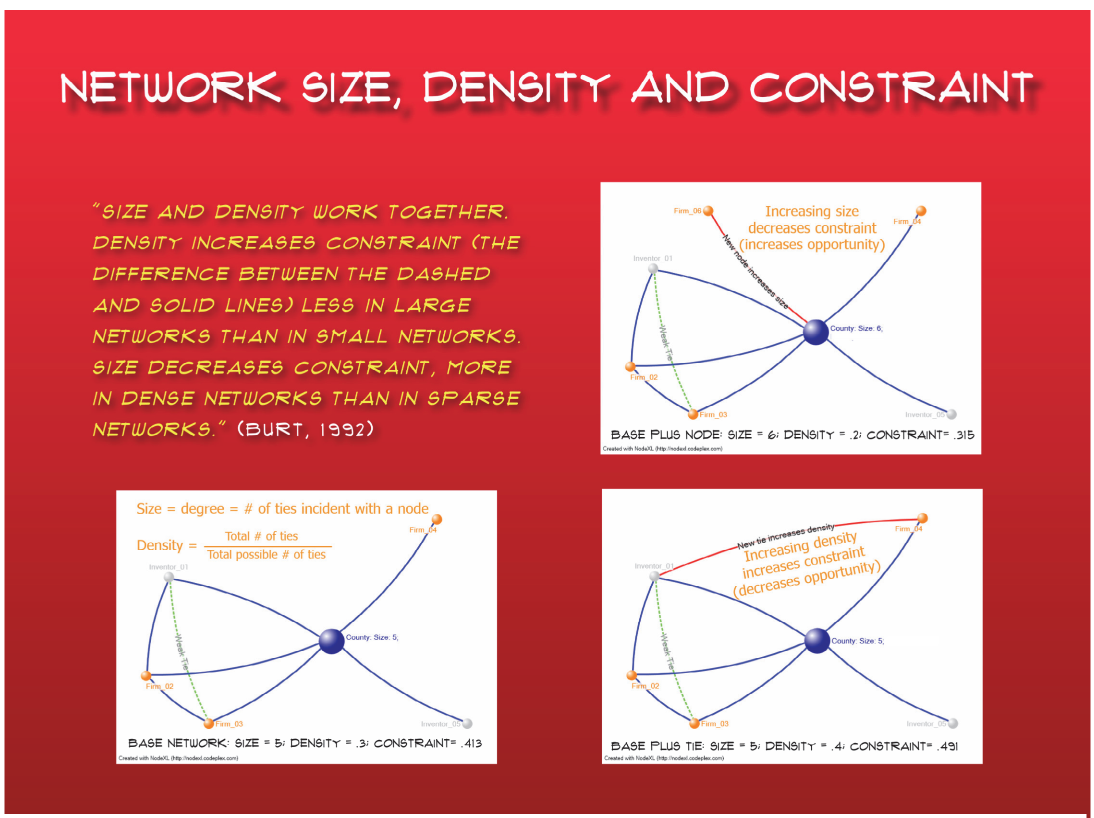

Figure6.8: How network size and density influence constraint

6.2.3 Does technological alignment affect economic growth?

The idea that the mix of local industry specializations affects economic growth is well established in economic thought and is the basis for analytic techniques including location quotients and shift-share analysis. Concentrations of specific groups of industries within a region form regional industry clusters that have become the foundation of much of our current economic development policy. Industry concentration represents one type of technological alignment that exists between local industries and the broader market. This research considers two other types of technological alignment as well: alignment between patent technologies and the market, and alignment between industries and patent technologies. These relationships are illustrated in figure 8. While the idea of industry-to-market

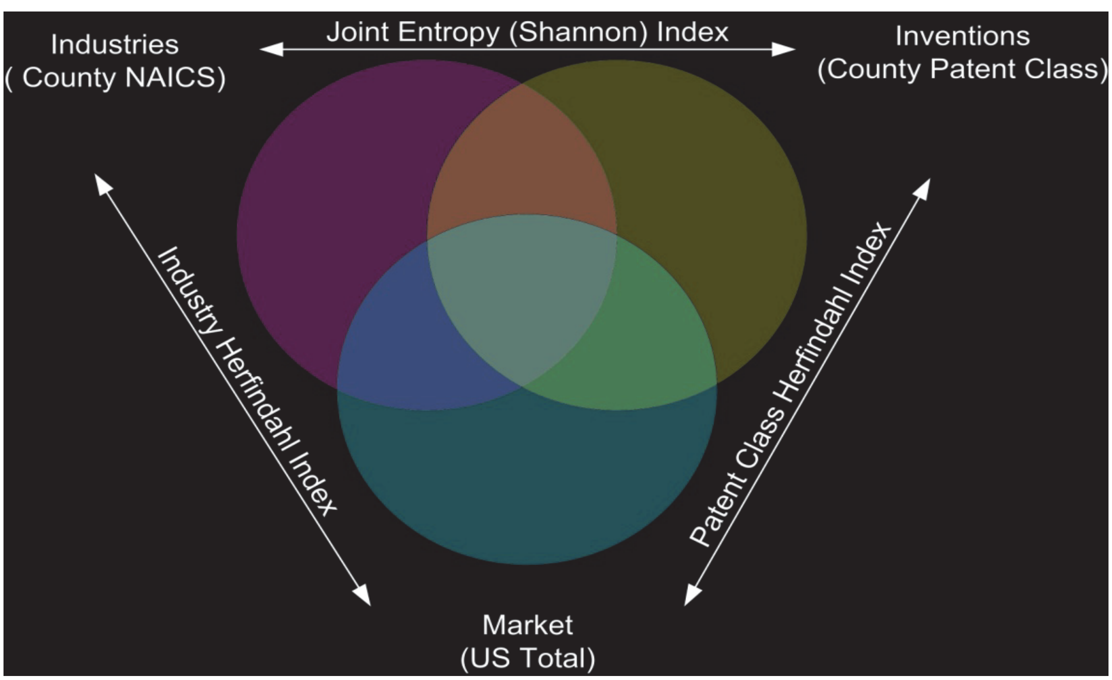

Figure 6.9: Conceptual view and measures of technological alignment

alignment is well established, this notion of three-way alignment between invention, production and the market is less so. It borrows concepts and metrics from prior research, notably Strumsky, Lobo, & Fleming, (2005), and Marx, Strumsky and Fleming (2009) and combines them in new ways.

The basic notion of technological alignment in this research is as follows. For local innovation to drive manufacturing job growth the inventions (represented by patents) should be a product that the market will buy (patent to market alignment); and the county should have some productive capacity and strength in the industries that make the products (industry to market alignment, and industry to patent alignment). This research uses Herfindahl indexes to measure industry to market and patent to market alignments. Herfindahl indexes are generally used as indicators of market share and are more sensitive than location quotients. The higher the county's aggregate market share for manufacturing industries, the more aligned its industries are with the market. Similarly, the greater the county's aggregate share of patent technologies (represented by patent classes), the more aligned it is on the inventive side of figure 8. In terms of industry-to-patent alignment, when aggregated over many industries and patent technology classifications, the industry to patent alignment measure becomes an indicator of relative specialization or diversity in the local economy.

The regression results suggest that technological alignment does influence economic growth; more so for manufacturing employment (table 5) than for manufacturing value added (table 6). As expected the influence of industry alignment was strongest. The regression coefficients were positive and highly significant over the entire 17 years for manufacturing employment and 15 of 17 years for value added. The *Patent Herfindahl* variable was highly significant, significant or mildly significant in years 1 through 4 for manufacturing employment. The signs of the regression coefficients were negative, indicating that higher concentrations of patent technology classes are correlated with declines in manufacturing employment. This finding is consistent with higher concentrations of patenting in metro regions through most of the 1990's along with more rapid declines in manufacturing employment over the entire 17 year period (see figures 2 and 4). *Patent Herfindahl* had no significant influence on manufacturing value added.

Joint Entropy[63], the measure of patent-to-industry alignment was highly significant, significant and mildly significant in years 1 through 7 for manufacturing employment and years 3 through 13 for value added. The signs of the regression coefficients were positive, indicating that increases in joint entropy in year 0 were correlated with positive growth in subsequent years. Essentially, this suggests that county economies that were diversifying were more likely to experience economic growth than those that were becoming more specialized and concentrated. This finding runs counter to most of the cluster literature which suggests that "strengthening" clusters by increasing the concentration of specialized industries is the key to economic growth. However most cluster strategies tend to discuss this process in the abstract, or in the context of a specific case study about an emerging cluster (see for example Porter, 1998; Muro and Katz, 2010; Saxenian, 1994). Older

[63] The term entropy is most often used in the physical sciences, especially thermodynamics, but more recently it has also been used in evaluating electronic data. Entropy refers to the level of disorder in a system. Systems with high entropy have a high level of disorder. Considering a county's economy as a system, low entropy would refer to an economy that is highly concentrated in a few industries and patent classifications. High entropy would refer to an economy with greater diversity.

industrial regions such as those found in Pennsylvania and much of the Rust Belt have established clusters in mature or declining industries and face different challenges. These challenges may include “lock-in” and path dependent behavior (see for example, Bresnahan, Gambardella, & Saxenian, 2004; Farschi, Janne, & McCann, 2009). There are some parallels between these findings and those of Hage (1999) with respect to increasing complexity of the division of labor in the context of organizational structure. Hage concludes that the complex division of labor has been „underappreciated because of the various ways in which it has been measured,“ In similar fashion the metrics used to identify and measure clusters may reinforce an underappreciation of economic diversity within a regional economy. From the perspective of policy and practice, these findings provide evidence supporting the basic concepts and economics of agglomeration and clusters; however local conditions may warrant very different economic development strategies

6.2.4 Are innovation networks drivers of economic development in regions that lack the institutions and density present in agglomeration regions?

Concerning the main research question of whether innovation networks are drivers of economic development in manufacturing regions that lack the institutions and density found in major metro regions, the answer is “yes” although few regions are deliberately pursuing network strategies. Mayer (2009; 2011) established that second tier regions could in fact be innovative despite the lack of major research universities or other institutional supports. Her case studies provided qualitative observations of the importance of certain key relationships and networks in facilitating innovation and entrepreneurship in the study regions. The research presented in this paper provides empirical evidence that innovation-based growth in second tier manufacturing regions is linked to the *structure* of innovation networks and the *flows* of information and resources through those networks. This research finds further that both network size and network density are important. In urban areas network density may be comingled with spatial density. However increasing network density by facilitating connections between the various actors within a county's innovation network can have a direct, positive influence on manufacturing employment over the short run (1 – 3 years).

Chapter 7: Conclusions

Economic development seeks to increase employment and wealth for a given geography. Thus for networks to be drivers of economic development the model must present a set of independent variables upon which economic developers may exert some influence that will lead to local growth in jobs, wealth or both. Spatial agglomeration and specialized industry clusters are already widely accepted as economic development drivers. Therefore it is important to distinguish the effects of innovation networks from these factors. To determine whether innovation networks present such opportunities independent of the influences of agglomeration and specialized industry clusters (technological alignment) three intermediate questions were posed: *1) does network structure affect economic growth? 2) Does the spatial density and arrangement of networks affect economic growth? 3) Does technological alignment affect economic growth?* Each of these intermediate questions addressed a different dimension and a different group of variables in the analysis, corresponding to network variables, agglomeration variables and technology variables respectively. Drawing conclusions regarding these three intermediate questions will establish the basis for final conclusions on the main question.

7.1 Summary of Research Findings

1. Network structure influences manufacturing employment *but not* value added.

2. Network flows influences both maufacturing employment *and* value added.

3. Agglomeration influences manufacturing employment.

    a. The *Local* variable was highly significant from years 1 through 16.

    b. The *Urban* variable was significant or mildly significant through year 10.

4. Agglomeration influences had no influence on manufacturing value added.

5. *Average Establishment Size* influences both manufacturing employment *and* value added.

6. Network influences contribute to factors of agglomeration, especially urbanization economies. They also appear to be independent of agglomeration to some extent.

7. The spatial arrangement of networks displays much more connectivity with distant actors than previously thought. It appears therefore that social distance may be at least as important as spatial distance when it comes to innovation networks and the growth of manufacturing employment.

8. Innovation networks may substitute for certain influences associated with urbanization economies. Network density may be at least as important if not more so than spatial density.

9. Technological alignment influences manufacturing employment and value added.

    a. The influence of industry alignment was strongest.

    b. The *Patent Herfindahl* variable was significant in years 1 through 4 for manufacturing employment.

    c. Joint Entropy, the measure of patent-to-industry alignment was highly significant, significant and mildly significant in years 1 through 7 for manufacturing employment and years 3 through 13 for value added. The signs of the regression coefficients were positive, indicating that increases in joint entropy in year 0 were correlated with positive growth in subsequent years. Essentially, this suggests that county economies that were diversifying were more likely to experience economic growth than those that were becoming more specialized and concentrated.

10. From the perspective of policy and practice, these findings provide evidence supporting the basic concepts and economics of agglomeration and clusters; however the also suggest local conditions may warrant very different economic development strategies.

7.2 Intermediate Research Questions Revisited

Concerning the question of whether network structure affects economic growth the model found a clear correlation between measures of network structure, network flow and manufacturing employment in subsequent years. Measures of network flow also had an influence on manufacturing value added in subsequent years. Therefore the simple answer to the first question is yes, network structure and flow do affect economic growth.

Concerning the question of whether the spatial density and arrangement of networks affects economic growth, findings 3 through 8 above summarize the observed relationships between agglomeration influences (spatial density and arrangement) and corresponding network structure (network size, density and opportunity). Agglomeration factors do affect manufacturing employment but not value added. It appears that innovation networks in tier 2 counties may be able to substitute for certain factors associated with urbanization economies.

Concerning the question of whether technological alignment influences economic growth, findings 9a – 9c above provide clear evidence that technological alignment does influence economic growth, but not always in ways suggested by current policies.

7.3 Are Innovation Networks Drivers of Economic Development for Tier 2 Regions that lack Major Research Universities and Density?

Concerning the main research question the research findings offer sufficient evidence to support the claim that innovation networks are (or could be} drivers of economic development in tier 2 manufacturing regions. I show that the answers to each of the three intermediate questions are "yes" and that with respect to questions 2 and 3, network effects are independent of these other factors. If networks did not exert any influence independently of agglomeration and clustering then the answer to the main question would be "no". However, since an independent influence was found the answer is "yes" because economic developers can take actions that influence the innovation networks in such a way that they increase the rate of growth of manufacturing jobs independently of the size of the county or which clusters the county may specialize in. Agglomeration and technological alignment remain important factors and economic development remains easier is urban areas with strong industry clusters. However, given that economic developers in second tier regions must work with the spatial density and industry clusters that are present in the region, the conclusion that innovation networks present cost-effective opportunities for economic development action with measurable results is welcome news. Network structure influences manufacturing job growth, and network flows influence both manufacturing employment and value added. Therefore targeted network strategies can compensate to some extent for the lack of spatial density and institutional resources in tier 2 regions.

7.4 Implications for Policy and Practice

In broad terms the research presented in this paper provides empirical evidence that supports a range of policy recommendations offered by Mayer (2011; 2009); Feldman (2007); and Braujnerhelm & Feldman, (2006) regarding the support of nascent industry clusters. It suggests that innovation and its economic impacts are not limited to major metropolitan regions, but rather are widespread, with significant effects in second tier and to a lesser extent, rural regions as well. There are always unique events and conditions contributing to the development of specific technological specializations in specific regions. Yet this research suggests that many opportunities for the growth of regional innovation clusters are embedded in the structure of the networks which connect both local and distant actors involved in the innovation process. Increasing *network* density by facilitating interaction among network actors can have a direct impact on manufacturing employment over the short run (1 – 3 years) in tier 2 and rural counties as well as metropolitan areas. This deliberate process facilitates the kinds of technological externalities associated with *spatial* density in urbanization economies.

This process of "networking" is already part of the economic development lexicon, but is not always specific in terms of the parties involved or the outcomes sought. Used properly, targeted networking may achieve significant results at a fraction of the cost of other economic development approaches. Moreover, such approaches are not biased towards major metropolitan regions due to their inherent infrastructure and resource endowments. Making targeted connections can work anywhere, and the network models developed in Chapter 4 provide specific insights into which connections are likely to yield results.

The research presented in this paper also identifies several metrics associated with the growth of manufacturing employment and value added that are not among the more popular economic development metrics. These include average establishment size, the industry Herfindahl, joint entropy and SBIR funding, which may provide early indicators for future growth trends. With additional research and sensitivity analysis to calibrate the variable coefficients, this model may provide some early indicators in terms of the impact of policies or practices on manufacturing employment and value added.

7.5 Policy Implications of SBIR Findings

The strong and persistent influence of SBIR/STTR funding on both manufacturing employment and value added may have particular policy implications. Given the challenges of the recent SBIR reauthorization process, this finding deserves further research. While section 3.2.2 discussed several possible explanations for this finding, a definitive cause remains beyond the scope of this paper. Many federal investments are made with the intention of stimulating employment in the near term, although this is not a primary objective of the SBIR / STTR program[64]. Federal investments made under this program are made with the broad expectation that facilitating innovation leads to economic growth, although this impact has rarely if ever been measured at the county level. Several implications for policy and practice may be drawn from this finding.

First, additional research is warranted to determine the causal mechanisms at work in this relationship. At one end of the spectrum of possibilities this could simply be due to a "self-selection" bias in the data in which the preponderance of firms that receive SBIR funding are already growth oriented. On the other end of the spectrum the result could be an indication of program effectiveness for SBIR/STTR. While the program was recently reauthorized by Congress, evidence of program effectiveness in terms of its effect on manufacturing employment and value added may be useful in future deliberations regarding this program.

Second, efforts by local economic development organizations to support SBIR/STTR applications and to boost the success rates of the applications that are submitted may have direct and long lasting effects on local manufacturing employment and value added.

[64] The primary objective of the SBIR / STTR program is the commercialization of new technologies. There is a general sense that successful commercialization leads to economic growth, and the potential impact of SBIR investments in broad terms are considered as part of the review process. However the focus of the application and review process is predominantly technical in nature. The ubiquitous "number of jobs create" question that is a part of so many federal applications is not one of the considerations for this program.

7.6 Limitations and Future Research

The limitations of the research presented in this paper and the opportunities for future research which it suggests have been noted throughout and are briefly summarized here. First, this research looks at the narrow spectrum of innovation represented by product (utility) patents and innovation networks defined by a limited number of different types of relationships. It examines a narrow range of economic impacts limited to manufacturing employment and value added. In so doing it does not purport to represent the entire domain of activities that constitute innovation nor the full range of measurable impacts resulting from them. These remain subject to debate as noted at the outset of this paper. Further research that includes more extensive networks and additional relationships is being pursued for innovation networks in Maryland with support from the U.S. Economic Development Administration.

The variables used to control for the effects of agglomeration are simple measures based on known spatial agglomerations, existing measures of urban intensity, and assumptions about the geographic extent of localization and urbanization economies. While these variables appear to model agglomeration effectively and also appear to capture basic network – agglomeration effects, they should not be interpreted as anything more than simple control variables. Additional research with more sophisticated measures of agglomeration may be warranted to explore these effects in greater detail.

Additional research on the influence of SBIR/STTR funding as discussed in section 6.5 is warranted, as is additional research that measures the impact of various other sources of innovation funding. Longitudinal analysis on the impact of funding sources at various points in the innovation process may provide greater insight into the stages of innovation and the contours of the so-called valley of death, where many innovations fail to progress due to lack of funding.

Advances and Contributions of the Network Model

1. This research models the process and activity of innovation in terms of multi-relational, dynamic networks among several types of actors over time, drawn from multiple data sources.

2. The model resolves significant problems with earlier network models which attempted to contain networks within a spatial framework. By treating spatial units as nodes within the network rather than attributes of other actors, the spatial unit of analysis problem is resolved. Re-conceiving actors' locational attributes as relationships (ties) with "place" nodes facilitates dynamic or longitudinal analysis over multiple relations and time periods where relationships and locations may change. It also permits actors to maintain relationships with multiple places simultaneously; reflecting, for example, the reality of multi-establishment firms and a highly mobile workforce. Finally, this approach facilitates analysis of economic impacts at a smaller geographic scale such as counties because the economic data are modeled as attributes of places.

3. The use of 3-dimensional modeling methods significantly enhances the visualization of innovation networks and facilitates more rapid, intuitive and accurate understanding of how such networks are structured and how they function.

4. Visual inspection of the networks tends to verify the presence of industry clusters and spatial agglomeration in major metropolitan regions, for example biotechnology and pharmaceuticals in the Philadelphia metro region. It also tends to confirm prior research indicating that innovation tends to be more concentrated in major metropolitan regions, since all the counties comprising the two major metropolitan regions in Pennsylvania (Philadelphia and Pittsburgh) are found in the core.

5. However, while confirming these previous findings, this research and a visual inspection of the 3-D model also reveals an active periphery that, while less dense in both spatial and network terms, nonetheless produced an equal number of patents as the core. The application of group centrality and core-periphery measures developed by Everett and Borgatti (2005) in future research may offer significant additional evidence of active innovation networks beyond the core. This would have important implications for economic development policies and practices intended to promote regional innovation, since most current policies are anchored in the assumptions of spatial agglomeration. The visual evidence in figures 5.1 and 5.2, for example, as well as the interactive models suggests that second tier regions are part of functional, competitive innovation networks that have adapted to lower densities and dispersed resources. Advancing and supporting innovation in this tier will require a different set of policies and practices that are based on network structure rather than spatial agglomeration.

6. This research suggests that in the aggregate, innovation networks exhibit a core-periphery structure and that they appear to be scale free networks. This may validate small world approaches to the study of innovation. It also suggests that one future research direction is the identification and study of so-called "rich clubs" or high-degree innovation network hubs and how they are connected to each other, following the work of Xu, Zhang, Li, & Small (2011).

Limitations of the Network Model

1. While introducing a multi-relational, dynamic (longitudinal) network among several types of actors drawn from multiple data sources, this network model remains partial and incomplete, as nearly all network models are.

2. In terms of the patent relation (and by extension the related-patent relation), there are limitations inherent in the patent sample selection criteria that may influence the interpretation of the results. For example, this research only considers product (utility) patents and deliberately ignores innovation in services, design and agriculture in order to simplify the model.

3. The identification and inclusion of relations in this research attempted to include actors and relationships that have been identified in prior research as important to innovation, while facing real constraints of data availability.

Each relation has strengths and weaknesses in terms of its data. The longstanding concerns with patent data have been discussed previously, and these concerns are largely mitigated by the way in which the data are used in this application.

Identifying accurate firm location was also a challenge with the patent data, and 28%

of firms in the data set have no location ties. The available SBIR / STTR data identifies federal agencies and recipient firms, but specifics concerning the technology classification or principal investigators are not currently available without individual inspection of over 5,000 documents. The PA DCED has similar limitations and is also unavailable from 1990 – 1999. The DCED data required some judgment and experience in the selection of which programs were applicable and which ones were not. Matching data records both within the data sets and between sets also presented a challenge due to differences in spelling, punctuation, abbreviations and the like. The data also had no consistent way of capturing relationships between firms such as subsidiaries, mergers and acquisitions, for example.

Patent assignments (i.e. the permanent transfer of rights) are the dominant form of technology development / technology transfer recognized in this data. This reflects only a portion of the mechanisms by which innovation is undertaken and shared. The precise nature of some relationships is unknown, and this imposes limitations in terms of the valuation of ties. For example, the ties that exist between inventors and assignee firms represent simply that value has been exchanged through the assignment of patent rights. Whether those inventors are employees, owners, consultants or have other relationships with the assignees is unknown. The relative importance of any individual patent in terms of its technology, it's 'innovativeness", the amount of time and resources invested, etc. is unknown, thus all patent relationships are valued equally as "1". Ties between inventors and location are based on county of residence at the time of patent application. However the relative quality or strength of that tie is unknown, thus they are all valued equally as "1". Similarly, the extent of the relationship between firms and locations is unknown, thus all firm-location ties are valued as "1". Clearly these and similar issues lead to overvaluing some ties and undervaluing others. The extent and impact of this issue is unknown.

4. The relative valuation of ties among the various relations is also an issue that is not fully resolved. This issue is rooted in the questions of the relative importance and valuation of various factors in the innovation process. It is also part of the complexity of multi-relational models. While the relative valuation assumptions are considered a reasonable first cut, they are also somewhat arbitrary and should be validated by further research.

5. In similar fashion, certain temporal assumptions need to be validated by additional research. The data records events, however these events are milestones representing work and relationships that existed for some time prior to the event and that will persist for some time after the event. To attempt to address this in some way, this research marks events only by year, and then extends the duration one year forward and one year back for total network duration of three years. While these assumptions are considered a reasonable first cut, they are also somewhat arbitrary and should be validated by further research.

6. The technology-based weak ties in this network are subject to the limitations of 4 and 5 above. They also introduce a new issue in that these ties represent a first cut at modeling probability-based ties that are likely and deemed important to the innovation process, but which are nonetheless *presumed* rather than measured. Weak

ties are important sources of new ideas, knowledge spillovers and new opportunities, yet they are inherently difficult to measure. While the inclusion, selection method, and valuation of these ties are considered reasonable and they help produce a model that appears to be realistic, additional research is needed to further develop and validate more accurate methods.

In summary, this research develops a new multi-relational dynamic approach to visualizing, understanding and measuring innovation networks that produces a series of network models that appear to fit well with existing conditions and prior research. However several of the parameters of these models have been estimated. Care has been taken to make "reasonable" estimates, and to disclose the parameters that have been estimated and the factors contributing to the estimates so that readers may judge their reasonableness independently.

Directions for future research based on the Network Model

1. Conduct sensitivity analysis to develop more objective tie values for different relations.

2. Identification and inclusion of additional relations and data sources, perhaps through the use of STICK ontology, under development in the University of Maryland's College of Information Sciences (see Wang, 2011; Zhang, Qu & Huang, 2011).

3. Additional research is warranted into the core-periphery structure and the scale free nature of innovation networks. Uncovering the elemental structures of groups of

innovation hubs or "rich clubs" may provide insights into how to influence the larger innovation network.

4. Working with SBA to extract the additional information related to SBIR / STTR as noted in limitation #3 may prove valuable.

5. Concurrent research on the use of SNA to model local economies as networks using input-output data and census occupational data has shown some promise. Integrating a realistic network model of the local economy with the innovation network data may yield some interesting insights. The addition of industry classifications (NAICS) to firms could also prove beneficial.

6. The full implications of the findings of this research on economic development policy and practice need to be explored. Evaluation of group centrality for specific groups of counties that form administrative regions – say federal economic development districts (EDD's) or local development districts (LDD's) for example, may help identify policy levers to adjust policies and practices related to regional innovation.

Appendices

None

Glossary

Term	Definition
Alter	Refers to the node or actor with which the ego (i.e. the node in question) shares a tie
Constraint	A measure of the absence of structural holes in the ego's network; represents the level of entrepreneurial opportunity present in the network structure
Density, network	the ratio of the number of ties that exist in a network to the number of possible ties (between all actors) in the network; sometimes interpreted as the efficiency of the network
Density, spatial	A measure of the spatial structure of the network that refers to how close together actors are in physical space
Effective Size	The total number of ties in an ego's network minus the number of redundant ties
Ego	Refers to the node or actor in question; the node at the center of an ego network
Innovation	the design, invention, development and/or implementation of new or altered products, services, processes, systems, organizational structures, or business models for the purpose of creating new value for customers in a way that improves the financial returns for the firm (Schramm, et. al., 2008)
Innovation network	a network of actors and relationships involved in the innovation process
Network	A collection of nodes (actors) and ties (relationships)
Network fragment	A partial network
Node	Refers to an actor in a social network
One-mode network	Refers to an actor X actor network; is represented by a square matrix where column and row labels are identical. (see section 1.2, pp 4 - 5
Physical space	In a multi-dimensional system, physical space refers to the dimension corresponding to geospatial location
Relational space	In a multi-dimensional system, relational space refers to the dimension corresponding to actor-actor relationships, regardless of the actors' physical location. For example, social networking sites like Facebook exist primarily in relational space.
Sectoral differences	Differences in the level of influence and interaction within the network attributable to the technology sector of the actors or innovation; sector is synonymous in intent to "industry sector" or "technology class" although the coding is different for each.
Sectoral influences	See Sectoral differences.
Size	See Effective size.
Social network	A collection of actors (nodes) and the relationships (ties) that connect them
Social Network Analysis (SNA)	A collection of methods for analyzing the structure and characteristics of networks of related actors based primarily on relational data. SNA methods are grounded in graph theory and matrix algebra.
Tie	Refers to the relationship between two nodes (actors) in a network
Two-mode network	An actor X event network represented in a rectangular matrix where rows correspond to actors and columns correspond to events (e.g. patents)

Bibliography

Adam, S., & Kriesi, H. (2007). The network approach. *Theories of the policy process*, Ed. P. Sabatier. Boulder, CO: Westview Press.

Ahuja, G. (2000). Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly.* 45(3) 425-455.

Albrechts, L., & Mandelbaum, S. J. (2005). *The network society: a new context for planning?* Taylor & Francis.

Altshuler, A.A. (1967). *The City Planning Process: A Political Analysis*. Ithaca, New York: Cornell University Press.

Arnstein, S. (1969). A Ladder of Citizen Participation. *Journal of the American Planning Association*, 35(4), 216-224.

Arundel, A. and Kabla, I. (1998). What Percentage of Innovations are Patented? Empirical Estimates from European Firms. *Research Policy.* 27. 127-141.

Berke, P., Smith, G. & Lyles W. (2010). Planning for Resiliency: An Evaluation of Coastal State Hazard Mitigation Plans. Available online at: http://www.ie.unc.edu/cscd/publications.cfm#dma.

Bertuglia, C. S., Lombardo, S., and Nijkamp, P., Eds. (1997). *Innovative Behaviour in Space and Time.* Advances in Spatial Science. New York, Springer.

Bettencourt, L., Lobo, J., & Strumsky, D. (2007). Invention in the city: Increasing returns to scale in metropolitan patenting. *Research Policy, 36*, 107-120.

Blien, U. and G. Maier, Eds. (2008). *The Economics of Regional Clusters: Networks, Technology and Policy*. New Horizons in Regional Science, Edward Elgar.

Bolton, R. (1993). "Place Prosperity Versus People Prosperity Revisited: An Old Issue with a New Angle", in Robert D. Ebel and R. D. Norton, (ed.) Research in Urban Economics (vol.9): Structuring Direct Aid: People versus Places, Greenwich, CT: JAI Press.

Booher, D. E., & Innes, J. E. (2002). Network power in collaborative planning. *Journal of planning education and research*, *21*(3), 221.

Borgatti, S. (2008). Creating Knowledge: Network Structure and Innovation. LINKS Center Essays. Boston, LINKS Center. **2009**.

Borgatti, S. and Everett, M. (1999). "Models of Core / Periphery Structures." Social Networks **21**: 375-395.

Borgatti, S., & Li, X. (2009). On Social Network Analysis in a Supply Chain Context Journal of Supply Chain Management

Borgatti, S., Mehra, A., Brass, D., & Labianca, G. (2008). Network Analysis in the Social Sciences Science, 323, 892-895.

Borich, G. (2008). *The Broader Social Network of Community Planning: an Investigation into who Plans at the Local Level and How they do it.* University of Illinois Urbana-Champaign, Urbana, IL.

Bott, E. (1957). *Family and social network: Roles, norms, and external relationships in ordinary urban families*: Routledge.

Bowman, J.M. and Darmody, B. (2008). The Power of Place: a National Strategy for Building America's Communities of Innovation. Association of University Research Parks, Tucson AZ.

Bourdieu, P. (1986) The forms of capital. In J. Richardson (Ed.) *Handbook of Theory and Research for the Sociology of Education* (New York, Greenwood), 241-258.

Braunerhjelm, P. and M. Feldman (2006). *Cluster Genesis: Technology-Based Industrial Development*. New York, Oxford University Press.

Breschi, S. (2000). "The geography of innovation: A cross-sector analysis." *Regional Studies* **34**(3): 213-229.

Breschi, S., F. Lissoni, et al. (2005). The Geography of Knowledge Spillovers: Conceptual Issues and Measurement Problems. in *Clusters, Networks and Innovation*. S. Breschi and F. Malerba (eds). New York, Oxford University Press**:** 343-371.

Breschi, S., & Malerba, F. (2005). Clusters, networks, and innovation: Research results and new directions. *Clusters, Networks, and Innovation*, 1–26.

Breschi, S., & Malerba, F. (Eds.). (2005). *Clusters, Networks and Innovation*. New York: Oxford University Press.

Bresnahan, T., Gambardella, A., & Saxenian, A. (2004). Old-Economy Inputs for New-Economy Outcomes What Have We Learned? Building High-tech Clusters: Silicon Valley and Beyond. In S. Breschi & F. Malerba (Eds.), *Clusters, Networks and Innovation* (pp. 331). Oxford: Oxford University Press.

Bridge, G. (2002). *The Neighborhood and Social Networks*: University of Glasgow.

Brocker, J., Dohse, D. and Rudiger, S., Eds. (2003). *Innovation Clusters and Interregional Competition*. Advances in Spatial Science. New York, Springer.

Brookings Institution. (2012). *Why—and Which—Manufacturing Matters: Innovation and Production in the United States.* Symposium and webcast. February 22, 2012. http://www.brookings.edu/events/2012/0222_manufacturing_matters.aspx.

Burt, R. S. (1992). *Structural Holes: the Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, R.S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology*, 110(2), 349-399.

Butler, M. and Beale, C. (1994). *Rural-Urban Continuum Codes for Metro and Nonmetro Counties.* Washington DC: U.S. Economic Research Service.

Butts, C. T. (2009). Revisiting the foundations of network analysis. *science*, *325*(5939), 414.

Camagni, R., Ed. (1991). *Innovation Networks: Spatial Perspectives*. New York, Belhaven Press.

Carrasco, J., Hogan, B., Wellman, B., & Miller, E. (2007). Collecting social network data to study social activity-travel behavior: an egocentric approach. *Environment and Planning B: Planning and Design*, 35, 961-980.

Carrasco J A, Miller E J, 2006, ``Exploring the propensity to perform social activities: a social network approach'' Transportation 33 463-480.

Carter, A. (2007). Measurement of the Clustering and Dispersion of Innovation. In K. Polenske (Ed.), *The Economic Geography of Innovation*. Cambridge: Cambridge University Press.

Castells, M. (2001). *The rise of the network society*. Oxford: Blackwell Publishers.

Chan, K., & Liebowitz, J. (2006). The Synergy of Social Network Analysis and Knowledge Mapping: A Case Study. *International Journal of Management and Decision Making, 7*(1), 19-35.

Clark, A. (2007). *Understanding Community: A review of networks, ties and contacts*. Manchester: University of Manchester.

Clark, G., Feldman, M. and Gertler, M., Eds. (2000). *The Oxford Handbook of Economic Geography*. New York, Oxford University Press.

Cockburn, I. and Griliches, Z. (1988). Industry Effects and Appropriability Measures in the Stock Market's Valuation of R & D and Patents. *American Economic Review.* **78**(2). 419-423.

Coleman, J. (1988). Social Capital in the Creation of Human Capital. American Journal of Sociology, 94(Supplement: Organizations and Institutions: Sociological and Economic Approaches to the Analysis of Social Structure), S95-S120.

Contractor, N. (2011). Personal communication, August 23, 2011.

Cowan, R. (2005). Network models of innovation and knowledge diffusion. *Clusters, networks, and innovation*, 29.

Cowan, R. (2005). *Universities and the Knowledge Economy*. Paper presented at the Advancing Knowledge and the Knowledge Economy Conference, Washington DC, January 10, 2005.

Cowhey, P. (2012) Remarks presented at the Brookings Institution, Washington DC, February 22, 2012. http://www.brookings.edu/events/2012/0222_manufacturing_matters.aspx.

Crossley, N., Prell, C., & Scott, A. J. (2009). Social Network Analysis: Introduction to Special Edition. *Methodological Innovations Online, 4*, 1 -7.

Davidoff, P. (1965). Advocacy and Pluralism in Planning, *Journal of the American Planning Association*, 31(4), 331-338.

Davies, A. (2002). Power, Politics and Networks: Shaping Partnerships for Sustainable Communities. *Area, 34*(2), 190-203.

Davis, A., Gardner, B., & Gardner, M. (1941). *Deep South: A social anthropological study of caste and class*: Univ of South Carolina Pr.

DeJordy, R. (2009). Social Network Analysis. On *Research Methods for the Global Classroom* [PowerPoint presentation]. Richmond, VA.

deNooy, W., Mrvar, A. and Batagelj, V. (2005). *Exploratory Social Network Analysis with Pajek*. New York, Cambridge University Press.

DeSantis, M. (2006). Purposeful Networking. *Economic Development Journal, 5*(1), 30-38.

Doak, J., & Parker, G. (2002). *'Pre-Plan Mapping', Networks, Capital Resources and Community Strategies in England*. Reading, UK: University of Reading.

Durlauf, S. N. (2002). On The Empirics Of Social Capital*. *The Economic Journal, 112*(483), F459-F479.

Eraydin, A., Koroglu, A., Ozturk, H., & Yasar, S. (2008). Network Governance for Competitiveness: The Role of Policy Networks in the Economic Performance of Settlements in the Izmir Region. *Urban Studies, 45*(11), 2291-2321.

Fagerberg, J., Mowery, D., & Nelson, R. (Eds.). (2005). *The Oxford Handbook of Innovation*. Oxford: Oxford University Press.

Fagerberg, J., & Verspagen, B. (2006). *Innovation Studies -an Emerging Discipline (or what)? A Study of Global Networks of Innovation Scholars*. Paper presented at the The Future of Science, Technology and Innovation Policy.

Fainstein, S.S. (2005). Local networks and capital building. IN Albrechts, L., & Mandelbaum, S. J. (eds.) *The network society: a new context for planning?* New York: Routledge.

Farschi, M., Janne, O., and McCann, P. (2009). *Technological Change and Mature Industrial Regions: Firms, Knowledge and Policy*. Northampton, MA. Edward Elgar Publishing, Inc.

Feldman, M. P. (2007). Perspectives on Entrepreneurship and Cluster Formation: Biotechnology in the U.S. Capitol Region. In K. Polenske (Ed.), *The Economic Geography of Innovation*. Cambridge: Cambridge University Press.

Feldman, M. and Link, A. (eds). (2001). *Innovation Policy in the Knowledge-Based Economy*. Boston, Kluwer Academic Publishers.

Feldman, M., Link, A. and Siegel, D. (2002) The Economics of Science and Technology: an Overview of Initiatives to Foster Innovation, Entrepreneurship and Economic Growth. Norwell, MA. Kluwer Academic Publishers.

Feser, E. (2003). What Regions Do Rather than Make: A Proposed Set of Knowledge-based Occupation Clusters. *Urban Studies, 40*(10).

Feser, E., Sweeney, S., & Renski, H. (2005). A Descriptive Analysis of Discrete U.S. Industrial Complexes. *Journal of Regional Science, 45*(2).

Fisher, R., Ury, W., & Patton, B. (1991). *Getting to yes: Negotiating agreement without giving in*. Penguin Group USA.

Florida, R. (2002). *The rise of the creative class: and how it's transforming work, leisure, community and everyday life*. Basic Civitas Books.

Florida, R. (2005). *The flight of the creative class: The new global competition for talent*. Harper Business.

Forester, J. (1989). *Planning in the face of power*. Berkeley: University of California Press.

Forester, J. (1993). *Critical Theory, Public Policy and Planning Practice: Towards a Critical Pragmatism*. Albany: State University of New York Press.

Foth, M. (2006). Analyzing the Factors Influencing the Successful Design and Uptake of Interactive Systems to Support Social Networks in Urban Neighborhoods. *International Journal of Technology and Human Interaction, 2*(2), 65-79.

Franklin, T. (2011). 2010 TRE Roundtable Annual Meeting. December 4-6, 2011. http://www.trenetworks.org/; accessed 12/4/2011.

Franklin, T. (2010). 2010 TRE Roundtable Annual Meeting. December 7-8, 2010. http://www.trenetworks.org/events/annual_meeting_2010.php; accessed 12/4/2011.

Friedmann, J. (1987). *Planning in the public domain : from knowledge to action*. Princeton, N.J.: Princeton University Press.

Fruchterman, T. and Reingold, E. (1991). "Graph Drawing by Force Directed Placement." *Software Practice and Experience* **2**(1): 1129-1164.

Fujita, M., and Thisse, J., (2002). *Economics of Agglomeration: Cities, Industrial Location and Regional Growth.* New York: Cambridge University Press.

Gertler, M. (2007). Tacit Knowledge in Production Systems: How Important is Geography? *The Economic Geography of Innovation*. K. Polenske (ed). New York, Cambridge University Press**:** 87-111.

Gertler, M. and Y. Levitte (2005). Local Nodes in Global Networks: The Geography of Knowledge Flows in Biotechnology Innovation. *Industry and Innovation* **12**(4): 487-507.

Glaeser, E. L., Laibson, D., & Sacerdote, B. (2002). An Economic Approach to Social Capital*. *The Economic Journal, 112*(483), F437-F458.

Granovetter, M. (1973). The Strength of Weak Ties. *The American Journal of Sociology, 78*(6), 1360-1380.

Granovetter, M. (1983), The strength of weak ties: A network theory revisited. *Sociological theory*, 1(1), 201–233.

Greene, W. (2008). *Econometric Analysis*. Upper Saddle Creek, NJ, Pearson Prentice Hall.

Griliches, Z. (1996). The discovery of the residual: a historical note. *Journal of Economic Literature, 34*(3), 1324-1330.

Griliches, Z. (1990). Patent statistics as economic indicators: a survey. *Journal of Economic Literature*, 1661-1707.

Hage, J. (2011). Restoring the Innovative Edge: Driving the Evolution of Science and Technology, Stanford Business Books.

Hage, J. and Hollingsworth, J. R. (2000). "A Strategy for the Analysis of Idea Innovation Networks and Institutions." Organization Studies **21**(5): 971-1004.

HAGE, J. and MEEUS, M. (2009). "Innovation, Science, and Institutional Change: A Research Handbook (Paperback)." Recherche **67**: 02.

Hagen, G., Killinger, D., & Streeter, R. (1997). An Analysis of Communications Networks Among Tampa Bay Economic Development Organizations. *Connections*, 20(2), 13-22.

Hajer, M., & Zonneveld, W. (2000). Spatial Planning in the Network Society - Rethinking the Principles of Planning in the Netherlands. *European Planning Studies, 8*(3), 337-355.

Haltiwanger and Jarmin (2011). Who Creates Jobs? Small vs. Large vs. Young. Working Paper, August 2011.

Hanna, K. S. (2000). The paradox of participation and the hidden role of information: A case study. *Journal of the American Planning Association*, *66*(4), 398–410.

Hansson, F., Husted, K., & Vestergaard, J. (2005). Second generation science parks: from structural holes jockeys to social capital catalysts of the knowledge society. *Technovation, 25*, 1039-1049.

Hawkins, C. V. (2010). Competition and Cooperation: Local Government Joint Ventures for Economic Development. *Journal of Urban Affairs*, 32, 253-275.

Heaney, M., & McClurg, S. (2009). Social Networks and American Politics: Introduction to the Special Issue. *American Politics Research, 37*(5), 727-741.

Helper, S., Krueger, T. and Wial, H. (2012). Why Does Manufacturing Matter? Which Manufacturing Matters? - Manufacturing, Job Creation, Wages, Competitiveness. Paper presented at the Brooking Institution, Washington DC, February 22, 2012. http://www.brookings.edu/papers/2012/0222_manufacturing_helper_krueger_wial.aspx.

Helper, S. and Stanley, M. (2006). Creating Innovation Networks among Manufacturing Firms: How Effective Extension Programs Work. Economic

Development through Entrepreneurship: Government, University and Business Linkages. S. Shane, Edward Elgar.

Henry, A. D., M. Lubell and M. McCoy. (2010). Belief Systems and Social Capital as Drivers of Policy Network Structure: The Case of California Regional Planning, *Journal of Public Administration Research and Theory*, Online advance access July 2010.

Hoch, C. (1994). *What planners do : power, politics, and persuasion*. Chicago, IL: Planners Press: American Planning Association.

Holman, N. (2008). Community Participation: Using Social Network Analysis to Improve Developmental Benefits. *Environment and Planning C, 26*, 525-543.

Hutchinson, J., & Vidal, A. (2004). Using Social Capital to Help Integrate Planning Theory, Research, and Practice. *Journal of the American Planning Association, 70*(2), 142-192.

Innes, J. E. (1996). Planning through consensus building: A new view of the comprehensive planning ideal. *Journal of the American Planning Association*, *62*(4), 460–472.

Innes, J. E. (2004). Consensus building: clarifications for the critics. *Planning theory*, *3*(1), 5-20.

Innes, J.E. (2005). Networks and Planning Thought. IN Albrechts, L., & Mandelbaum, S. J. (eds.) *The network society: a new context for planning?* New York: Routledge.

Innes, J. E., & Booher, D. E. (1999). Consensus building and complex adaptive systems. *Journal of the American Planning Association*, *65*(4), 412–423.

Innes, J. E., & Booher, D. E. (2010). *Planning with Complexity: An Introduction to Collaborative Rationality for Public Policy* (1st ed.). Routledge.

Jackson, M. O. (2008). *Social and economic networks*. Princeton University Press.

Jacobs, J. (1961). The Death and Life of Great American Cities. Penguin Press.

Karlsson, C., Johansson, B. and Stough, R., Eds. (2005). *Industrial Clusters and Inter-firm Networks*. New Horizons in Regional Science. Northampton, MA, Edward Elgar Publishing Inc.

Kastelle, T., & Steen, J. (2010). Introduction: Using network analysis to understand innovation. *Innovation: Management, Policy & Practice, 12*(1), 2-4.

Keilbach, M. (2000). Spatial Knowledge Spillovers and the Dynamics of Agglomeration and Regional Growth. New York, Physica-Verlag.

Kleit, R. G. (2001). The Role of Social Networks in Scattered-Site Public Housing Residents' Search for Jobs. *Housing Policy Debate, 12*(3), 541-573.

Krebs, V., & Holley, J. (2006). *Building Smart Communities Through Network Weaving*. Appalachian Center for Economic Networks.

Koehly, L. and Pattison, P., (2005). Random Graph Models for Social Networks: Multiple Relations or Multiple Raters. In Carrington, P., Scott, J. and Wasserman, S. (eds) *Models and Methods in Social Network Analysis,* Cambridge University Press, New York. 98-116.

Krackhardt, David and Robert N. Stern (1988). Informal networks and organizational crises: an experimental simulation. Social Psychology Quarterly 51(2), 123-140.

Krumholz, N., & Forester, J. (1990). *Making equity planning work : leadership in the public sector*. Philadelphia: Temple University Press.

Lam, A. (2005). Organizational Innovation. The Oxford Handbook of Innovation. J. Fagerberg, D. Mowery and R. Nelson. New York, Oxford University Press**:** 115-147.

Levy, J. (2003). What local economic developers actually do: Location quotients versus press releases. *Readings in planning theory*, 262.

Leydesdorff, L. (2006). The Knowledge-Based Economy: Modeled, Measured, Simulated. Boca Raton, Universal Publishers. 392 pp.

Liebowitz, J. (2007). *Social Networking: The Essence of Innovation*. Lanham, MD: Scarecrow Press.

Lin, N. (2001). *Social Capital: A Theory of Social Structure in Action.* New York: Cambridge University Press.

Lin, N. Cook, K. and Burt, R. (2001). *Social Capital: Theory and Research*. New York: Aldine de Gruyter.

Lukes, S. (1974). *Power: A radical view*. New York: Macmillan Press.

Malerba, F. (2005). Sectoral Systems: How and Why Innovation Differs across Sectors. The Oxford Handbook of Innovation. J. Fagerberg, Mowery, D. and Nelson, R. New York, Oxford University Press**:** 380-406.

Mandarano, L. A. (2009). Social Network Analysis of Social Capital in Collaborative Planning, *Society & Natural Resources*: Routledge.

Marshall, A. (1932). Industry and Trade (3d ed.); London: Macmillan.

Marx, M., Strumsky, D., & Fleming, L. (2007). Noncompetes and Inventor Mobility: Specialists, Stars, and the Michigan Experiment.

Mayer, H. (2009). Bootstrapping High-Tech: Evidence from Three Emerging High Technology Metropolitan Areas. Metro Economy Series for the Metropolitan Policy Program at Brookings. B. Institution. Washington DC, Brookings Institution.

Mayer, H. (2011). Entrepreneurship and Innovation in Second Tier Regions. Northampton, MA, Edward Elgar Publishing Inc.

Mills, K., Reynolds, E. and Reamer, A. (2008). Clusters and Competitiveness: A New Federal Role for Stimulating Regional Economies. *Blueprint for*

American Prosperity. Brookings Institution. Washington, DC, Brookings Institution**:** 51.

Missouri State Data Center. MABLE/Geocorr*2K*: Geographic Correspondence Engine with Census 2000 Geography. http://mcdc2.missouri.edu/websas/geocorr2k.html. Last accessed December 9, 2011.

Monge, P. and Contractor, N. (2003). *Theories of Communications Networks*. New York, Oxford University Press.

Moreno, J. L. (1934). Who shall survive? A new approach to the problem of human interrelations. Washington: Nervous and Mental Disease Pub. Co.

Morrison, E. (2011). http://edmorrison.com/; accessed 12/4/2011.

Morrison, E. (2010a) Strategic Doing Brochure. Purdue Center for Regional Development.

Morrison, E. (2010b) Moving from Strategic Planning to Strategic Doing in *Community Visioning Programs: Processes and Outcomes.* Hamm, G. and Walzer, N. (eds). Pre-publication draft chapter.

Mote, J., Jordan, G. and Hage, J. (2007). "Measuring Radical Innovation in Real Time." International Journal of Technology, Policy and Management **7**(4): 355-377.

Mote, J. E., Hage, J. T., Whitestone, Y. K. and Jordan, G. B. (2008). "Innovation, Networks and the Research Environment: Examining the Linkages." International Journal of Foresight and Innovation Policy **4**(3): 246-264.

Mote, J. E., Jordan, G., Hage, J. and Whitestone, Y. (2007). "New Directions in the Use of Network Analysis in Research and Product Development Evaluation." Research Evaluation **16**(3): 191-203.

Muro, M. & Katz, B., (2010). The New 'Cluster Moment': How Regional Innovation Clusters Can Foster the Next Economy. Washington, DC: Brookings Institution, White Paper published September 2010.

Newman, M. E. (2003). The structure and function of complex networks. *SIAM review*, *45*(2), 167–256.

Nguyen, D. (2007). The Spatial and Social Dimensions of Innovation. *Urban and Regional Planning and Design*. College Park, MD, University of Maryland. PhD: Urban and Regional Planning and Design 212.

Norton, R. K. (2005). Local commitment to state-mandated planning in coastal North Carolina. *Journal of Planning Education and Research*, *25*(2), 149. Okamura, K., & Vonortas, N. S. (2006). European Alliance and Knowledge Networks, *Technology Analysis & Strategic Management*: Routledge.

O'Kane, P., McGinley, R., & Kelly, O. (2009). Social Networking. University of Ulster.

Ostrom, E. (1998). A behavioral approach to the rational choice theory of collective action: Presidential address, American Political Science Association, 1997. *American Political Science Review*, *92*(1), 1–22.

Ostrom, E. (2005). *Understanding institutional diversity*. Princeton University Press.

Ostrom, E. (2007). Institutional Rational Choice: An Assessment of the Institutional Analysis and Development Framework, *Theories of the Policy Process*, Ed. P. Sabatier. Boulder, CO: Westview Press.

Owen-Smith, J. and Powell, W. (2004). Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organizational Science.* 15(1) 5-21.

Owen-Smith, J. and Powell, W. (2006). Accounting for emergence and novelty in Boston and Bay Area Biotechnology. In (Braunerhjelm, P. and Feldman, M. (eds) *Cluster Genesis: Technology-based Industrial Development.* New York: Oxford University Press. Chapter 4. 61-86.

Pavitt, K. (2005). Innovation Processes. The Oxford Handbook of Innovation. J. Fagerberg, D. Mowery and R. Nelson. New York, Oxford University Press**:** 86-114.

Pennsylvania Department of Community and Economic Development. Investment Tracker. http://www.dced.state.pa.us/investmenttracker/. Last accessed December 9, 2011.

Pianta, M. (2004). Innovation and employment. In J. Fagerberg, C. Mowery & R. Nelson (Eds.), *The Oxford Handbook of Innovation. Oxford University Press, Oxford*. Oxford: Oxford University Press.

Piselli, F. (2007). Communities, Places and Social Networks. *American Behavioral Scientist, 50*(7), 867878.

Polenske, K. (2007). *The economic geography of innovation*: Cambridge University Press. Porter, M. (1998a). Clusters and the new economics of competition. *Harvard business review, 76*(6), 77-90.

Porter, K., Whittington, K., & Powell, W. (2005). The institutional embeddedness of high-tech regions: relational foundations of the Boston biotechnology community. *Clusters, Networks, and Innovation*, 261 296.

Porter, M. (1998a). Clusters and the new economics of competition. *Harvard business review, 76*(6), 77-90.

Porter, M. (1998b). *The competitive advantage of nations: with a new introduction*: Free Press.

Porter, M. (1998c). *Competitive advantage: creating and sustaining superior performance: with a new introduction*: Free Press.

Porter, M. (1998d). *Competitive strategy: techniques for analyzing industries and competitors: with a new introduction*: Free Press.

Powell, W. W., Koput, K. W., and Smith-Doerr, L. (1996). "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology." *Administrative Science Quarterly* **41**: 116-145.

Prell, C., K. Hubacek, M. Reed. (2009). Stakeholder Analysis and Social Network Analysis in Natural Resource Management, *Society and Natural Resources*, 22(6), 501-518.

Prevezer, M. (2008). Technology Policies in Generating Biotechnology Clusters: A Comparison of China and the US. *European Planning Studies*, Routledge. **16:** 359-374.

Prevezer, M., Opsahl, T., & Panzarasa, P. (2008). Clusters and social networks: the role of geographical and social distances in the evolution. Paper presented at the entrepreneurship and innovation - organizations, institutions, systems and regions conference.

Provan, K., Veazie, M., & Staten, L. (2005). The Use of Network Analysis to Strengthen Community Partnerships. *Public Administration Review, 65*(5), 603-613.

Putnam, R. (1995). Bowling Alone: America's Declining Social Capital. *Journal of Democracy, 6*(1), 65-78.

Putnam, R. (2001). *Bowling Alone: America's Declining Social Capital.* New York: Simon & Schuster.

Putnam, R., Light, I., Briggs, X. d. S., Rohe, W. M., Vidal, A. C., Hutchinson, J., et al. (2004). Using Social Capital to Help Integrate Planning Theory, Research, and Practice: Preface. *Journal of the American Planning Association, 70*(2), 142 -192.

Reid, N., Carroll, M., & Smith, B. (2007). Critical Steps in the Cluster Building Process. *Economic Development Journal, 6*(4), 44-52.

Rittel, H. W., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy sciences*, *4*(2), 155–169.

Rubin, H. J. (1999). Shoot Anything that flies, Claim Anything that Falls. In B. a. Reese (Ed.), *Approaches to Economic Development*.

Rydin, Y., & Holman, N. (2004). Re-evaluating the Contribution of Social Capital in Achieving Sustainable Development. Local Environment, 9(2), 117-133.1. M. Granovetter, "The strength of weak ties: A network theory revisited," Sociological theory 1, no. 1 (1983): 201–233.

Safford, S. (2009). *Why the Garden Club Couldn't Save Youngstown*. Cambridge, MA: Harvard University Press.

Salvesen, D. (2005). The Coastal Barrier Resources Act: Has It Discouraged Coastal Development? *Coastal Management*, 33, 181-195.

Sani, M. (2011). Innovate Kansas. Kansas Opportunity Innovation Network (KOIN). Kansas State University, Manhattan, KS. http://innovatekansas.org/.

Saxenian, A. (1994). Regional advantage: culture and competition in Silicon Valley and Route 128 Harvard University Press. *Cambridge, MA*.

Saxenian, A., and Hsu, J. (2001). The Silicon Valley-Hsinchu connection: Technical communities and industrial upgrading. *Industrial and Corporate Change, 10*(4), 893.

SBA TechNet. http://web.sba.gov/tech-net/public/dsp_search.cfm. last accessed December 9, 2009.

Scott, J. (1991). *Social Network analysis: A Handbook*. London: Sage Publications.

Scholz, J. T., Berardo, R., & Kile, B. (2008). Do networks solve collective action problems? Credibility, search, and collaboration. *The Journal of Politics*, *70*(02), 393–406.

Schmookler, J. (1966). *Innovation and Economic Growth*. Cambridge: Harvard University Press.

Schneider, M., J. Scholz, M. Lubell, D. Mindruta, M. Edwardsen. (2003). Building Consensual Institutions: Networks and the National Estuary Program, American Journal of Political Science, 47(1), 143158.

Schramm, C. (2008). *Innovation Measurement: Tracking the state of innovation in the American economy*. Washington DC.

Siegel, J., Swanson, D., and Shryock, H., (2002). *The Methods and Materials of Demography.* San Diego: Elsevier Academic Press.

Simmie, J. (1997). Innovation, Networks and Learning Regions. London, Jessica Kingsley Publishers.

Singerman, P. (2010). Regional Innovation Clusters: A New Paradigm for Federal Economic Development Policy Washington DC, B&D Consulting

Solow, R. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Sorenson, O. (2003). Social Networks and Industrial Geography. *Journal of Evolutionary Economics, 13*, 513-527.

Sorenson, O. (2005). Social networks and the persistence of clusters: Evidence from the computer workstation industry. *Clusters, Networks, and Innovation*, 297.

Sorenson, O. and Singh, J. (2007). Science, social networks and spillovers. *Industry & Innovation, 14*(2), 219-238.

Stanley, B. (2005). Middle East City Networks and the "New Urbanism". *Cities, 22*(3), 189-199.

Storper, M. and J. Venables (2005). Buzz: Face to Face Contact and the Urban Economy. Clusters, Networks and Innovation. S. Breschi and F. Malerba. New York, Oxford University Press**:** 319-342.

SSTI (2006). A Resource Guide for Technology-based Economic Development: Positioning Universities as Drivers, Fostering Entrepreneurship, Increasing

Access to Capital. US Economic Development Administration, Washington DC.

Strumsky, D., Lobo, J., & Fleming, L. (2005). Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. *Los Alamos National Laboratory Technical Report LAUR-04-8798*.

Ter Wal, A., & Boschma, R. (2009). Applying Social Network analysis in Economic Geography: Framing some Key Analytic Issues. *Annals of Regional Science, 43*, 739-756.

Thamhain, H. J. (2003). "Managing Innovative R&D Teams." *R&D Management* **33**(3): 297-311.

Tickner, N. (2011). UMD to Map Innovation Opportunities, Aid Baltimore Redevelopment. University of Maryland, College Park MD. September 22, 2011. http://newsdesk.umd.edu/uniini/release.cfm?ArticleID=2515.

U.S. Census Bureau. County Business Patterns. http://www.census.gov/epcd/cbp/. Last accessed December 9, 2011.

U.S. Census Bureau. Economic Census. http://www.census.gov/econ/census07/www/contact_info/related_sites.html. Last accessed December 9, 2011.

U.S. Economic Research Service (2002a). Measuring Rurality: Urban Influence Codes. www.ers.usda.gov/briefing/rurality/urbaninf/ . April 12, 2002. Last accessed December 10, 2011.

U.S. Economic Research Service (2002b). Measuring Rurality: Urban Influence Codes. www.ers.usda.gov/briefing/rurality/typology/ . February 20, 2002. Last accessed December 10, 2011.

U.S. patents [electronic resource] : custom data extracts. [Washington, D.C.] : U.S. Patent and Trademark Office, Information Products Division, Patent Technology Monitoring Team, 2009. UMCP EPSL : Reference - T223.D7 - U6 2009

Valente, T., (2005). Network Models and Methods for Studying the Diffusion of Innovation. In Carrington, P., Scott, J. and Wasserman, S. (eds) *Models and Methods in Social Network Analysis,* Cambridge University Press, New York. 98-116.

Verspagen, B. (2005). Innovation and economic growth. In J. Fagerberg, D. Mowery & R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 487). Oxford: Oxford University Press.

Walker, G. Kogut, B. and Shan, W. (1997). Social Capital, Structural Holes and the Formation of an Industry Network. *Organizational Science*. 8(2) 109-125.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*: Cambridge University Press.

Watts, D. (2008). The "New" Science of Networks [PowerPoint]. New York: Columbia University.

Wellman, B. (1979). The Community Question: The Intimate Networks of East Yorkers *The American Journal of Sociology, 84*(5), 1201-1231.

Wellman, B. (1999). Networks in the Global Village: Life in Contemporary Communities. Boulder, CO: Westview Press.

Wellman, B. (2001a). Computer Networks as Social Networks. *Science, 293*, 4.

Wellman, B. (2001b). *The Persistence and Transformation of Community: From Neighbourhood Groups to Social Networks*. Report to the Law Commission of Canada.

Westlund, H., & Bolton, R. (2003). Local Social Capital and Entrepreneurship. *Small Business Economics, 21*, 77-113.

Whitford, J. and Potter, C. (2007). "Regional Economies, Open Networks and the Spatial Fragmentation of Production." *Socio-Economic Review* **2007**: 1-30.

Whitford, J. and Shrank, A. (2012).

Whittington, K., Owen-Smith, J., & Powell, W. (2009). Networks, Propinquity and Innovation in Knowledge-Intensive Industries. *Administrative Science Quarterly,* 54(1), 90-122.

Xu, X. K., Zhang, J., Li, P., and Small, M. (2011). "Changing motif distributions in complex networks by manipulating rich-club connections." Physica A: Statistical Mechanics and its Applications.