SOCIAL CAPITAL AS A DETERMINANT OF INNOVATION

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Abstract

This thesis explores the relationship between social capital and innovation across 40 regions in the United States. Data is drawn from the Social Capital Community Benchmark Survey, compiled by the John F. Kennedy School of Government and the Saguaro Seminar, and the MicroPatent CD-ROM Database from the USPTO. Innovative activity is modeled as a function of knowledge stocks, human capital, four aspects of social capital, and other control variables across six industries over 38 years. The results suggest that certain manifestations of social capital, such as levels of trust and cooperation, consistently have a positive impact on innovative activity. Furthermore, communities with greater levels of cooperation and better-established networks innovate even more in the presence of previous local knowledge.

KEYWORDS: (Social Capital, Cooperation, Trust, Innovation)

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CHAPTER I.

INTRODUCTION

This thesis explores the relationship between social capital and innovative activity across 40 regions in the United States. Innovation has become a vital area of study in a dynamic world where formal and informal interactions between individuals, firms, and institutions play a significant role in the process of knowledge creation. Technological change is vital for long-run economic growth (Metcalfe, 1988; Solow, 1957), accounting for up to 20 % of the average output growth in Western countries (Baier, Dwyer & Tamura, 2002). This change cannot occur in isolation. Instead, innovation depends largely on the interaction between firms and their environment (Fagelberg & Mowery, 2004).

Innovation varies significantly across geographic regions and tends to be highly concentrated. Countries and communities with superior innovative activity attain higher levels of productivity than less-innovative ones (Fagerberg, 1988). According to Bjorn & Meric (2005), the more knowledge-intensive the industry is, the more clustered it tends to be. On a global scale, OECD countries invent at contrastingly higher rates than non-OECD members; the distribution of patents is highly skewed even among industrialized nations.[1] Within the United States, Dorfman (1983) found that regions such as Silicon

[1] During the late 1980's, the United States, Japan, Germany, the United Kingdom, and France alone employed over 80 % of the OECD's research scientists and engineers (Eaton & Kortum, 1999). The difference in innovation is such that the inventive activity in the U.S. and Japan, the two major contributors, could drive more than two thirds of the growth of each of the five countries.

Valley in California, and Route 128 in Massachusetts, have earned a reputation for becoming world centers of innovation and high-technology. Dorfman further suggests that the conditions necessary to capture a disproportionate share of an industry in one single region are physical resources, labor supply and industrial clustering. This paper aims to shed some light on the factors driving the vastly different rates of innovation among regions, specifically by including social capital as a determinant. While it is true that access to labor and financial resources may foster innovation, other forms of capital may explain the geographic discrepancy in the creation of new knowledge.

Social capital affects productivity (Putnam, 2000) as well as the overall functioning of modern economies (Fukuyama, 1999), and it has a positive effect on innovation (Doh & Acs, 2009). Therefore, a growing body of literature aims to explain variations in innovation levels using social capital measures. Some authors have addressed the relationship at the national level (Dakhli & De Clercq, 2004; Doh & Acs, 2009), while others have focused on smaller subdivisions (Gallie & Legros, 2012). However, to this author's knowledge, no one has ever attempted to incorporate levels of social capital, technological capital, and human capital at the regional level in the United States.

In this study, I posit two hypotheses. First, I intend to measure the effect of four different dimensions of social capital on innovative activity, holding other determinants of innovation constant. Dasgupta (2001) suggested that "certain types of social capital suffer from negative productivity, while others enjoy positive productivity" (p. 6). The empirical literature predicts that many dimensions of social capital will have positive effects on innovative activity, but will vary in magnitude. Thus, I expect at least some of the dimensions of social capital to directly determine innovative activity. Moreover, the main control variables, human capital and previous technological capital, are expected to be strongly and positively correlated with innovation.

Second, I predict an increased effect of previous technological capital on future innovative activity in the presence of greater levels of regional social capital. In order to test this hypothesis, I measure technological capital by developing two measures of previous knowledge per region called knowledge stocks.

Social capital can be broadly defined as “the features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit” (Putnam, 1995, p. 66). Intuitively, with higher levels of social capital, local previous knowledge is expected to have a larger effect on innovative activity than nonlocal knowledge. I develop two models which find support, for the most part, for these two hypotheses. The analysis drawn from this paper provides the reader with the specific effects of each of the dimensions of social capital proposed in six different sectors of the economy.

Consistent with previous literature (Dakhli & De Clerq, 2004; Guiso, Sapiensa & Zingales, 2004; Knack & Keefer, 1997; Landry et. al, 2000; Tabellini & Guido, 2005) I study several dimensions (or manifestations) of social capital. The dimensions are: levels of trust, associative activity, norms of civic cooperation, and networks.

This paper adds to the current literature in several ways. First, the study is conducted at the regional level in the United States, supporting the findings of previous studies in other areas of the world, and providing support for the argument that greater levels of social capital conduct to more innovation, *ceteris paribus*. The validity of studies at the national level is often compromised by differences in patent regulations and political climate across countries. Because all the regions considered in this paper are subject to the same federal laws and patent conventions, the reader can be confident that macroeconomic effects are minimized, while maintaining a rich variation in the regions' levels of social and human capital.

Second, I create a strong measure of technological capital beyond patent counts or dollars spent in Research and Development (R&D). While these figures may be handy and helpful to some degree, the innovation literature has identified many limitations. In an effort to give justice to the complexity of the innovative process, I use data from the United States Patent and Trademark Office (USPTO) to create two knowledge stocks for each regression. Following Popp (2002), the constructed stocks of knowledge account for knowledge decay and diffusion and serve as strong measures of previous technological resources available for the marginal inventor.

Third, given the multidimensional nature of social capital, I study four major manifestations of this phenomenon. I will discuss the overall effect that social capital has on innovation, and present and analyze results for each dimension separately.

Fourth, the inclusion of interaction terms in the model allows for a rich analysis on the relation between technological capital and social capital, as determinants of innovation. The findings of this paper suggest that increasing levels of social capital may have different effects depending on the nature of previous knowledge accumulated in the region. As government regulation may foster or limit innovation (see for instance Aghion et al, 2009), understanding attitudes and values inherent in a region's culture may allow regional and federal policymakers to allocate resources more efficiently. Similarly, agents in the private sector may look at means to increase levels of different social capital manifestations, anticipating a positive effect on regional innovation across the United States.

The remainder of this paper is organized as follows. Section II reviews selected literature on innovation, culture, and social capital. Section III presents the data. Section IV explores the method underlying the research outlined in this paper. Section V tests the data to answer the research questions at hand, while providing an analysis of the results obtained. Section VI presents concluding remarks and suggests further areas of study.

CHAPTER II.

LITERATURE REVIEW

The recent introduction of nontraditional factors into economic research has spawned a concise but well-defined branch of literature that explores the relationship between culture and innovation. Culture can be broadly defined as "those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation" (Sapienza, Zingales, & Guiso, 2006). Using this definition, and focusing specifically on the interaction between culture and innovation, existing literature covers the topics of religious affiliation, ethnicity, beliefs and preferences, and social capital, among others.

While many studies analyze the effect of geographic proximity on innovation (Bosetti et al 2008; Dechezlepretre et al 2011; Verdolini & Galeotti, 2011), few emphasize the effects of cultural proximity. Most tend to look at the similarities and differences in ethnic and religious composition (see for instance Dohmen et al., 2006; Zingales, Sapienza, & Guiso, 2004). In this line of literature, Sapienza et al., (2006) proposed that language, religious affiliation, and ethnicity help us to understand the complex process of inventive activity.

Other studies adopt aspects of culture aiming to measure them comparatively across national or regional economies. Hofstede (1980) developed a systematic framework for assessing cultural differences across more than 70 countries. He suggested five dimensions of culture (Power Distance, Individualism, Uncertainty Avoidance, Masculinity, and Long Term Orientation) and provided data based on surveys conducted with IBM managers around the globe in the 1950's. Based on his framework, measurable statistical results have demonstrated a positive relationship between innovation rates and individualistic cultures (Shane, 1992), as well as innovation and higher tolerance to uncertainty (Shane, 1995).

Defining Social Capital

Hanifan (1916) was the first to use the term social capital, referring to "good will, fellowship, sympathy, and social intercourse among the individuals and families that make up a social unit" (Putnam, 2000, p. 19). Alternatively, Arneil (2006) recognizes sociologist James Coleman's definition as "the set of resources that inhere in family relations and in community organizations that are useful for the development of children" (p. 4). This paper follows the definition of social capital from Putnam (1995) that reads: "the features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (p.66). Putnam's definition is increasingly used in economic literature (Jones, 2005; Knack & Keefer, 1997; White, 2002) since it allows modeling different manifestations of social capital that have social and economic value. The core idea of social capital theory is that social networks have value (Putnam, 2000), and the purpose of this study is to identify and model the effect of that value in the process of innovation.

Between social capital and other forms of capital such as financial and human capital, there is one main difference. As Arneil (2006) points out, the proceeds from investment in social capital will often benefit other agents rather than the individual making the investment. Thus, the study of social capital becomes one of vast importance for development economics, as it shows characteristics of a public good. Nonetheless, it can also be seen as a private input in production, to the extent that the worth of networks, norms, and social trust is reflected in wages and salaries (Dasgupta, 2001). Under this assumption, social capital "can be thought of as a factor of production" (p. 31). This approach is particularly useful to model the effects of social capital at the regional or national level.

Empirical and theoretical studies recognize the intangible and multidimensional nature of social capital (see for example, Dakhli & De Clercq, 2004; Dasgupta, 2001; Knack & Keefer, 1997; Landru, Amara & Lamari, 2002; Putnam, 1993; Putnam 2000). While connections among individuals may be key for economic development and innovation, the consequent levels of trust, and norms of reciprocity and cooperation, are just as important and valuable to society as the connections *per se*. Intuitively, higher levels of social capital allow stakeholders to spend less time networking, crafting contracts, and enforcing the law, encouraging more innovation, and more interaction among individuals. In fact, Fukuyama (1999) identifies the economic function of social capital to be the reduction of "transaction costs associated with the formal coordination mechanisms like contracts, hierarchies, bureaucratic rules, and the like" (p. 4).

Empirical Studies on Social Capital

Putnam (1993) was arguably the first to account for the effect of social capital in economic performance. The author examines the northern and southern regions of Italy drawing the relationship between greater civic activity and efficient management of public goods by regional governments. At the regional level, notable exponents studied the economics of social capital on 54 regions of Western Europe (Beugelsdijk & van Schaik, 2005), in the European north and south (Bornhost et al., 2004), and in five Australian communities (Onyx & Bullen, 2000).

Since Putnam incorporated civic activity into economic analysis, subsequent research has explored the effect of several aspects of social capital on other manifestations of economic performance. Aghion et al. (2009) found that government regulation is highly dependent on the levels of trust in a society. Similarly, the trust and trustworthiness achieved in an economy affects the performance of institutions, such as governments and large businesses (Porta et. al., 1997). Further economic literature explores the impact of social capital on economic development (Guiso, Sapienza, & Zingales, 2004; Tabellini & Guido, 2005), growth (Whiteley, 2000), trade patterns across nations (Guiso, Sapienza, & Zingales, 2004), and the accumulation of physical capital and investment returns (Knack & Keefer, 1996). It is also suggested that higher rates of entrepreneurship tend to occur in societies with higher levels of trust after controlling for economy-wide variables (Guiso et al., 2006; Knack & Keefer, 1996).

Social Capital and Innovation

The overlap between social capital and innovation has been explored by a few researchers on a global scale. Landry et al. (2000) tackled it directly, looking at manufacturing companies in Southwest Montreal. The authors use a compelling two-stage decision model, with focus on the individual firm as a unit of measurement, and a slightly different selection of proxies for social capital than the rest of the literature: business, information, and research network assets, participation assets, and relational assets. Their findings indicate that "increases […] in participation assets and relational assets, contribute more than any other explanatory variable to the increased likelihood of innovation of firms.” (p14) In other words, networks between coworkers and between companies have economic value and translate specifically into a greater probability to innovate.

In another regional study, Gallie & Legros (2012) focused on the effect of human capital and technological capital on innovation across France. R&D expenditure approximated technological capital, while a new approach was given to measuring human capital; the authors collected data on employee training and found that both “R&D intensity and training have a positive, significant effect on patenting activity” (p8).

Dakhli & De Clercq (2004) modeled the effects of human and social capital on innovation, using the World Values Survey to approximate five dimensions of social capital. Innovation data was drawn from a World Bank database of country-level patent counts (including those filed by residents and nonresidents in a country), R&D expenditures and high-technology exportations. The authors found that “generalized trust and institutional trust are positively correlated with at least one of the innovation measures” (p.121). However, their results lacked evidence for a relationship between innovation and associative activity or norms of civic cooperation.

Finally, Doh & Acs (2009) constructed a social capital index to explain innovation. The study controls for capital expenditure, entrepreneurship, and human capital, among other variables. Running a country-level analysis, the authors found a positive relationship between the dependent and independent variables, providing more evidence on the interrelation between social capital and innovation.

While these studies provide reflections on the effect of social capital on innovation, the specific case of the United States remains an unexplored territory. The last two studies present a conceptual framework for development but fail to offer a reliable measure of innovative activity. A regional approach specifically within the U.S. provides a comparable measure for innovation across different communities, while conserving independency in human and social capital measures. Moreover, the question of the extent to which previous technological capital affects future innovation in the presence of social capital remains unanswered. This paper addresses it directly by developing a robust method that accounts for the interaction between social and technological capital across six different sectors of the economy.

CHAPTER III.

DATA

The multidimensional nature of social capital calls for a careful study of several measures and manifestations of this complex phenomenon. In this study I aim to approximate four manifestations in several communities in the United States. By doing so, the current levels of social capital in a community can be identified, separated, and addressed individually. All data gathered at the individual household level were aggregated by region and matched with corresponding levels of innovative activity, technological capital, and other variables.

Regional innovation is measured as the total number of inventions in each community that were patented between 1975 and 2004. Other data gathered measure levels of technological capital, human capital, income, and population density for each region.

Data from the U.S. Patent and Trademark Office (USPTO) are used to model innovation and technological capital. Patents are sorted by grant year and only successful nongovernment U.S. patents are taken into consideration. The dataset includes 4,619,307 patents granted by the USPTO from 1975 to 2011. Three-quarters of the data were granted before 2005 and are used directly in the regression analysis together with levels of social capital. Patents from 2005 to 2011 are used to estimate weights based on patent citations.

Data on social capital were gathered from the Social Capital Community Benchmark Survey (SCCBS), conducted in 42 communities across 29 states. The survey comprises over 26,000 responses and is the largest survey ever compiled on civic engagement in the United States ("Social Capital Community Benchmark Survey," 2000). It measures various manifestations of social capital as well as demographic information, such as household income, regional population density and levels of education. The survey was conducted by phone using random-digit-dialing over a four-month period. The average length of the interview was 26 minutes.

The SCCBS was sponsored by 15 organizations. Each organization decided what specific area to survey, as well as the number of interviews per area. The areas were chosen in different regions across the United States and vary greatly in size. Some areas may only be cities, while other areas cover several counties or even complete states. Within the areas chosen, proportionate random sampling was used to select the households surveyed. The majority of the samples range in size from 500 to 1,500 interviews. Experts at the John F. Kennedy School of Government at Harvard and the Saguaro Seminar undertook the survey design and questionnaire construction. Respondents were selected randomly from all adults in the household surveyed. Besides the survey by region, the SCCBS was conducted at the national level, with a sample size of 3,003 observations. The list of communities, sample sizes and sponsors can be found on Appendix I.

26,131 individual observations from the SCCBS and millions of patents were distributed by region and separated by year. In the end, an original panel dataset was compiled, including information on 38 years for the 40 regions listed in Table 3.1.

TABLE 3.1

REGIONS STUDIED

Regions			
1	Phoenix/Maricopa Co.	21	Yakima (WA)
2	Atlanta Metro	22	Montana
3	Baton Rouge	23	Indiana
4	Birmingham Metro	24	Fremont/Newaygo Co.
5	Charlotte region/14 county	25	Cleveland/Cuyahoga Co.
6	Syracuse/Onondaga County	26	New Hampshire
7	Chicago Metro	27	Greensboro/Guilford Co
8	Cincinnati Metro	28	Peninsula-Silicon Valley
9	East Tennessee	29	Lewiston-Auburn (ME)
10	Houston/Harris County	30	Bismarck (ND)
11	Kanawha Valley (WV)	31	Seattle
12	Kalamazoo Co. (MI)	32	Grand Rapids (city)
13	Los Angeles Co.	33	Boston (city)
14	St. Paul Metro	34	Boulder (CO)
15	San Diego Co.	35	Delaware
16	San Francisco (city)	36	Rochester Metro (NY)
17	Detroit Metro/7-co.	37	Minneapolis
18	Winston-Salem/Forsyth Co.	38	South Dakota
19	York (PA)	39	Denver (city/co.)
20	Central Oregon	40	National/rest of US

Source: SCCBS

Measures of Social Capital

The measures of social capital are defined in four dimensions aiming to obtain a greater understanding about their individual effect on innovative activity. A strong, accepted measure of generalized trust is based on the question: “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people?” Following Knack & Keefer (1997), generalized trust was estimated as the percentage of respondents in each region answering “people can be trusted” (after deleting the “don’t know” and “refused” responses). Institutional trust was measured relying on a combination of four survey questions on the level of trust towards the respondent’s church or place of worship, local news media, police, and local government.

The range of responses was 1 to 4 (1: Trust them a lot, 2: Trust them some, 3: Trust them only a little, 4: Trust them not at all) and the percentage of respondents who “trust a lot”, or “trust some” in each institution per region surveyed was averaged across the four questions to generate the measure of institutional trust. In order to decrease multicorrelation among social capital variables, both measures of trust, generalized and institutional, were averaged into one single variable, and indexed on a scale from 0 to 100. The final variable *TRUST* shows large variation across regions, with a mean and standard deviation of 50.6 and 8.7 units. Houston is the region with the smallest levels of trust (36), and Bismarck, ND reports the largest (68.58).

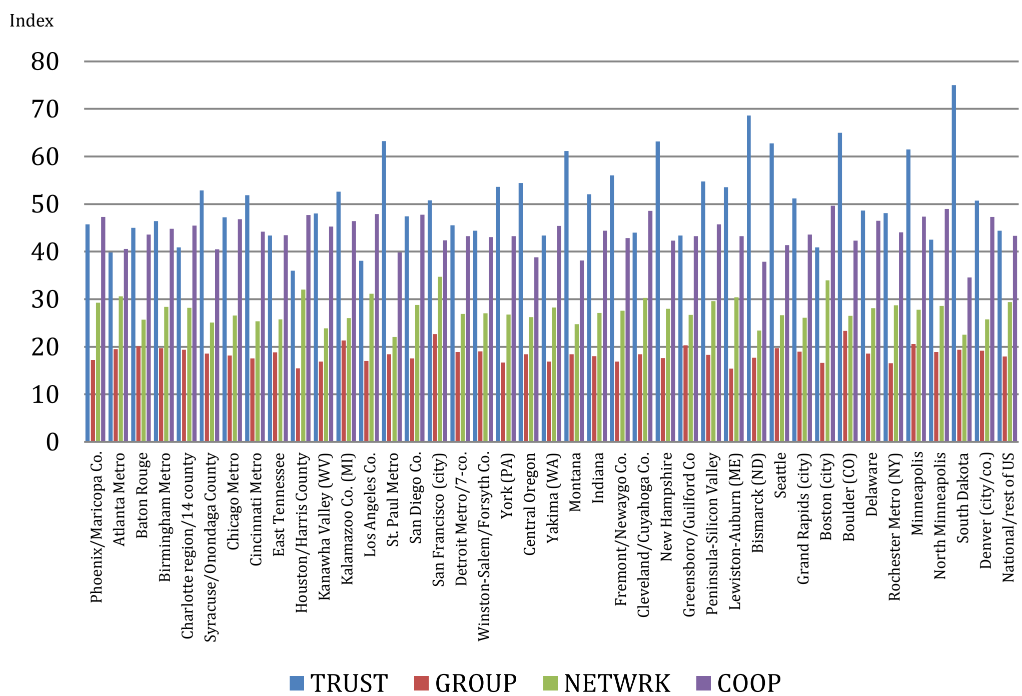
The importance of civic cooperation was reflected by another question in the survey. Respondents were asked the likelihood of cooperation in their community given the following hypothetical scenario: “if public officials asked everyone to conserve water or electricity because of some emergency, how likely is it that people in your community would cooperate?” Answers are scaled from 1 to 4 and indexed in a 100-unit scale; an average per region is calculated to build *COOP*. This variable has mean 43.9 and standard deviation 3.28, with values between 34.5 and 49.6.

Associative activity is incorporated based on the number of groups to which a respondent belongs, from youth organizations, to business associations, and support groups. The SCCBS asked respondents about 18 formal and 8 informal groups. The number of groups to which surveyed individuals belong were averaged by region and compiled into *GROUP*, which has mean 18.5 groups and standard deviation 1.67 for the whole sample. Boulder, CO is the region with the highest average of groups with 23.35 and Lewiston-Auburn, ME shows the lowest with 15.38.

Finally, the degree of networks is approximated by the frequency of interaction with immediate neighbors on a 1-7 scale reflecting interaction just about everyday, several times a week, several times a month, once a month, several times a year, once a year or less, or never. The regional averages were indexed on a 100-point scale and used to generate *NETWRK*, which reflects relatively low levels of networks with a minimum value of 22.06, maximum 34.68, mean 27.57 and standard deviation of 2.7 units. The four measures of social capital are incorporated in the model separately and are at the core of this study. Figure 3.1 shows the four social capital constructs per region.

FIGURE 3.1

INDEXED SOCIAL CAPITAL VARIABLES PER REGION



Measures of Innovation

Using patent data to measure innovation brings great advantages to this analysis, most importantly it provides information on the nature of the applicant, including physical location (Dechezlepretre et al., 2011). Each patent record has the inventor's addresses, which is used to build innovation measures per region. Moreover, each record is given a United States patent classification (USPC). The USPTO has developed a patent classification system that separates inventions depending on technical features into approximately 400 patent classes (Hall, Jaffe & Trajtenberg, 2001). Thus patent data is useful for approximating innovation in a specific industry.

Some argue against the use of patents to measure innovation (Desrochers, 1998). Indisputably, using patents brings problems of classification, as inventions can be useful in more than one sector or industry. This problem is addressed by using the OECD Technology Concordance (Johnson, 2002) to transform the patent data into sectors by the inventions' industry of manufacture. Another problem with patent data is that not all inventions are patented, and not all innovative activity becomes an invention, since product modifications and certain activities that are not patentable (Dakhli & De Clercq, 2004). Moreover, the relationship between patents and inventions may vary across industries because secrecy may be required (Popp, 2002). Finally, the problem of intrinsic variability suggests that the technical and economic significance of a patent is not equivalent (Griliches, 1998), a vital limitation of which the reader should be aware. Nonetheless, patents still remain the most objective, measurable, and readily available proxy for innovative activity. Other limitations of patent data, such as variability of patent law among countries, and differences in propensity to patent among industries (both acknowledged in Dakhli & De Clercq, 2004) are corrected by the nature of the research specific to this paper.

Following Trajtenberg (2001), descriptions of different technologies were matched with patent classifications, resulting in a set of six sectors lumping 36 sub-classifications given by the USPTO (for a complete list, see Appendix II). Using Johnson's (1999) methodology, the probability that each USPC would fall into one of the six sectors was calculated and given to each patent in this analysis. Therefore, innovation and previous knowledge for each region was calculated as a sum of probabilities for each one of the following industries: drugs and medical, computers and communications, electrical and electronics, chemical, mechanical, and other industries.

The process of assigning patents to specific regions was undertaken using ArcGIS software. The latitudes and longitudes of the author's address were distributed among the territories defined in Appendix I. Many patents are co-authored and individual authors may live in different locations. Therefore, instead of using a count of patents per region, this study calculates fractions of authorship. Each patent granted to a single author adds one point of authorship to the author's region, while a patent co-authored by two individuals from different regions adds half a point of authorship to each author's region. The number of authors per patent varied between 1 and 32, with an average of 1.14 authors per patent. Table 3.2 displays the sum of fractions of authorship equivalent to the 3,375,130 patents granted between 1975 and 2005. Figure 1 provides a visual representation of the patents' authorship among regions.

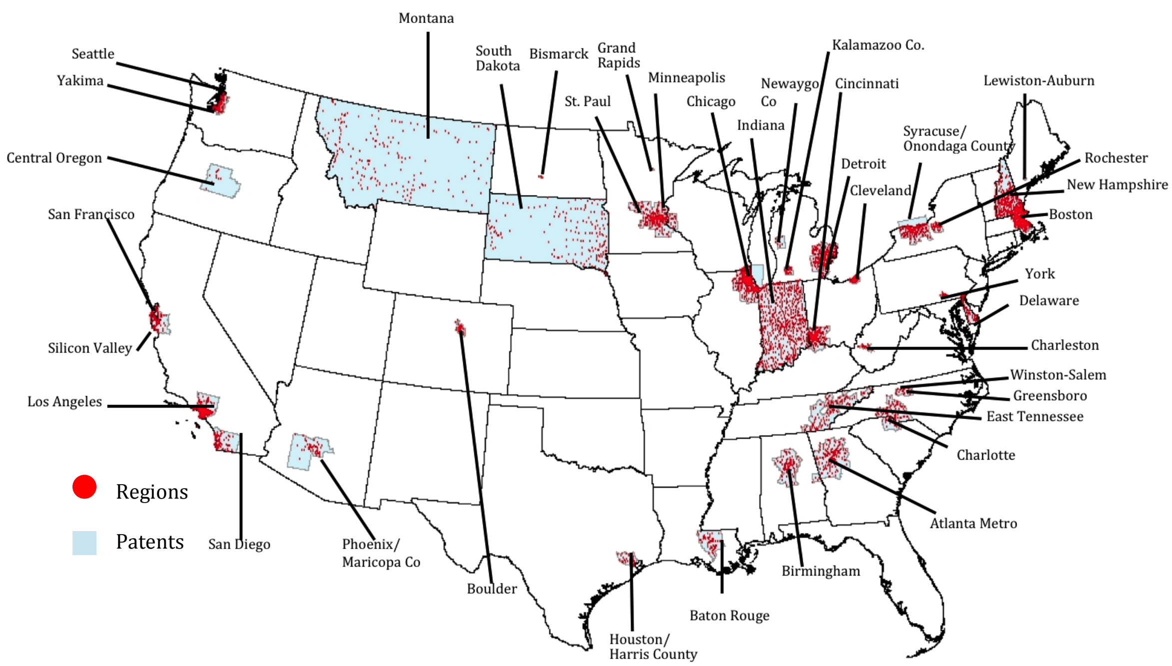
TABLE 3.2

PATENT AUTHORSHIP UNITS BY SECTOR

Sector	Patents Granted
Drugs and Medical	447,701
Computers and Communications	476,047
Electronics	607,806
Chemical	623,150
Mechanical	665,998
Other Industries	626,879

FIGURE 3.2

REGIONS STUDIED AND PATENT ALLOCATIONS



Building Stocks of Knowledge

Including information on technological opportunity is of prime importance to fully portray the factors that drive innovation (Popp, 2002). To measure previous technological capital for each region, I used patent data from years 1975 to 2004 to build stocks of knowledge. These variables indicate the previous resources available for an innovator. I added fractions of authorship per region in each sector for each year study, over 40 different regions. Equation 3.1 defines the stocks of knowledge:

$$K_{r,t} = \sum_{s=0}^{t} PAT_{r,t}\, exp[-\beta_1(t-s)]\{1-exp[-\beta_2(t-s)]\} \tag{3.1}$$

Where *K* is the stock of knowledge and *PAT* represents patent authorship fractions distributed across regions *r* over years *t*. β_1 and β_2 represent the rates of decay and diffusion respectively. The rate of decay or "obsolescence" represents the process through which a patent becomes outdated and outperformed by newer inventions, and it is linked to the concept of creative destruction. The rate of diffusion represents a patent's potential for knowledge spillovers. Finally, *(t-s)* represents the time lag between the grant year of the patent yielding previous technological resources and the grant year of the patent that benefits from such knowledge.

Using a methodology proposed by Jaffe & Caballero (1993), β_1 and β_2 capture the probability that a patent will be cited by subsequent patents. Therefore, the knowledge stocks account for the usefulness of the knowledge represented by each patent, rather than simple patent counts. Bacchiocchi & Montobbio (2010) used this exact methodology to build knowledge stocks for the same six industries used in this paper. Given the similarity of my study, I calibrated their beta coefficients and used them to develop my own stocks of knowledge based on the USPTO data previously described. Table 3.3 displays values for the rates of decay and diffusion for each of the sectors studied.

TABLE 3.3

CALIBRATED COEFFICIENTS BY INDUSTRY

Sector	**α**	**β_1**	**β_2**
Drugs and Med.	1.58	0.82	0.00095
Comp and Comm.	2.86	1.20	0.00094
Electronics	1.55	1.14	0.00093
Chemical	1.00	1.00	0.00094
Mechanical	1.15	1.10	0.00094
Others	0.99	0.97	0.00095

SOURCE: Bacchiocchi and Montobio (2010)

I developed two knowledge stocks for each industry, *KLOC* and *KNON*. The former contains previous local knowledge and the later contains previous nonlocal knowledge; that is, patents granted inside the US but outside of the region of interest. By developing two separate variables rather than one single knowledge stock, I am able to discern the effect that knowledge has on subsequent innovation depending on where it was generated. The knowledge stocks are used to approximate previous capital expenditure, as well as the knowledge that existed before the marginal invention was granted. In that way, the stocks of knowledge substitute R&D expenditure figures used in previous literature. 240 knowledge stocks were built in order to account for the yearly knowledge accumulation in each of the 40 regions and six sectors.

Other Data

Constructing other variables for this model required data at the regional level that could be matched with the measures of social capital, innovation, and technological capital. The SCCBS included information relevant to build three control variables. Human capital is approximated by the percentage of respondents who reported to have a bachelor's degree or a higher degree of education. Income was measured on a 7-point scale on brackets between $0 and over $100,000. Finally, the survey also contained information on population density in 1997 for each of the areas studied. The three control variables were included into the final six data sets, which reflect information on each region with different levels of innovation and technological capital by year and by sector.

All units of measurement for data from the SCCBS are based on scales that reflect only the magnitude of the variables, except for population density. Table 3.4 shows descriptive statistics for all the variables used in this study divided by industry of patent.

TABLE 3.4

STATISTICAL SUMMARY BY INDUSTRY

	Drugs & Medicalss				**Computers & Communications**			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Innovation	0.028	0.123	0.000	0.923	0.031	0.129	0.000	0.926
Local K	0.143	0.850	0.000	11.797	0.203	1.111	0.000	14.106
Nonlocal K	5.611	3.880	0.160	13.190	7.970	3.949	0.709	15.717
Gen Trust	50.660	8.700	36.000	75.000	50.660	8.700	36.000	75.000
Inst Trust	73.475	2.971	67.775	85.213	73.475	2.971	67.775	85.213
Group	18.508	1.648	15.381	23.356	18.508	1.648	15.381	23.356
Network	27.583	2.680	22.068	34.686	27.583	2.680	22.068	34.686
Cooperation	43.971	3.268	34.583	49.632	43.971	3.268	34.583	49.632
Human Cap	67.205	8.177	50.996	85.200	67.205	8.177	50.996	85.200
Income	2.984	0.381	2.129	4.090	2.984	0.381	2.129	4.090
Pop density	3439	4051	79	21768	3439	4051	79	21768
	Chemical				**Mechanical**			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Innovation	0.027	0.128	0.000	0.938	0.026	0.127	0.000	0.958
Local K	0.233	1.213	0.000	12.097	0.395	2.080	0.000	21.733
Nonlocal K	9.195	2.547	0.661	13.289	15.576	4.603	0.967	23.845
Gen Trust	50.660	8.700	36.000	75.000	50.660	8.700	36.000	75.000
Inst Trust	73.475	2.971	67.775	85.213	73.475	2.971	67.775	85.213
Group	18.508	1.648	15.381	23.356	18.508	1.648	15.381	23.356
Network	27.583	2.680	22.068	34.686	27.583	2.680	22.068	34.686
Cooperation	43.971	3.268	34.583	49.632	43.971	3.268	34.583	49.632
Human Cap	67.205	8.177	50.996	85.200	67.205	8.177	50.996	85.200
Income	2.984	0.381	2.129	4.090	2.984	0.381	2.129	4.090
Pop density	3439	4051	79	21768	3439	4051	79	21768
	Electronics				**Other Industries**			
Innovation	0.028	0.128	0.000	0.942	0.025	0.121	0.000	0.955
Local K	0.216	1.311	0.000	19.500	0.546	2.928	0.000	32.972
Nonlocal K	8.494	5.438	0.587	20.898	21.514	8.392	1.770	36.270
Gen Trust	50.660	8.700	36.000	75.000	50.660	8.700	36.000	75.000
Inst Trust	73.475	2.971	67.775	85.213	73.475	2.971	67.775	85.213
Group	18.508	1.648	15.381	23.356	18.508	1.648	15.381	23.356
Network	27.583	2.680	22.068	34.686	27.583	2.680	22.068	34.686
Cooperation	43.971	3.268	34.583	49.632	43.971	3.268	34.583	49.632
Human Cap	67.205	8.177	50.996	85.200	67.205	8.177	50.996	85.200
Income	2.984	0.381	2.129	4.090	2.984	0.381	2.129	4.090
Pop density	3439	4051	79	21768	3439	4051	79	21768

CHAPTER IV.

METHOD

Consistent with the literature on social capital and innovation, this paper treats innovative activity as an output resulting from the combination of different forms of capital. In particular, the number of patents in a single region as a share of all patents granted in the U.S. is defined as a function of social capital, human capital, existing knowledge from within the region and outside of it, and other control variables.

In order to analyze each industry separately, six regressions were estimated using industry-specific patent data. Two models are constructed and six regressions estimated for each. The first one is a simple OLS regression and the second one includes interaction terms. The simple model is defined by Equation 4.1.

$$
\begin{aligned}
Log(PAT_{i,r,t}/TOTPAT_{i,t}) = \alpha &+ \beta_1\, TRUST_{i,r} + \beta_2\, COOP_{i,r} + \beta_3\, NETWRK_{i,r} + \beta_4\, GROUP_{i,r} \\
&+ \beta_5\, KLOC_{i,r,t-1} + \beta_6\, KNON_{i,r,t-1} + \beta_7\, HC_{i,r} \\
&+ \beta_8\, INC_{i,r} + \beta_9\, POPDNS_{i,r} + \varepsilon_{rt}
\end{aligned} \tag{4.1}
$$

Where $PAT_{i,r,t}$ indicates the number of patents granted in region r, and year t, falling into each one of the six sectors i studied. $TOTPAT_{i,t}$ is the total successful patent applications granted nationally for sector i and year t. $TRUST_{i,r}$, $COOP_{i,r}$, $NETWRK_{i,r}$ and $GROUP_{i,r}$ approximate the four dimensions of social capital for each region, namely levels of trust, civic cooperation, networks, and associative activity. $KLOC_{i,r,t-1}$ and $KNON_{i,r,t-1}$ represent the knowledge or existing technological capital used to innovate in each region *r* on period *t-1*. *KLOC* measures previous local knowledge, while *KNON* approximates the existing inventions outside of the community at hand. $HC_{i,r}$, $INC_{i,r}$ and $POPDNS_{i,r}$ are measures of human capital, income and population density respectively.

The dependent variable, innovative activity, is specified as the natural log of a percentage of patents for the region. By using a percentage rather than the raw patent count, the model accounts for growth in the sector while respecting exogenous changes in patenting behavior (Popp, 2002).

Inclusion of Interaction Terms

Besides the simple model outlined in Equation 4.1, another semi-log OLS was calculated using interaction terms between the knowledge stocks and the social capital measures. The purpose of the second model (Equation 4.2) is to estimate the effect of previous local and nonlocal knowledge on innovation, depending on the levels of regional social capital, via interaction terms.

$$\begin{aligned} Log(PAT_{i,r,t}/TOTPAT_{i,t}) = {} & \alpha + \beta_1\, TRUST_{i,r} + \beta_2\, COOP_{i,r} + \beta_3\, NETWRK_{i,r} + \beta_4 \\ & GROUP_{i,r} + \beta_5\, KLOC_{i,r,t-1} + \beta_6\, KNON_{i,r,t-1} + \beta_7\, HC_{i,r} + \beta_8\, INC_{i,r} + \beta_9\, POPDNS_{i,r} \\ & + \beta_{10}\, KLOC{*}TRUST_{i,r,t} + \beta_{11}\, KLOC{*}COOP_{i,r,t} + \beta_{12}\, KLOC{*}NETWRK_{i,r,t} \\ & + \beta_{13}\, KLOC{*}GROUP_{i,r,t} + \beta_{14}\, KNON{*}TRUST_{i,r,t} + \beta_{15}\, KNON{*}COOP_{i,r,t} \\ & + \beta_{16}\, KNON{*}NETWRK_{i,r,t} + \beta_{17}\, KNON{*}GROUP_{i,r,t} + \varepsilon_{rt} \end{aligned} \tag{4.2}$$

This model enables a richer analysis that is based not only on the presence of different types of social capital, but also on the joint effect between previous knowledge and social capital. In other words, it allows the testing of the second hypothesis, which predicts an increased effect of previous technological capital on future innovative activity in the presence of greater levels of regional social capital. The results that follow explore the effect of social capital individually as well as the interaction between previous knowledge and social capital manifestations.

An OLS regression is chosen over other estimation methods given the nature of social capital. Recall that the literature assumes social capital to be incorporated in the analysis as a cultural variable and by definition any changes in social capital should be reflected very slowly over time. Therefore, a single level of social capital per region is assumed to exist in the years studied. Furthermore, as a cultural factor, social capital is assumed to be always desirable and therefore never display a negative value. Using other methods would imply breaking some of these assumptions. A fixed effects estimation would yield truncated results, as only the variables that change over the time studied would be reported. Similarly, although the use of independent variables built on survey data may suggest that a Tobit model may help correct for answers including a “zero” value or some other cutoff (Stewart, 2009), my model assumes that the latent variable and the observed dependent variable will be equal at all times. That is, the latent variable for social capital will never be negative. Thus, an OLS estimation becomes even more appealing as it allows to understand the effects of both, knowledge-based and social capital variables, while still treating social capital as the culture-specific factor that is not accounted by other explanatory variables.

CHAPTER V.

RESULTS

The six simple OLS regressions and the other six with interaction terms were estimated to measure the effect of social capital on innovation. Several tests were conducted on each regression to detect and address econometric problems. A White test and a Breusch-Pagan test suggested the presence of heteroskedasticity in the analysis. Therefore, the results reported in Table 5.1 include robust standard errors in order to correct this problem. A time variable was added in order to decrease autocorrelation among social capital variables. However, the data still present problems of autocorrelation, showing F-statistics between 7.09 and 26.1 depending on the industry. Similarly, the two original measures of trust were merged, obtaining limited multicollinearity between social capital and knowledge variables. However, multicollinearity is a very real empirical challenge among social capital dimensions.

Adjusted R-squared values in the simple, robust OLS regression range from 51.1 % to 66.5 %, depending on the sector studied. Overall, there is high statistical significance for most variables in all industries. 54 % of the variance in innovative activity in the drugs and medical industry is explained by the model. Computers and communications display the greatest Adj. R-squared value, with 66.5, followed by electrical and electronics with 58.7 and chemical with 54.3. The Adj. R-squared for the mechanical sector and other industries are 51.9 and 51.1 respectively.

The magnitude and sign of the coefficients from the first model show evidence supporting this study's main hypothesis. Previous local knowledge has a large, positive, and significant effect on subsequent innovation for each one of the six sectors studied. Similarly, the knowledge stock derived from outside of the region is negatively correlated with the measure of innovation and statistically significant in four out of the six industries. The large number of nonlocal patents compared to the local ones may explain the negative correlation. Coefficients for drugs and medical, and chemical may not be significant because of industry-specific practices. As Popp (2002) points out, in the chemical industry a large number of new innovations are patented. Thus, the large size of the industry may play a specific role when accounting for the patents outside of a delimited region that is not present in other industries.

Human capital and other control variables behave as expected, and are statistically significant in the model. The greater the share of population with a college degree, the more innovative a region tends to be. Similarly, a region with higher levels of household income tends to be more innovative, *ceteris paribus*. The correlation between income and innovation is very strong, and statistically significant to the 1 % level in all sectors except for drugs and medical, where it is statistically significant at the 10 % level.

The social capital dimensions show different effects on innovation, which is worth analyzing in depth. All together, the four variables explain an increase of seven points in the model. Looking at the regression for drugs and medical, the Adj. R-squared value without considering social capital equals 0.47. The fact that 7 % of the change in innovative activity can be explained by accounting for trust, associative activity, networks, and civic cooperation, suggests that social capital indeed is an important determinant for innovation.

Norms of civic cooperation and networks have a positive effect on regional innovative activity across sectors. Civic cooperation specifically is statistically significant across industries, with the highest coefficients in the drugs and medical and mechanical sectors. The positive effect of network capacity is significant in the computers and communications, electrical and electronics, and chemical sectors. Contrarily to the predictions in this study, evidence was found to suggest a negative impact of associative activity on innovation. Consistently across industries, the average number of formal and informal groups to which a subject belongs was negatively correlated to the levels of innovation in each region. This suggests that grouping activity may hinder to a certain extent the possibility to innovate. Theoretically, this claim is supported by Fukuyama (1999), as long as the regions studied act more as traditional social groups, rather than modern societies. The so-called "radius of trust" refers to the circle of people among whom cooperative norms are operative (p. 3). Theory claims that negative externalities may emerge from a small radius of trust, in which the priorities or values of a specific group are praised over general societal values, hence limiting the region's overall innovative capacity. Furthermore, given limited time resources of each individual, regions with higher levels of grouping activities may not spend as much time innovating or more specifically patenting inventions.

Trust, the final social capital variable, has a positive and significant effect on innovative activity in the following sectors: drugs and medical, computers and communications, and electrical and electronics. It shows a negative effect in the chemical industry, which could be caused by sector-specific factors that may encourage the enforcement of formal agreements instead of actions based on goodwill, trust, and trustworthiness. Overall, manifestations of social capital are shown to have different effects on innovation. Norms of civic cooperation, network capacity, and levels of trust, have a positive effect on regional innovative activity.

The second model analyzed in this paper adds robustness to the results, by providing more evidence that social capital indeed has an effect on innovative activity. Table 5.2 reports the coefficients from an OLS with interaction terms.

These results confirm that norms of civic cooperation are positively correlated with innovative activity. Furthermore, not only does a region benefit from cooperation, but the stronger the practice of civic cooperation, the stronger the effect of previous knowledge in future innovation. The effect is positive when the previous knowledge comes from within the region, and it is statistically significant across the six sectors studied. The coefficients are much stronger than the ones from the simple robust OLS, especially in the drugs and medical sector. Furthermore, the interaction terms between nonlocal knowledge and norms of civic cooperation across sectors suggest a somehow less strong negative and statistically significant relation with innovative activity in four out of six sectors.

TABLE 5.1

ROBUST OLS ESTIMATIONS

	Drugs & Med.		Comp and Comm.		Electronics		Chemical		Mechanical		Other Industries	
Local K	0.912	***	0.703	***	0.523	***	0.773	***	0.402	***	0.270	***
	(8.44)		(8.50)		(7.08)		(13.69)		(10.57)		(9.13)	
Nonlocal K	-0.05		-0.126	**	-0.112	***	-0.024		-0.068	**	-0.040	*
	(-1.81)		(-3.11)		(-5.33)		(-0.57)		(-2.62)		(-2.37)	
Trust	0.048	***	0.059	***	0.042	***	-0.029	**	0.014		-0.015	
	(4.33)		(5.30)		(3.92)		(-2.86)		(1.28)		(-1.36)	
Groups	-0.204	***	-0.476	***	-0.365	***	-0.217	***	-0.295	***	-0.225	***
	(-7.80)		(-15.56)		(-12.37)		(-7.40)		(-10.28)		(-7.72)	
Networks	0.012		0.176	***	0.119	***	-0.049	*	0.046		0.020	
	(0.49)		(7.29)		(4.43)		(-2.06)		(1.80)		(0.81)	
Cooperation	0.149	***	0.082	***	0.096	***	0.145	***	0.065	***	0.062	***
	(9.5)		(5.20)		(6.36)		(9.00)		(4.48)		(3.96)	
Human Capital	0.024	*	0.090	***	0.016		0.041	***	0.034	***	0.031	**
	(2.1)		(7.83)		(1.53)		(3.75)		(3.33)		(3.28)	
Income	1.091	*	1.029	***	1.580	***	1.071	***	1.526	***	1.522	***
	(6.38)		(5.99)		(10.39)		(5.82)		(9.03)		(9.34)	
Pop Density	0.000	***	0.000	***	0.000	***	0.000	***	0.000	***	0.000	***
	(10.91)		(5.49)		(8.27)		(5.49)		(4.72)		(4.77)	
Year			0.000		0.021		-0.009		0.010		0.012	
			(-0.01)		1.65		(-0.81)		(0.80)		(0.78)	
Constant	-1.176		-17.497		-57.421	*	6.371		-31.823		-34.737	
	(-0.5)		(-0.49)		(-2.24)		(0.29)		(-1.30)		(-1.12)	
R-sqr	0.543		0.665		0.587		0.543		0.519		0.511	
Obs	1061		980		1075		1113		1163		1182	
***: 1% **:2% *: 10% significance level												

TABLE 5.2

ROBUST OLS ESTIMATIONS WITH INTERACTION TERMS

	Drugs & Med.		Comp and Comm.		Electronics		Chemical		Mechanical		Other Industries	
Local K	-102.020	***	10.988		-13.545		-194.295	***	-17.774		-16.077	
	(-4.61)		(0.63)		(-1.07)		(-8.67)		(-1.02)		(-1.51)	
Nonlocal K	-0.528		*-0.979	*	-0.276		1.248	*	0.074		0.104	
	(-1.64)		(-2.56)		(-1.16)		(2.50)		(0.28)		(0.66)	
Trust	0.01		0.017		0.021		-0.037		-0.015		-0.033	
	(0.6)		(0.79)		(1.18)		(-0.96)		(-0.42)		(-1.23)	
Groups	-0.283	***	-0.532	***	-0.367	***	-0.253	**	-0.173		-0.114	
	(-7.92)		(-8.46)		(-8.34)		(-2.92)		(-1.94)		(-1.78)	
Networks	-0.004		0.172	***	0.202	***	-0.055		0.280	***	0.144	***
	(-0.12)		(3.78)		(4.83)		(-0.82)		(3.78)		(2.58)	
Cooperation	0.105	***	0.001		0.054		0.194	**	-0.045		-0.007	
	(3.98)		(0.02)		1.89		(3.18)		(-0.78)		(-0.14)	
Human Capital	0.022	*	0.073	***	0.009		0.045	***	0.039	***	0.023	*
	(2.12)		(6.54)		(0.88)		(5.01)		(4.37)		(2.53)	
Income	0.629	***	0.821	***	1.138	***	0.571	***	0.738	***	1.034	***
	(4.00)		(5.14)		(7.52)		(3.71)		(5.44)		(7.56)	
Pop Density	0.000	***	0.000	***	0.000	***	0.000	***	0.000		0.000	*
	(9.01)		(4.64)		(5.26)		(4.04)		(1.86)		(2.41)	
Local K*Trust	0.177		-0.256		-0.342	*	2.108	***	0.538	***	0.183	
	(0.56)		(-1.85)		(-2.56)		(8.96)		(3.92)		(1.73)	
Local K*Group	2.990	***	0.956		2.150	***	-0.757		-0.949		-0.381	
	(4.49)		(1.53)		(3.61)		(-1.35)		(-1.95)		(1.24)	
Local K*Networks	-3.114	***	-3.236	***	-2.924	***	-0.760	**	-1.975	***	-1.027	***
	(-7.15)		(-13.02)		(-10.05)		(-2.61)		(-9.69)		(-7.98)	
Local K*Coop	3.009	***	1.904	***	1.877	***	2.487	***	1.424	***	0.983	***
	(7.68)		(9.77)		(8.24)		(10.87)		(7.54)		(10.11)	
Year	-0.012		-0.013		0.011		-0.002		0.007		0.005	
	(-1.03)		(-0.80)		(0.89)		(-0.25)		(0.64)		(0.35)	
***: 1% **:2% *: 10% significance level												

TABLE 5.2. CONTINUED

ROBUST OLS ESTIMATIONS WITH INTERACTION TERMS

	Drugs & Med.		Comp and Comm.		Electronics		Chemical		Mechanical		Other Industries	
Nonlocal K*Trust	0.001		0.004		0.002		-0.008	*	-0.000		-0.001	
	(0.6)		(1.42)		(0.86)		(-2.02)		(-0.05)		(-0.57)	
Nonlocal K*Group	0.023	***	0.019	*	0.010	*	0.011		0.003		0.003	
	(3.78)		(2.55)		(2.12)		(1.21)		(0.47)		(1.11)	
Nonlocal K*Networks	0.021	***	0.023	***	0.007		0.009		0.001		0.002	
	(3.61)		(3.88)		(1.83)		(1.35)		(0.11)		(0.98)	
Nonlocal K*Cooperation	-0.015	***	-0.008		-0.007	*	-0.029	***	-0.005		-0.005	*
	(-3.78)		(-1.84)		(-2.46)		(-4.52)		(-1.28)		(-2.49)	
Constant	14.187		16.075		-33.434		-6.246		-25.364		-19.598	
	(0.62)		(0.51)		(-1.41)		(-0.32)		(-1.20)		(-0.71)	
R-sqr	0.64		0.736		0.654		0.660		0.660		0.626	
Obs	1061		980		1075		1113		1163		1182	
***: 1% **:2% *: 10% significance level												

Associative activity is positively related to innovation in the presence of previous knowledge. This may reflect the interaction in formal and informal groups between previous innovators and current ones. In the drugs and medical, and electrical and electronics sectors, both local and nonlocal knowledge interact positively with associative activity. The effect is greater for local knowledge, although it is also statistically significant for nonlocal knowledge in the computers and communications industries.

In the electrical and electronics, chemical, and mechanical sectors, a region with higher levels of trust provides a greater impact of previous local knowledge on innovation. When the interaction terms are included in the regression, the effect of trust alone is statistically insignificant. This result may suggest that trust is a catalyst for innovative activity but it may not be sufficiently strong to boost innovation on its own.

Unexpectedly, greater propensity to network results in lower innovative activity in regions with higher local knowledge banks. However, in the presence of past nonlocal knowledge, network capacity has a positive effect on innovation, at least in the first three sectors studied. Given the fact that previous local knowledge tends to be much smaller than previous nonlocal knowledge, the impact of network capacity on innovation may be subject to the size and nature of possible knowledge spillovers within a community. Further research on this specific topic could be potentially useful to the literature on innovation and social capital given that this model provides information on the specific effects of the combination of previous knowledge and social capital dimensions such as networks.

Computers and communications is again the sector with the highest Adjusted R-squared value, reporting a strong 73.6 % of the variation in the natural log of the innovative activity measured around its mean explained by the model. The smallest Adjusted R-squared value obtained with interaction terms is a compelling 62.6 % for other industries.

The marginal effects of all the dependent variables in the presence of interaction terms were calculated to analyze elasticities. Out of the social capital variables, civic cooperation shows the greatest marginal effect on innovation. Averaging the elasticities on the six industries studied, a one-unit increase in the civic cooperation index generates 0.47 extra units of innovation. Similarly, a marginal increase in the levels of trust increases innovative activity by 0.05 units. Associative activity and networks have a negative effect equal to 0.12 and 0.39 units of innovation per unit increase. Table 5.3 reports the marginal effects for all the variables across sectors, with standard errors in parenthesis.

These results suggest that not all dimensions of social capital affect innovative activity to the same magnitude. Civic cooperation translates into more innovative activity consistently across industries and under different models tested. In the drugs and medical sector, a region that has a previous local knowledge of 0.14 (the average of the sample), a one unit increase in the cooperation index will produce a 0.52 increase in innovative activity.

The interaction terms suggest that efforts should not only be placed on developing cooperation, networks and trust; rather, creating a solid base of local existing knowledge and social capital simultaneously may boost innovative activity even further. Associative activity, which initially seemed to act against innovation, is shown to increase innovative activity in the presence of previous local knowledge. The results are useful to regional and national stakeholders as will be reflected in the next section.

TABLE 5.3

MARGINAL EFFECTS OF DEPENDENT VARIABLES ACROSS INDUSTRIES

Variable	**Drugs & Med.**	**Comp & Comm.**	**Electronics**	**Chemical**	**Mechanical**	**Other Industries**	**Average**
Local K	11.22	7.29	7.19	10.66	6.15	3.15	11.22
	(0.75)	(0.56)	(0.63)	(0.51)	(0.41)	(0.26)	(0.75)
Nonlocal K	-0.08	-0.11	-0.11	-0.07	-0.07	-0.04	-0.08
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)
Trust	0.05	0.01	-0.05	0.42	0.21	0.06	0.05
	(0.04)	(0.02)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)
Groups	0.34	-0.18	0.24	-0.34	-0.52	-0.26	0.34
	(0.07)	(0.13)	(0.13)	(0.12)	(0.17)	(0.15)	(0.07)
Networks	-0.39	-0.42	-0.45	-0.16	-0.53	-0.38	-0.39
	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.06)	(0.05)
Cooperation	0.51	0.40	0.45	0.56	0.47	0.44	0.51
	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.04)	(0.04)
Human Cap	0.02	0.07	0.01	0.04	0.04	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income	0.63	0.84	1.14	0.57	0.74	1.03	0.63
	(0.16)	(0.16)	(0.15)	(0.15)	(0.14)	(0.14)	(0.16)
Pop Den	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

CHAPTER VI.

CONCLUSION

This paper analyzes the relationship between social capital and innovation by answering two questions: Does social capital determine innovation? And more importantly, does social capital combined with previous technological capital spur future innovative activity? To address these questions I reviewed current literature to find a proven method that includes social capital as a factor of innovative activity. The literature also points to the multidimensional nature of social capital, as well as to the complexity of definition (and therefore, of measurement). Therefore, I added four dimensions of social capital: levels of trust, associative activity, degree of networks and norms of civic cooperation, as well as a measure of human capital to the traditional determinants of innovation. Based on previous studies on innovation, I built a strong measure of technological capital in the form of knowledge stocks, which is specifically useful to answer my second hypothesis.

Using a proven survey of over 26,000 Americans in 40 regions, and 38 years of patent data, I created a panel dataset with levels of technological, human, and social capital. I separated the patents into six different sectors aiming to analyze the effect of social capital on innovation across industries.

The set of regressions outlined in this paper allow for the interpretation of novel results based on the coefficients of interaction terms between measures of technological capital and social capital. The evidence makes contributions to the scanty empirical literature on social capital and innovation, suggesting that different measures of social capital have different effects on innovative activity at the regional level in the United States. Specifically, levels of civic cooperation contribute more than any other measure of social capital to innovative activity across all industries, with an average marginal effect of 0.47 units of innovative activity.

Regarding the interaction between social capital and previous technological capital, I find evidence of positive effects between local knowledge and three measures of social capital: levels of trust, associative activity, and norms of civic cooperation. Similarly, networks and previous nonlocal knowledge have a jointly significant, positive effect in two sectors of the economy.

The results should be carefully interpreted for a range of reasons. The units of measurement for previous innovation are based on probabilities, rather than actual counts. Social capital constructs are indexed based on averages and by no means reflect the full scope of this complex and intangible process. Nonetheless, each one of the four constructs has been carefully designed based on solid theoretical backgrounds, drawing from comparable methods used in previous studies.

There are obvious data limitations in this study. Problems of multicollinearity among social capital measures are a major empirical challenge that could be fixed by carefully defining and gathering data for more specific measures of social capital. Furthermore, the analysis undertaken clearly focuses on certain regions in the United States, omitting many other regions for which data on social capital is unavailable.

This study contributes to the advancement of knowledge on innovative activity by demonstrating that greater associative activity alone is not enough to increase innovation. In fact, the simple model suggests a significant and negative effect on innovation across sectors. However, in the presence of previous knowledge, greater associative activity tends to show a positive effect on innovation.

Previous technological capital has a very strong effect on future innovation, confirming intuitive predictions. The inclusion of knowledge stocks to estimate this form of capital is novel in the literature of social capital substituting R&D expenditure, a measure with many limitations specifically for a regional analysis. The two knowledge stocks reflect local and nonlocal previous technological capital, and demonstrate the impact of social capital under different circumstances. While levels of trust, associative activity, and cooperation boost innovation in the presence of local knowledge stocks, networks have a negative effect unless combined with nonlocal previous knowledge.

The results in each industry provide compelling insights for policymaking. The multi-sectoral nature of this analysis offers robust checks for stakeholders in each sector, confirming that local and nonlocal previous technological capital explain regional innovative activity. Electrical and electronics is the sector with greatest statistical significance for the interaction between knowledge stocks and social capital measures. The analysis indicates that human capital and three measures of social capital positively contribute to the innovative process, holding everything else constant. Depending on the nature of the existing knowledge, and the measure of social capital at hand, the effect on innovation may change in direction and magnitude. The combination of local knowledge and most measures of social capital consistently determine greater innovative activity across six sectors of the economy.

Future researchers should focus on other aspects of social capital whenever data allows for it. The inclusion of knowledge stocks as a measure of technological capital opens many doors for further analysis of the effect of social capital under different types of previous knowledge accumulation. As technology evolves, the scope of analysis for social capital measures may become more specific and reliable studies at the individual or company level may be undertaken to expand the applicability of this investigation. In-depth analyses of specific industries, as well as closely defined aspects of human capital may provide more evidence on the field. Regional empirical research in areas outside of the United States could further expand the limited, yet growing literature on nontraditional determinants of innovation.

APPENDIX I

REGIONS, SPONSORS AND SAMPLE SIZES

Sponsor	Region	Sample Size
Arizona Community Foundation (C.F)	Maricopa County	501
C.F> For Greater Atlanta	Counties: DeKalb, Fulton, Cobb, Rockdale, Henry	510
Forum 25/Batpm Rouge Area Foundation	East Baton Rouge Parish	500
C.F. of Greater Birmingham (AL)	Counties: Jefferson, Shelby	500
Boston Foundation	City of Boston (includes oversample of 200 in 4 zip codes)	604
C.F. Serving Boulder County	Boulder Co.	500
Foundation for the Carolinas	Counties: N.C.: Catawba, Iredell, Rowan, Cleveland, Lincoln, Gaston, Mecklenburg, Cabarrus, Stanly, Union, Anson; S.C.: York, Chester, Lancaster	1500
Central New York C.F.	Onondaga Co (includes City of Syracuse)	541
Chicago Community Trust	Counties: Lake, McHenry, Cook, DuPage, Kane and Will.	750
Greater Cincinnati Foundation	Counties: OH: Butler, Clermont, Hamilton, Warren; KY: Boone, Campbell, Kenton; IN: Dearborn	1001
Cleveland Foundation	Cuyahoga Co. (includes oversample of 100 Latinos)	1100
Delaware Division of State Service Centers/ Delaware C.F.	Kent County, Sussex County, city of Wilmington, non-Wilmington New Castle County	1379
Denver Foundation/Rose C.F./Piton Foundation	City and County of Denver	501
Anonymous funder	Portions of the "Oakland Corridor" (in W. Oakland, CA) covered by the following exchanges in Area Code 510: 208, 238, 268, 452, 465, 632, 652, 655, 663, 673, 763, 832, 834, 835, 839	500
East Tennessee Foundation	Counties: Anderson, Blount, Campbell, Claiborne, Cocke, Grainger, Greene, Hamblen, Hawkins, Hancock, Jefferson, Knox, Loudon, Monroe, McMinn, Morgan, Roane, Scott, Sevier, Union, Unicoi, and Washington.	500
Fremont Area C.F. (MI)	Newaygo County (with screening)	753
Grand Rapids C.F.	City of Grand Rapids	502
C.F. of Greater Greensboro	Guilford County, (includes oversample of 250 in Greensboro)	750
Greater Huston C.F.	Harris county Indiana Grantmakers Alliance State of Indiana	500
Greater Kanawha Valley Foundation	Counties: Kanawha, Putnam, Boone	1001

APPENDIX I (CONTINUED)

Sponsor	**Region**	**Sample Size**
Kalamazoo C.F.	Kalamazoo County	500
California C.F.	Los Angeles County	515
Maine C.F.	Cities/Towns: Lewiston, Auburn, Greene, Sabattus, Lisbon, Mechanic Falls, Poland, Turner, Wales, Minot	523
Montana C.F.	State of Montana	502
New Hampshire Charitable Foundation	State of NH. (includes oversample of 160 in Cheshire County and 40 in I-93 corridor"*)	711
Peninsula C.F./ C.F. Silicon Valley	Counties: San Mateo, Santa Clara Part of Alameda County: Fremont, Newark, Union City	1505
Rochester Area C.F.	Counties: Monroe, Wayne, Ontario, Livingston, Genesee, Orleans (includes oversample to achieve minimum of 100 Hispanics and 100 African Americans)	988
The St. Paul Foundation	Counties: Dakota, Ramsey, Washington	503
The San Diego Foundation	San Diego County	504
Walter & Elise Haas Fund	City & County of San Francisco	500
C.F. for Southeastern Michigan	Counties: Wayne, Oakland, Macomb, St.Clair, Wasthenaw, Monroe, Livingston	501
Winston-Salem Foundation	Forsyth County	750
York Foundation (PA)	York County	500
Northwest Area Foundation		
Minneapolis	City of Minneapolis	501
North Minneapolis	ZIP 55411 & ZIP 55405 north of I-394 (with screening)	452
S. Dakota (rural)	rural South Dakota	368
Central Oregon	central Oregon	500
Seattle	City of Seattle	502
Yakima	Yakima County	500
Bismarck	City of Bismarck	506

Source: USSCB

APPENDIX II

CLASSIFICATION OF PATENT CLASSES INTO SECTORS AND SUB-CATEGORIES

Sector	Sub-Cat Code	Sub-Cat Name	Patent Classes
Drugs & Medicals	31	Drugs	424, 514
	32	Surgery & Medicals Instruments	128, 600, 601, 602, 604, 606, 607
	33	Biotechnology	435, 800
	39	Miscellaneous-Drug&Med	351, 433, 623
Computers & Communications	21	Communications	178, 333, 340, 342, 343, 358, 367, 370, 375, 379, 385, 455
	22	Computer Hardware & Software	341, 380, 382, 395, 700, 701, 702, 704, 705, 706, 707, 708, 709, 710, 712, 713, 714
	23	Computer Peripherals	345, 347
	24	Information Storage	360, 365, 369, 711
Chemical	11	Agriculture, Food, Textiles	8, 19, 71, 127, 442, 504
	12	Coating	106,118, 401, 427
	13	Gas	48, 55, 95, 96
	14	Organic Compounds	534, 536, 540, 544, 546, 548, 549, 552, 554, 556, 558, 560, 562, 564, 568, 570
	15	Resins	520, 521, 522, 523, 524, 525, 526, 527, 528, 530
	19	Miscellaneous-chemical	23, 34, 44, 102, 117, 149, 156, 159, 162, 196, 201, 202, 203, 204, 205, 208, 210, 216, 222, 252, 260, 261, 349, 366, 416, 422, 423, 430, 436, 494, 501, 502, 510, 512, 516, 518, 585, 588
Electrical & Electronic	41	Electrical Devices	174, 200, 327, 329, 330, 331, 332, 334, 335, 336, 337, 338, 392, 439
	42	Electrical Lighting	313, 314, 315, 362, 372, 445
	443	Measuring & Testing	73, 324, 356, 374
	44	Nuclear & X-rays	250, 376, 378
	45	Power Systems	60, 136, 290, 310, 318, 320, 322, 323, 361, 363, 388, 429
	46	Semiconductor Devices	257, 326, 438, 505
	49	Miscellaneous-Elec.	191, 218, 219, 307, 346, 348, 377, 381, 386

APPENDIX II (CONTINUED)

Sector	Sub-Cat Code	Sub-Cat Name	Patent Classes
Mechanical	51	Materials Processing. & Handling	65, 82, 83, 125, 141, 142, 144, 173, 209, 221, 225, 226, 234, 241, 242, 264, 271, 407, 408, 409, 414, 425, 451, 493
	52	Metal Working	29, 72, 75, 76, 140, 147, 148, 163, 164, 228, 266, 270, 413,419, 420
	53	Motors, Engines & Parts	91, 92, 123, 185, 188, 192, 251, 303, 415, 417, 418, 464, 474, 475, 476, 477
	54	Optics	352, 353, 355, 359, 396, 399
	55	Transportation	104, 105, 114, 152, 180, 187, 213, 238, 244, 246, 258, 280, 293, 295, 296, 298, 301, 305, 410, 440
	59	Miscellaneous-Mechanical	7, 16, 42, 49, 51, 74, 81, 86, 89, 100, 124, 157, 184, 193, 194, 198, 212, 227, 235, 239, 254, 267, 291, 294, 384, 400, 402, 406, 411, 453, 454, 470, 482, 483, 492, 508
Others	61	Agriculture, Husbandry, Food	43, 47, 56, 99, 111, 119, 131, 426, 449, 452, 460
	62	Amusement Devices	273, 446, 463, 472, 473
	63	Apparel & Textile	2, 12, 24, 26, 28, 36, 38, 57, 66, 68, 69, 79, 87, 112, 139, 223, 450
	64	Earth Working & Wells	37, 166, 171, 172, 175, 299, 405, 507
	65	Furniture, House Fixtures	4, 5, 30, 70, 132, 182, 211, 256, 297, 312
	66	Heating	110, 122, 126, 165, 237, 373, 431, 432
	67	Pipes & Joints	138, 277, 285, 403
	68	Receptacles	53, 206, 215, 217, 220, 224, 229, 232, 383
	69	Miscellaneous-Others	1, 14, 15, 27, 33, 40, 52, 54, 59, 62, 63, 84, 101, 108, 109, 116, 134, 135, 137, 150, 160, 168, 169, 177, 181, 186, 190, 199, 231, 236, 245, 248, 249, 269, 276, 278, 279, 281, 283, 289, 292, 300, 368, 404, 412, 428, 434, 441, 462, 503

Source: Hall, Jaffe, & Trajtenberg (2001)

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