

The Psychology of Entrepreneurship and the Technological Frontier – A Spatial
Econometric Analysis of Regional Entrepreneurship in the United States

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To my beautiful wife Melissa and my two amazing children Jacob and Grace

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ABSTRACT

THE PSYCHOLOGY OF ENTREPRENEURSHIP AND THE TECHNOLOGICAL FRONTIER – A SPATIAL ECONOMETRIC ANALYSIS OF REGIONAL ENTREPRENEURSHIP IN THE UNITED STATES

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Theories of economic growth have long recognized that the majority of growth results from endogenous changes in technology that emerge from the profit motivated development of new knowledge. However, recent theorizing has suggested that the creation of knowledge in and of itself does not directly or immediately translate into changes in technological productivity as it must first be actively converted from concept into means of production. These developments have led to spatially interdependent models of economic growth that are based not only on the development of knowledge but also on the commercialization and diffusion of it. This dissertation seeks to empirically examine some of the key propositions of these new theoretical models. Specifically, the relationship between productivity and entrepreneurship will be scrutinized with respect to the technological frontier. As well, the concept of regional psychological capital will be probed as an explanation for the proclivity of entrepreneurial activity in certain regions.

CHAPTER 1 INTRODUCTION

It would be an understatement to say that entrepreneurship is in vogue today. It is celebrated within the scholarly literature, the public discourse and in the popular press. It is considered by many to be critical to the salvation of the U.S. economy and, for that matter, the whole of the industrialized world. To that end, regional development policies are increasingly being formulated with the explicit goal of stimulating entrepreneurship in order to induce economic growth (Hart 2003; Acs and Stough 2008).

Yet with the entrepreneurship literature mounting and with so many development policies being based on it, it is a bit surprising to reflect on the simple relationships that we have yet to sufficiently understand. In fact, there are a number of gaps in the scholarly literature as it relates to entrepreneurship that deserves closer attention. The first and most pressing concern is the very relationship between entrepreneurship and economic growth at the level of the functional regional economy. This relationship, in spite of the vastness of scholarly work on the topic, remains unclear. Surely, much evidence exists to support the entrepreneurial driven growth models on which many regional development policies are based. Yet on the other hand, the counter evidence is strong enough to warrant additional, and more refined empirical attention. The second and more

overlooked issue involves the question of whether entrepreneurship is a growth enhancing mechanism for all types of regional economies, technological leading and lagging alike. Numerous policies, such as those aimed at stimulating rural entrepreneurship and/or entrepreneurship in developing countries, implicitly assume that “entrepreneurship gardening” is always an advantageous growth strategy. This assumption, however, is at odds with several recent theoretical economic growth developments and is, to date, under analyzed in the empirical literature. Lastly, there is a substantial amount of uncertainty over the relevance of individual, and especially collective, psychological characteristics as determinants of entrepreneurship. While a well defined set of human psychological characteristics have often been associated with individual entrepreneurs, and while psychological capital has been linked with successful firms in fields such as organizational behavior, the possible regional manifestation of psychological characteristics as a form of “capital” has been completely ignored in the economics, regional science and policy literatures surrounding the determinants of entrepreneurship.

This dissertation takes a three pronged approach to help fill in these gaps in understanding. It will begin by first examining the impact of entrepreneurship on variation in regional productivity relative to its main theoretical rival, the stock of regional knowledge or rather technical knowhow. Attention will then turn to an examination of these relationships with respect to the technological frontier. Lastly, this dissertation will examine the efficacy of psychological capital as an important

determinant of regional entrepreneurship in order to provide the broader policy community with some initial empirical evidence regarding the relevance of psychological characteristics to entrepreneurship that is not tied to the study of individual entrepreneurs. As such, this dissertation can generally be described as an econometric analysis of the inputs and outcomes of regional entrepreneurship that relies on recent developments in the field of spatial econometrics.

1.1 Entrepreneurship and Growth

The sources of economic growth have been sought after by economists for centuries. Over time, their developments have been amalgamated into several primary theories that have come to dominate this literature. Made famous by Robert Solow and others, neoclassical theory ties economic growth to the endogenous accumulation of labor, savings and physical capital (Harrod 1939; Solow 1956; Swan 1956; Domar 1957). However, further neoclassical work found that, while labor and physical capital accumulation were important, they could not explain the lion's share of observed growth through time (Abramovitz 1956; Solow 1957). The unexplained portion was soon labeled the technical residual and was attributed to exogenous technological progress. So while identifying technical change as tantamount to economic growth, neoclassical theories failed to actually explain the vast majority of it.

The explanation was subsequently provided in the late 1980's by endogenous growth theory. This theory identified the purposeful creation of new knowledge as the fundamental driver of technical change and thus of economic growth or productivity (Romer 1986; 1990; Lucas 1988). This type of theoretical model relied on the creation of new knowledge and the process of human capital accumulation that produces it to posit that economic output meaningfully expands when new knowledge about ways of doing either old or new things yields more productive combinations of labor and capital, i.e. when it changes the state of the technology. Endogenous changes in technology yield increases in productivity, which in turn, enables the same quantities of resources to yield greater amounts of output.

In light of these developments, a large body of literature has arisen to empirically confirm the theoretical link between productivity and knowledge creation. However, there are many examples of places that seem to defy this relationship in the real world. In particular, the regional economies of Continental Europe are often used as a case in point. Despite high levels of investment in knowledge production, economic growth and productivity remain modest. Another example is the regional economies of the “rust belt” of the Midwestern United States. A large number of highly successful and well funded research universities exist across the entire region. As well, huge industrial research and development complexes exist in many of the region's cities, yet economic growth rates and levels of productivity increase have lagged behind other regions for at least the last few decades.

Recent theoretical work has sought to address this growth paradox by proposing the existence of a sizeable and very real gap between newly created and useable production knowledge that must be crossed by some mechanism. As a result, knowledge spillovers are not assumed to be automatic, as they are in endogenous growth models, and specific mechanisms must be in place in order for knowledge to “spillover”. Entrepreneurship, in particular, has been identified as a particularly important mechanism for converting new knowledge into useful production knowledge; especially with regard to new knowledge that radically deviates from routine convention or upsets existing revenue streams (Acs et al. 2004; Audretsch and Keilbach 2004).

The empirical evidence supporting this conjecture, however, is unsatisfactory, especially as it relates to the spatial or regional context. Despite the large body of evidence finding that a high propensity of entrepreneurship is related to increases in various regional economic outcomes, such as income and employment growth, the empirical evidence connecting entrepreneurship specifically to regional productivity differences is missing altogether or suffers from several weaknesses. This is a problem because, theoretically, entrepreneurship influences economic growth through technical progress. Therefore, an empirical relationship between employment or income growth and entrepreneurship may not necessarily support the theory because it fails to explicitly explore the technology term in a direct manner.

The purpose of Chapter 2 is to examine the relationship between regional total factor productivity and entrepreneurship in an effort to directly relate entrepreneurship to technical change while at the same time allowing for the direct infusion of knowledge into production. This will be done using a spatial econometric regression relationship that is able to overcome the menacing problems inherent in measuring both knowledge and entrepreneurship as well as in isolating the influences of these confounding covariates in a spatial and hence regional sense. As such, this approach is capable of providing more accurate estimates in the face of these deficiencies. These issues, while often acknowledged in the scholarly literature, have been largely untreated in the empirical sense.

1.2 Entrepreneurship, Growth and the Technological Frontier

Recent theoretical work in neo-Schumpeterian growth theory proclaims that innovative entrepreneurship is the specific mechanism through which productivity growth is introduced in advanced economies (Acemoglu, Aghion, and Zilibotti 2006). At the same time, productivity increases in lagging economies are considered to be brought about principally through technological diffusion or rather the imitation or importation of the frontier technologies (Acemoglu, Aghion, and Zilibotti 2006; Ertur and Koch 2008). Technological innovation, in these types of models, is considered to be brought about by the bustle of selection (the creation of new knowledge) made manifest in production by innovative entrepreneurs. On the contrary, technological diffusion is thought to be driven

by capital investment channeled through established firms (Acemoglu, Aghion and Zilibotti 2006).

It is quite obvious that these theoretical arguments fundamentally involve technological interdependence between economies. In fact, technological interdependence fundamentally governs the dynamics of these models and leads to spatial regression models in a reduced form (Ertur and Koch 2008). Specifically, the interdependence facilitates the diffusion of technologies from leading economies to lagging economies which enhances laggard productivity and which is driven by investments channeled through existing firms. Productivity gains in technologically leading economies results from innovative entrepreneurship (i.e. through the creation of new and innovative firms). As a result, these models imply that the technological state of any given regional economy, relative to the technological frontier, determines whether or not innovative activities are important channels for productivity growth.

If one were to concede that innovation is indeed brought about by entrepreneurship, then one could presume that entrepreneurship should drive productivity growth in economies on the frontier while productivity growth off the frontier should be brought about through the diffusion of technologies via existing organizations; in the form of foreign direct investment, or more generally, by investments made by existing firms based in other places. However, for this to be confirmed, the data should show that entrepreneurship propels productivity expansion in economies near the technological frontier while it does

not in economies far off the frontier. Within the context of a spatial model of the spatial durbin form, one would expect to find large direct effects with regard to entrepreneurship in technologically advanced economies and small direct effects in technologically lagging economies. This would reflect the fact that laggard economies receive larger productivity impacts from technological diffusion than they do from entrepreneurship. Furthermore, it would support the premise that economies near the technological frontier must innovate in order to become more productive while economies may not have to.

The purpose of Chapter 2 is to test this theoretical proposition. Specifically, it will test the efficacy of the application of these theories as they relate to entrepreneurship and productivity growth in a sample of regional economies. Consequently, the technological frontier will be defined and these theoretical claims will be tested in the context of differences in regional productivity using an appropriate spatial econometric technique.

1.3 Psychological Capital as a Determinant of Regional Entrepreneurship

Two alternative approaches to identifying the important determinants of entrepreneurship have been utilized in the literature. The first approach has been to study individual entrepreneurs in order to identify commonly shared characteristics among entrepreneurial individuals. The general emphasis is on individual differences between who does and who does not engage in entrepreneurship. The second approach has focused on the structural economic differences across regional economies in an effort to explain

variation in entrepreneurial activities that are due to differences in various supply side regional characteristics and economic conditions. This approach places emphasis not on the individual but rather on the environments within which they emerge.

The literature based on the study of the individual has identified several common determinants of entrepreneurial individuals. One such determinant is a set of social relationships with and between important players. These relationships have come to be described as social networks. Theoretically, they are important because they lower the transaction costs of starting an entrepreneurial venture due to the high levels of trust between the players (Williamson 1991). Another important characteristic of entrepreneurs is their relatively high levels of educational attainment (Evans and Leighton 1990). While this is certainly not always the case and many successful entrepreneurs defy this, high levels of education are an established distinguishing characteristic of entrepreneurial individuals.

A large and very curious piece of this literature specifically focuses on individual psychological characteristics. Risk tolerance is one explicit psychological characteristic that has been widely ascribed to entrepreneurial individuals. The evidence consistently finds that entrepreneurs are risk tolerant individuals, which makes them more willing to bear the burden of “Knightian” uncertainty that is inherent in an entrepreneurial venture (Kilstrom and Laffont 1979; Brockhaus 1980; Van Praag and Cramer 2001; Stewart and Roth 2001). Other individual-level studies suggest that a strong sense of self-efficacy, or the unyielding belief in one’s ability, plays a large role in who engages in

entrepreneurial activities (Chen, Greene and Crick 1998; Markman et al. 2002). Lastly, other research has found that individuals whom possess a strong need for achievement and a high tolerance for ambiguity are more likely to engage in entrepreneurship than are those who do not possess these traits (McClelland 1961; Budner 1982; Schere 1982; Begley and Boyd 1987; Collins et al. 2000).

The regional approach to entrepreneurship research has tended to leave aside individual characteristics focusing instead on regional-level structural factors. This body of literature argues that opportunities are objective and that they are not homogeneously distributed across geographic space. As a consequence, structural differences are the important determinants of entrepreneurship and not the individual differences. This type of scholarly approach has focused primarily on factors that affect the creation of opportunities as well as on the factors that decrease the barriers to their exploitation. This literature has identified low transport costs, high human capital concentrations, advantageous employment and industrial structures, extensive research and development activities, and abundant financial capital availability as critical factors (Bartik 1989; Reynolds et al. 1994; Dunn and Holtz-Eakin 2000; Acs et al. 2007). In addition, other scholarly work in this vein has argued that further basic structural factors previously linked to dynamic economies, like population, employment and income growth, are important determinants of entrepreneurship (Acs and Armington 2002).

While clearly in the minority, some regional scientists have begun to place more emphasis on the regional manifestation of individual traits. In particular, psychological factors have begun to surface in regional analysis of entrepreneurial activities through the concepts of: social capital, creativity and tolerance. Coleman (1988; 1990) and Putman (1993), among others, have argued that regional stocks of social capital facilitate higher levels of trust and cooperation among regional agents. Other factors with definite psychological undertones, such as, creativity and tolerance, are increasingly being used in regional analyses of entrepreneurial activities. The arguments for these latter factors have been based on the idea that agglomerations of intrinsically creative individuals along with a tolerant and open regional environment make the economy more accepting of and willing to fund radical ideas (Lee et al. 2004; Florida 2002; Mellander and Florida 2006). These agglomerations have been credited to play the role of creative capital and are posited to exist as a stock that is available at varying levels to the regional economy.

While it is certainly true that the individual and regional-level investigative approaches to entrepreneurship have different points of view, both seek to explain variation in entrepreneurial activities and have contributed substantially. The study of individual entrepreneurs has provided sizeable evidence indicating that certain psychological traits are central determinants of entrepreneurship. The regional economic advance, on the other hand, has demonstrated that many structural characteristics within the regional environment are crucial factors facilitating entrepreneurship as well. Additionally, while this perspective has yet to fully address the issue of psychological characteristics, it has

provided some early indications that psychologically based factors, such as: social capital, creativity and tolerance, have important influences on entrepreneurial activities at the regional-level as well.

Taking these perspectives together, it seems quite clear that the discovery and exploitation of opportunities by entrepreneurs is allied to both the person and their place (Schoonhoven and Romanelli 2001; Thornton and Flynn 2005). In other words, the nexus of person, place and the emergence of entrepreneurial endeavors in geographic space likely depends, to varying extents, on both psychological characteristics as well as on the structure of the environment within which it emerges.

Given these facts, it is likely the case that both psychological characteristics and structural variables are critical determinants of entrepreneurship. Yet there are significant holes in the literature as it pertains to the psychological factors. The most prominent of these is the fact that the theoretically important individual psychological variables have not yet been explicitly included in regionally based empirical studies. As a result of this, we scholars have no basis on which to gage how important these variables are to regional entrepreneurship; if they are even important at all. A second, and yet very related, gap in the literature involves how to think about individual psychological traits when considering regional systems of entrepreneurship. If these traits reside exclusively within the individual, does this fact prohibit their being relevant to regional planning?

Furthermore, how should we think about the psychological traits when considering regional economies and the role of entrepreneurship in them?

The purpose of Chapter 3 is to examine the relevance of psychological characteristics at the regional level and to propose that psychological capital may be the context within which to consider these characteristics at this level of aggregation. To do this, Chapter 3 will contain an assessment of the importance of psychological traits to entrepreneurship at the level of the functional region by creating a regional index of psychological capital. An investigation of whether enough variation in psychological capital exists as well as whether or not it has any impacts on regional levels of entrepreneurship will be carried out using recent advances in Bayesian Model Comparison and Bayesian Model Averaging techniques for several classes of spatial econometric models.

CHAPTER 2 THE IMPACT OF ENTREPRENEURSHIP ON REGIONAL TOTAL FACTOR PRODUCTIVITY

2.1 Introduction

The quest for the sources of economic growth has been undertaken by countless scholars of the economic system over many centuries. The many insights their pursuits have provided have been consolidated into several theories which have come to dominate our understanding of economic progression. Neoclassical theories posit that the accumulation of labor and physical capital are the fundamental endogenous sources of economic growth (Harrod 1939; Solow 1956; Swan 1956; Domar 1957). Further Neoclassical work has provided significant evidence that while labor and capital accumulation are important factors underlying economic progress, technical change and its ensuing productivity augmentations are the primary means by which economies expand (Abramovitz 1956; Solow 1957). Yet, while identifying technical change as tantamount to economic growth, neoclassical theories fail to successfully explain the very genesis of technical change in the first place.

The development of endogenous growth theory has provided a coherent step beyond exogenous growth models by effectively endogenizing the creation of new knowledge

and identifying it as the fundamental driver of technical change and subsequently economic growth (Romer 1986; 1990; Lucas 1988). This theoretical model relies on the creation of new knowledge and the process of human capital accumulation that produces it to posit that economic output expands when new knowledge about ways of doing things yields more productive combinations of labor and capital at the firm and, consequently, the regional-level. As a result, endogenous changes in technology yield increases in productivity, which enable the same quantities of resources to yield greater amounts of output, or rather, more efficient combinations of resources. Thus, the production of new knowledge leads to a new and higher steady-state equilibrium.

Indubitably, a large body of literature has arisen to empirically confirm the theoretical link between productivity and knowledge creation (see for example Adams 1990; Lichtenberg 1993; Caballero and Jaffe 1993; Coe and Helpman 1995; LeSage and Fischer 2008). However, newly created knowledge does not necessarily lend itself directly to productivity growth and the nexus of the two is certainly not bound to happen within the original knowledge producing firm or region. Therefore, it is not knowledge in and of itself that leads to productivity increases, but rather, it is the financially viable commercialization of that newly created knowledge which does.

The separation of newly created knowledge from its commercialized counterpart is nothing new to scholarly discussion, however, as many economists have previously identified a considerable gap between new knowledge and economically useful

knowledge (Arrow 1962; Acs et al. 2004; Audretsch and Keilbach 2004; Acs et al. 2008). On the other hand, while well documented and rather obvious to the astute observer, it has to often been neglected in regional economic theorizing as it pertains to economic progression.

Recent work in this vein has sought to incorporate the gap between newly created and useable production knowledge by identifying several important mechanisms which bridge this gap, capturing and harnessing new information to yield increased productivity. Entrepreneurship, in particular, has been espoused by many to be an extremely important mechanism for converting new knowledge into useful production knowledge; especially with regard to new knowledge that radically deviates from routine convention or upsets existing revenue streams (Acs et al. 2004; Audretsch and Keilbach 2004). However, the empirical evidence linking entrepreneurship directly to productivity increases is noticeably thin; especially as it relates to the spatial or regional context.

A large body of evidence does find a high propensity of entrepreneurship to be significantly related to increases in various regional economic outcomes, such as income and employment growth (Ashcroft and Love 1996; Fritsch 1997; Audretsch and Fritsch 2002; Acs and Armington 2002; Van Stel and Storey 2004; Blanchflower 2000; Carree et al. 2002; Acs et al. 2004; Klapper et al. 2006; Carree and Thurik 2008). However, empirical evidence connecting entrepreneurship specifically to regional productivity differences is surprisingly sparse. At the same time, this connection would certainly help

confirm or even refute both the existence of the knowledge gap and of entrepreneurship as a key conversion mechanism.

The research that has attempted to link entrepreneurship to productivity suffers from numerous problems. For one, it tends to rely on country-level or industry-level data, which is apt to mask the complex regional dynamic between R&D (or newly created knowledge) and its commercial application (see for example Disney et al. 2003; Scarpetta et al. 2002; Thurik et al. 2008). Second, this literature largely fails to account for physical and/or human capital stocks when estimating regional productivity (see for example Holtz-Eakin and Kao 2003; Heden 2005; Foster et al. 2006; Hakkala 2006). As a result, much of the variation in the productivities may have little to do with differences in technology. This makes it difficult to accurately identify the effects of the explanatory variables. Lastly, the vast majority of this empirical work has not appropriately dealt with the complex spatial interactions at play in the regional setting by applying the appropriate spatial econometric estimation routines. This is because none of the empirical work relating entrepreneurship to productivity has empirically acknowledged, a priori, the explicit deficiencies inherent in any particular measure of entrepreneurship or knowledge. This is a considerable problem because the immeasurable and thus omitted portions of knowledge and entrepreneurship will likely result in the existence of spatial correlation not only in the dependent variable or error terms, but also in the explanatory variables. As a result, the impacts of these types of explanatory variables would be inaccurately measured and so may result in incorrect conclusions. As a result, the true

empirical relationship between regional entrepreneurship and productivity remains uncertain; as does the relevance of the theoretical knowledge gap.

This Chapter intends to examine the relationships between regional total factor productivity, entrepreneurship and knowledge using a regression based spatial econometric approach that is better able to quantify these relationships. In so doing, it provides an excellent framework for uniquely linking knowledge and entrepreneurship to differences in regional productivity. Further, this research will provide an assessment of the contributions of each of these factors to variations in factor productivities across regional economies. As such, this research will provide concrete conclusions regarding which is more relevant to increasing regional productivity and thus whether entrepreneurship is truly an important bridge of the knowledge gap.

This chapter will proceed in the following manner. Section 2.2 will provide a derivation and a rationale for the specific total factor productivity relationship to be examined as well as the form of the specific spatial relationship that will be used for model estimation. Section 2.3 will discuss the dataset with an emphasis on how entrepreneurship and knowledge will be measured. Section 2.4 will present the results, while the last section in this chapter, section 2.5, will contain the conclusions.

2.2 Model Specification

The production function has long been used as the starting point for productivity analysis (Thurik et al. 2008). Given the structure of the production function, the relationships between entrepreneurship, knowledge and total factor productivity can be made explicit. This type of approach has roots in growth accounting, where economic output is decomposed into its different components (Abramovitz 1956; Solow 1957). The residual obtained after the decomposition of output into its labor and capital shares is often referred to as either the Solow residual or total factor productivity (it will be referred to here as total factor productivity). Mankiew et al. (1992) added human capital to the model, resulting in what has been called the augmented Solow model. This form will be used in this chapter to compute total factor productivity.

The computation of regional total factor productivity here begins with the Cobb-Douglas production function shown in relation 2.1, where A represents the state of the technology and K and L represent capital and labor inputs.

$$Y = AK^{\alpha}L^{\beta} \quad (2.1)$$

In logarithmic terms, the production structure becomes that shown in equation 2.2, with α and β representing the shares of output attributable to capital and labor.

$$\ln(y) = \ln(a) + \alpha \ln(k) + \beta \ln(l) \quad (2.2)$$

Augmenting the production structure to include a measure of human capital yields an expression for the augmented Solow model, which shown in relation 2.3, where h represents human capital.

$$\ln\left(\frac{y}{l}\right) = \ln(a) + \alpha \ln\left(\frac{k}{l}\right) + \beta \left(\frac{h}{l}\right) \quad (2.3)$$

The productivity expression, shown in 2.3, provides a tangible basis for the empirical investigation of the determinants of total factor productivity that shall follow as it relates output per unit labor to the state of the technology, the capital to labor ratio and the amount of human capital per unit of labor. A total factor productivity (*tfp*) relationship can be derived from relation 2.3 by algebraically solving it for the logarithm of *a*. This solution is shown in 2.4.

$$tfp = \ln(a) = \ln\left(\frac{y}{l}\right) - \alpha \ln\left(\frac{k}{l}\right) - \beta \ln\left(\frac{h}{l}\right) \quad (2.4)$$

The primary focus of this chapter is to examine to what extent regional stocks of entrepreneurial activities influence the technology parameter *a* relative to regional stocks of knowledge. A key point of note here is that *tfp* is a residual because it represents the share of output not attributable to physical capital, labor or human capital.

There are a number of ways to compute *tfp*, such as directly calculating the regional share of labor and capital in total output, based on payroll's and the dollar value of the capital stock's share of total output. An alternative could be to estimate relation 2.3 using least-squares to obtain estimates of α and β , which could then be used to calculate *tfp* as in 2.4. Furthermore, one could calculate or estimate only α and assume constant returns to scale so as to impose the condition that $\beta = 1 - \alpha$.

Recent work by LeSage and Fischer (2008) and LeSage and Pace (2009) has used the *tfp* approach to assess the impact of knowledge stocks on regional total factor productivity. To do so, they derived a spatial model of the same form as shall be used in this chapter.

The particular form of the model is driven by the highly plausible and easily testable a priori assumption that their empirical proxy for knowledge stocks was deficient. Specifically, they hypothesized that the reliance on patent stocks as a proxy for knowledge failed to capture the true stock of technical knowledge available in regional production relationships. As a result, the authors posited the existence of a portion of knowledge K that was unmeasured, which they labeled K^* , and was omitted from their model. In effect, they admitted up front that their measure of knowledge was deficient; an admission most would not disagree with. They used this insight combined with prior knowledge that any empirical measure of regional technical knowhow, such as: patents, entrepreneurship, educational attainment, research and development expenditure, scholarly publications, ect., tends to exhibit spatial dependence (see for example Autant-Bernard 2001; 2007; Parent and LeSage 2007) to arrive at the appropriate spatial specification. If both the measured variable (what they label K) and the unmeasured omitted variable (what they label K^*) exhibit spatial dependence, then one can show that a spatial relationship will result (LeSage and Fischer 2008). More precisely, either a spatial error or a spatial durbin relationship will result, depending on whether or not there exists spatial dependence between the omitted and included variables.

While this work pertained specifically to the relationship between tfp and knowledge stocks, an identical argument could be made with regard to entrepreneurship. This is because it is well known that empirical proxies for entrepreneurship are imperfect in whatever form they take on; be it self-employed, the number of small firms, the number

of new firms, the number of single establishment new firms, ect. and that these proxies tend to exhibit spatial dependence (Acs et al. 2008). As a result, one can derive a similar spatial relationship that includes empirical proxies for both entrepreneurship and knowledge, based on the a priori assumption that these specific empirical proxies are both deficient.

This can be shown best by following the developments of LeSage and Pace (2009, pp. 27-28) in the context of the relationship this chapter seeks to explore (the relationship between tfp and entrepreneurship and knowledge, shown in 2.5).

$$TFP = \beta_1 e + e^* + \beta_2 a + a^* \quad (2.5)$$

In 2.5 TFP represents the logarithm of total factor productivity, e represents an n by 1 vector of logged cross-sectional observations on the portion of technical knowhow attributable to entrepreneurship, a denotes an n by 1 vector of logged cross-sectional observations on the portion due to knowledge and e^* and a^* represent the unmeasured portions of entrepreneurship and knowledge, respectively.

Rewriting 2.5 in terms of measured and unmeasured variables, 2.5 becomes 2.6, where, y takes the place of TFP , x denotes the observed portion and x^* represents the unobserved portion. Note that the disturbance term is omitted to simplify the discovery of the parameters (LeSage and Pace 2009).

$$y = x\beta + x^*\gamma \quad (2.6)$$

In the case where both x and x^* are observable, the solution of the linear system would yield an exact β and γ . In the case where x^* is not observed, uncorrelated with x and is spherical (i.e. it has a uniform variance and exhibits no correlation), then β can still be exactly uncovered. This is because in this situation, $x^*\gamma$ functions as a disturbance term and so can be labeled as shown in expression 2.7.

$$y = x\beta + \varepsilon \quad (2.7)$$

Equation 2.7 characterizes the normal linear model with *iid* disturbances. As such, the ordinary least-squares estimate of β would be BLUE (best linear unbiased estimator).

Suppose now a state of affairs where the explanatory variable vector x^* is unobserved but follows the spatial autoregressive process shown in 2.8.

$$x^* = \rho W x^* + d = (I_n - \rho W)^{-1} d \quad (2.8)$$

Here, ρ is a scalar parameter reflecting the strength of the spatial correlation, d is an $n \times 1$ vector of disturbances that follow a normal distribution with a mean of zero and a constant variance and W is an $n \times n$ spatial weight matrix with non-zero values in positions reflective of neighboring locations. Further assume that W is invertible and has rows that sum to unity. Substituting 2.8 into 2.6 results in equation 2.9 and reflects the generalized normal linear model with non-spherical disturbances.

$$\begin{aligned} y &= x\beta + \gamma d (I_n - \rho W)^{-1} \\ &= x\beta + (I_n - \rho W)^{-1} u \end{aligned} \quad (2.9)$$

In 2.9, γ has the effect of increasing the variance of d . In this situation, least-squares estimates of β are no longer the most efficient yet remain unbiased.

If the omitted variable x^* were to exhibit correlation with x , as is highly likely in the application contained in this chapter, then x and u are not uncorrelated. Still following LeSage and Pace (2009, pp. 27-28), one can show the impact of this situation by imposing that u depends linearly on x and a normally distributed error term q that has a mean of zero and exhibits a constant variance σ_q^2 . This is shown in relation 2.10.

$$u = x\vartheta + q \quad (2.10)$$

Substituting 2.10 into 2.9 results in the expression for the data generating process shown in 2.11.

$$\begin{aligned} y &= x\beta + (I_n - \rho W)^{-1}(x\vartheta + q) \\ &= x\beta + (I_n - \rho W)^{-1}x\vartheta + (I_n - \rho W)^{-1}q \end{aligned} \quad (2.11)$$

As can be seen from 2.11, least-squares estimates for β will no longer be unbiased due to the linear dependence of u on x . Multiplying through by $(I_n - \rho W)$ and resolving for y will transform 2.11 into a form with *iid* errors that is shown in 2.12.

$$y = \rho W y + x(\beta + \vartheta) + W x(-\rho\beta) + q \quad (2.12)$$

This is known as a spatial durbin model as it includes a spatially lagged dependent variable and a spatially lagged independent variable in addition to the explanatory variable x . Therefore, if unobserved portions of both knowledge and entrepreneurship exist and are correlated with the observed portions, then the resulting model is a spatial durbin model containing both of these explanatory variables, their spatial lags and a spatially lagged dependent variable.

There exist two focal empirical implications that come to pass from these developments. First, if the included and excluded proxies for knowledge and entrepreneurship (e and e^* and a and a^*) are correlated, then spatial lags of both the dependent and independent variables are to be included in the regression model, in order to produce unbiased and consistent estimates of the impacts of the stated variables on total factor productivity (LeSage and Fischer 2008). Second, again assuming the stated correlation, the responses of tfp to knowledge and entrepreneurship (the partial derivatives $\frac{dftp}{da}$ and $\frac{dftp}{de}$) will take on the form of $n \times n$ matrices (which are shown in equations 2.13 and 2.14), which facilitate spatial spillover impacts from a change in an x-variable in region i on the y-variable in region j ; as opposed to OLS or SEM partials that ignore these spillovers impacts (LeSage and Fischer 2008).

$$\frac{dftp}{da} = (I_n - \rho W)^{-1}(I_n \alpha_3 + W a \alpha_4) \quad (2.13)$$

$$\frac{dftp}{de} = (I_n - \varphi W)^{-1}(I_n \alpha_1 + W e \alpha_2) \quad (2.14)$$

In light of these implications, previous research relating total factor productivity to entrepreneurship likely presents coefficient estimates that are biased and inconsistent, as it overwhelmingly fails to empirically concede that some portion of the true amounts of regional knowledge and entrepreneurship are excluded from the model and that the excluded portions are likely correlated with the included portions. This would have the effect of biasing the parameter estimates for the reasons discussed above. As a result, the impacts of these variables have been improperly estimated in nearly all previous research.

2.3 Data

To examine the regional impacts of entrepreneurship and knowledge on regional total factor productivity, a panel of the 49 continental U.S. states (including DC as a state-level observation) covering the period 1997-2003 was constructed and pooled. U.S. states were utilized as they constitute the smallest regional-level observations that are associated with reliable data on output; a critical variable. The time horizon for the study was limited on the former side by the change in industrial coding schemes that occurred in 1997 and on the latter side by the lack of available data on single establishment firm formations after 2003. Alaska and Hawaii were excluded from the dataset because of their isolation from the continental states. Lastly, log transformations were taken on all variables so as to facilitate elasticity inferences with regard to the parameter estimates.

Total Factor Productivity

Total factor productivity is estimated according to the augmented Solow model shown in relation 2.4. To compute these values, gross state product (GSP) data was obtained from the Bureau of Economic Analysis (BEA) in year 2000 dollars. State-level physical capital stocks are not available. As a result, the physical capital stocks for each state had to be estimated. To do this, the method of Garofalo and Yamarik (2002) was utilized at the two-digit industry level. This methodology involves apportioning the constant dollar value of the national capital stock series, provided by the BEA, to the state-level using the dollar value of GSP in constant dollars. In other words, the national capital stock is

multiplied by the ratio of state-level income in a given industry to the national income in that industry. The state-level industry estimates for the physical capital stock are then summed over all industries to arrive at the total state-level capital stock estimate. This procedure is summarized by equations 2.15 and 2.16 below.

$$k_{i,j}(t) = \left[\frac{y_{i,j}(t)}{Y_i(t)} \right] K_i(t) \quad (2.15)$$

$$k_i(t) = \sum_{j=1}^{19} k_{i,j}(t) \quad (2.16)$$

In these expressions, i , denotes the specific industry and, j , denotes the particular state. Further, the uppercase letters denote national totals while the lowercase letters denote state-level values. It should be noted here, as it was in Garofalo and Yamarik (2002) that this methodology implicitly assumes a constant capital to output ratio within each industry. Written another way, it assumes that each industry is in a common steady-state (Garofalo and Yamarik 2002). If the capital to output ratio for a particular industry in given state is less than the steady-state value, then the estimate of the capital stock for that state would be overestimated. The opposite would occur if the capital to output ratio exceeds the steady-state (Garofalo and Yamarik 2002). The labor force was measured by state-level payroll (again in year 2000 dollars), which was provided by the Bureau of Labor Statistics (BLS). Human capital stocks were obtained from the U.S. Census Bureau and were measured as the number persons aged 25 years or more who have obtained at least a bachelors degree. These data were then plugged into the equation 2.3 in order to estimate $\hat{\alpha}$ and $\hat{\beta}$ via least-squares. Finally, tfp was computed by plugging the data and $\hat{\alpha}$ and $\hat{\beta}$ into equation 2.4.

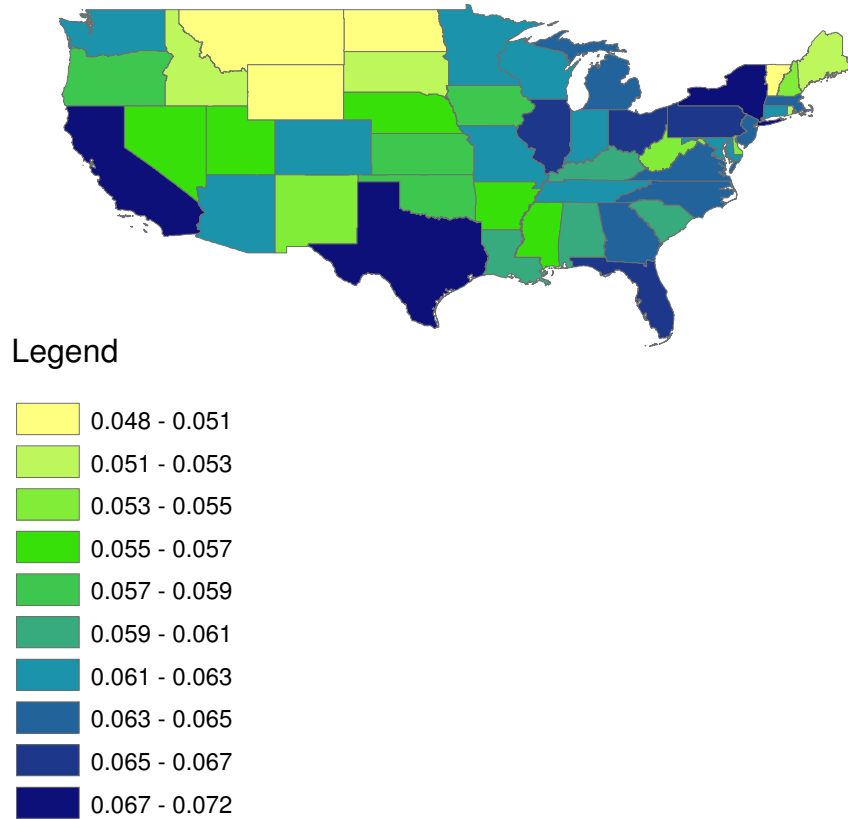


Figure 1. Average Total Factor Productivity by State 1997 – 2003

Figure 1 presents the geographic distribution of the average of the total factor productivity estimates across the period. It reveals that *tfp*'s are generally largest along both coasts, great lakes states, and in Texas. Total factor productivity values tend to be smallest in the states of the upper plains and appalachian regions of the United States.

Knowledge

The stock of knowledge available to each state was constructed using the total number of patents granted in each state as provided by the U.S. Patent and Trademark Office. It is well known that patents represent a problematic measure of the stock of knowledge available to regional economies. This is due to the fact that not all knowledge is patented and that which is tends to be produced in the private sector and is concentrated in certain types of industries. As a result, there likely exists a considerable amount of knowledge that is not included in the stock of patents. Remember, however, that this type of deficiency is accommodated by the particular form of the spatial regression model that is implemented here; through the a priori assumption that the included variable measuring knowledge is likely omitting a significant amount of the true knowledge that is available to any regional economy. As a result, the usage of patent stocks to represent regional knowledge should not be a problem here, as the omitted knowledge will not bias the coefficient estimates under the regression framework that is applied.

Figure 2 presents the geographic distribution of averaged knowledge stocks as measured by patenting activities over the period 1997-2003. Knowledge stocks are largest on the west coast and in the great lakes states. Texas and Florida also exhibit large knowledge stocks.

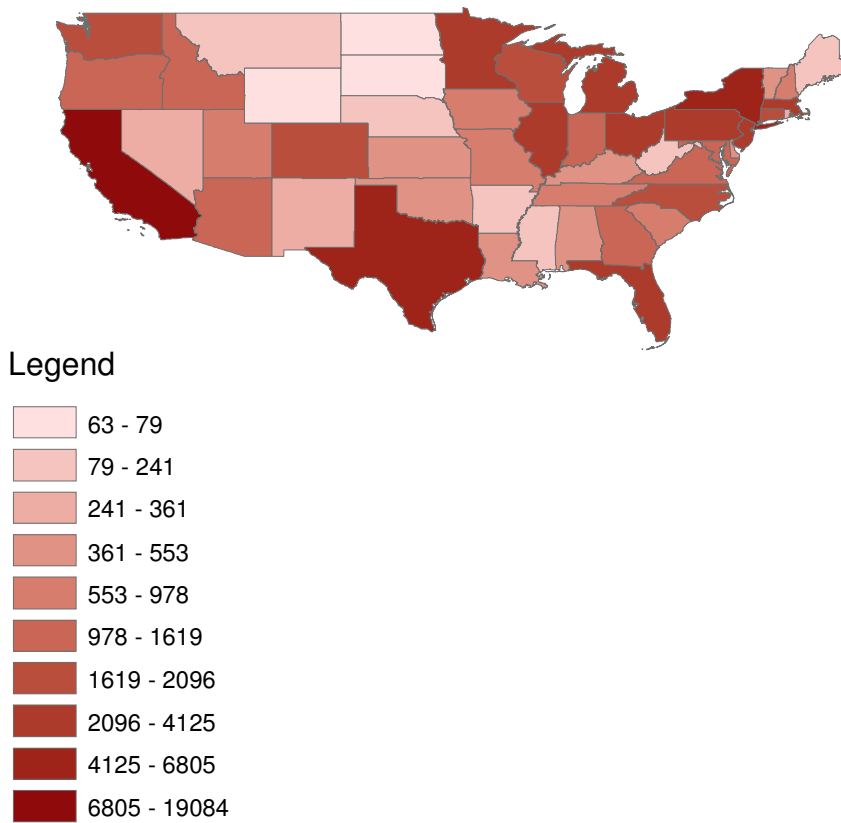


Figure 2. Average Knowledge Stocks by State 1997 - 2003

Entrepreneurship

There are a number of ways that scholars have measured entrepreneurship in previous research. The most common are: the number of self-employed individuals, the number of small firms, the number of small and medium sized firms (SME's), the total number of new establishments or the total number of new single establishments. Each of these

methods of measuring entrepreneurship is associated with some strengths and some weaknesses. For example, the number of self-employed individuals includes entrepreneurship at the earliest stage. On the other hand, this type of measure tends to be very coarse as it includes over 8.5 million Americans; most of which are not attempting to grow a new firm based on their exploitation of new knowledge (Glaeser 2007). The number of small firms, SME's and the total number of new establishments are likewise very coarse measures and so include many firms which are entirely replicative or are branches of some parent establishment. Furthermore, many of the small and medium sized firms are not at all new. Perhaps the best measure of entrepreneurship is the number of single establishment firm formations. This method excludes new branch plants and reflects the organization of a new company. As a result, it tends to best represent new forms of organizing labor and capital in the production of economic goods. Entrepreneurship is measured by single establishment firm formations in this research for these reasons.

Figure 3 presents the distribution of the level of entrepreneurial activities by state, as measured by the average total number of single establishment firm formations over the period 1997 - 2003. Entrepreneurial activity is largest on the east and west coasts as well as in the great lakes region. Texas also contains a large amount of entrepreneurship. Aggregate entrepreneurial activities are smallest in the southern Mississippi delta states as well as in the upper plains states.

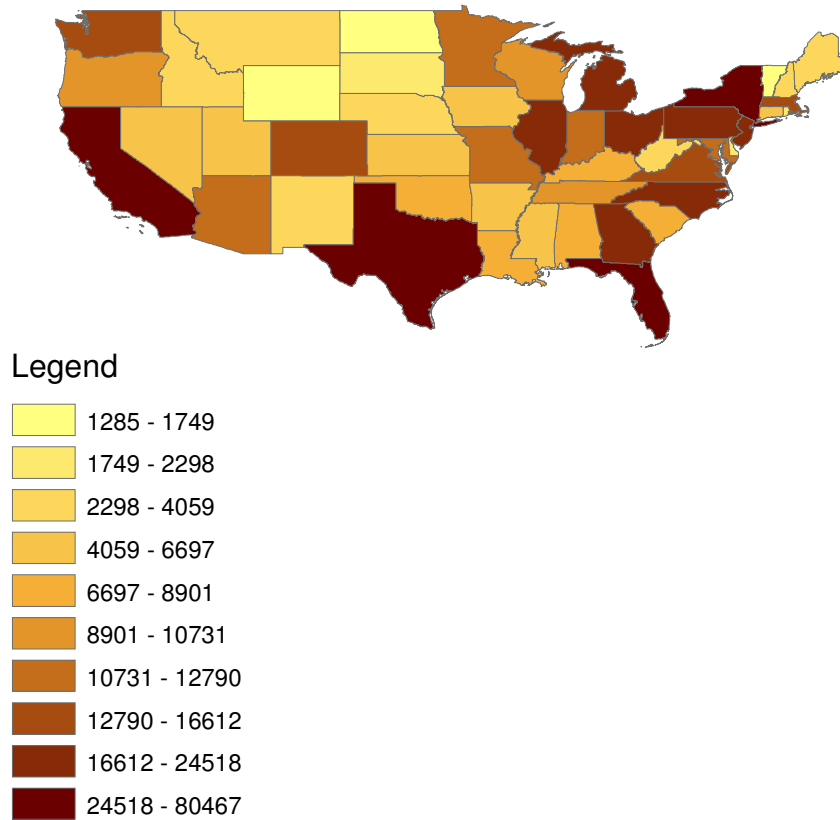


Figure 3. Average Level of Entrepreneurial Activities by State 1997 – 2003.

2.4 Results

Presentation of the results will follow accordingly. First, the specification tests for the regional connectivity structure will be presented. This was done by specifying a series of alternative row-normalized spatial weight matrices that were used to represent the set of candidate connectivity structures. The “winner” was selected using two metrics; the

maximum log-likelihood function value based on maximum likelihood estimation and the largest posterior model probability estimated via Bayesian MCMC methods. After selecting the spatial weight matrix that “best” fit the sample data, then the regression results and model specification tests will be presented.

The pooled nature of the sample data has resulted in 343 observations that were stacked into a $7n \times 1$ vector of observations of the dependent variable and a $7n \times 2$ matrix of observations of the independent variables. The pooling thus affected the specification of the spatial weight matrix as the connectivity structure is only $n \times n$. To implement spatial connectivity for the pooled model, the spatial weight matrix had to be formed according to the expression shown in 2.17.

$$W_{7n} = I_7 \otimes W_n \quad (2.17)$$

Where n represents the 49 single year observations, I an identity matrix and \otimes denotes the kronecker product.

Table 1 contains the model comparison results pertaining to the specification of the spatial weight matrix. Sixteen different specifications were considered, ranging from a first order contiguity specification that selects border sharing observations through a specification that selects the 15 nearest neighboring observations based on Euclidean distance between state-level centroid coordinates.

Table 1. Weight Matrix Comparison Results

Number of Neighbors	Log-likelihood	Posterior model probability
1st order contiguity	262.0354	0.3182
1 NN	222.2959	0.0000
2 NN	243.7346	0.0000
3 NN	255.6039	0.0002
4 NN	260.8112	0.0486
5 NN	253.6972	0.0001
6 NN	260.4709	0.0592
7 NN	260.2232	0.0645
8 NN	262.3976	0.4925
9 NN	258.7449	0.0167
10 NN	245.3867	0.0000
11 NN	235.0169	0.0000
12 NN	232.5277	0.0000
13 NN	227.3723	0.0000
14 NN	222.3940	0.0000
15 NN	221.5681	0.0000

These results demonstrate that a spatial weight matrix selecting the 8 nearest neighboring observations fits the sample data the best in terms of both measures of fit. As a result, this matrix will be used to define the spatial connectivity in the subsequent model estimation.

Bayesian MCMC parameter estimates for the pooled spatial durbin model shown in relation 2.18 are presented in Table 2.

$$tfp = \alpha_i n + \rho W t f p + \alpha_1 a + \alpha_2 W a + \alpha_3 e + \alpha_4 W e + \varepsilon \quad (2.18)$$

Here, tfp represents logged total factor productivity, i_n denotes a vector of ones included to reflect to non-zero mean of the dependent variable, W is the spatial weight matrix, a is logged knowledge, e is logged entrepreneurship and ε is an *iid* error term.

Table 2. Bayesian Spatial Durbin Model Estimates

Variable	Coefficient	Std-Deviation	p-level
Constant	-0.5511	0.2566	0.0140
Rho	0.4970	0.0643	0.0000
Knowledge	0.0272	0.0175	0.0607
W-Knowledge	0.0677	0.0317	0.0165
Entrepreneurship	0.4952	0.0237	0.0000
W-Entrepreneurship	-0.1686	0.0534	0.0014

Table 2 presents a number of important findings. For one, it provides inferences regarding whether the excluded and included variables for entrepreneurship and knowledge are correlated. This test is crucial here as the derivation provided in section 2.2 shows that it determines the appropriate model specification. As LeSage and Fischer (2008) point out, this can be formally tested by examining whether or not the common factor restriction holds. In other words, it can be tested by examining the whether the restrictions shown in relations 2.19 and 2.20 are true or not.

$$-\alpha_1\rho = \alpha_2 \quad (2.19)$$

$$-\alpha_3\rho = \alpha_4 \quad (2.20)$$

From Table 2 one can see that $-\alpha_1\rho = -0.0135$. This certainly is not equal to $\alpha_2 = 0.0272$. Further, the p-level associated with a t-test determining statistical significance is equal to 0.0000. Likewise, $-\alpha_3\rho = -0.2461$ which is not equal to -0.1686 ; the estimate

of α_4 . Again a t-test was implemented to ascertain that these values were statistically significantly different from each other. The resulting p-value of 0.0445 provides this indication. Thus, one can confidently conclude that the restrictions in 2.19 and 2.20 do not hold and, therefore, the SDM approach is appropriate.

These results also provide evidence suggesting that entrepreneurship may have a considerably larger impact on total factor productivity than does knowledge. This is due to the fact that the parameter estimates for both entrepreneurship and its spatial lag are considerably larger than their knowledge counterparts. However, as noted in section 2.2, these estimates do not accurately measure the magnitudes of these coefficients as they should be computed as in equations 2.13 and 2.14 above. Lastly, this simple two variable model explains over 90% of the variation in logged total factor productivity (r-squared = 0.9153).

Table 3 contains a set of mean direct, indirect and total effects of changes in entrepreneurship and knowledge on total factor productivity along with a 95% confidence interval around the means. These effects correspond to the own (main diagonal) and cross (off diagonal) partial derivatives, originally shown in relations 2.13 and 2.14. They can be interpreted as a change from one steady-state to another new steady-state in response to changes in knowledge and entrepreneurship (LeSage and Fischer 2008). While their computational form remains essentially the same, the pooling has changed

the exact calculation to that shown in equations 2.21 (knowledge) and 2.22 (entrepreneurship).

$$\frac{dftp}{da} = (I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1} ((I_7 \otimes I_n) \hat{\alpha}_1 + (I_7 \otimes Wa) \hat{\alpha}_2) \quad (2.21)$$

$$\frac{dftp}{de} = (I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1} ((I_7 \otimes I_n) \hat{\alpha}_3 + (I_7 \otimes We) \hat{\alpha}_4) \quad (2.22)$$

Column one contains information regarding the specific type of effect while columns 2-4 contain the lower, mean and upper bands pertaining to a 95% confidence interval around the means, which were computed from the 10,000 non-burn-in MCMC draws. From Table 3, one can observe that a 1% increase in entrepreneurship in one state would lead to a 1.16% increase in regional total factor productivity in the new steady-state equilibrium; where 0.5% was due to the direct (internal) effect and 0.6% was due to the indirect (external) spatial spillover effect.

Table 3. Direct, Indirect and Total Effect Estimates

Entrepreneurship	Lower 0.05	Mean	Upper 0.95
Direct Effect	0.4629	0.5018	0.5415
Indirect Effect	0.4583	0.6633	0.9059
Total Effect	0.9212	1.1651	1.4474
Knowledge			
All Direct Effect	0.0065	0.0339	0.0611
All Indirect Effect	0.1049	0.1952	0.2954
Total Effect	0.1114	0.2291	0.3565

The same increase in knowledge would lead to a much more modest 0.23% increase in regional total factor productivity, most of which was contributed by the indirect

(external) effect. This result suggests that entrepreneurship yields considerably larger adjustments to the steady-state equilibrium. Thus, entrepreneurship has considerably larger impacts on regional total factor productivity.

2.5 Conclusions

Theories of economic growth have overwhelmingly identified knowledge as the fundamental driver of economic expansion. Whether exogenously determined or endogenously determined, the focus remains the same; the creation of new knowledge leads to changes in the steady-state equilibrium. These changes are reflected in production by better technology or rather more productive combinations of labor and capital.

The implication of these theories is quite clear from the perspective of public policy; increase the stock of knowledge in an economy and it will expand. From the perspective of regional economics, the implication is likewise rather straight forward; expand the regional stock of knowledge and the local economy will grow.

However, there are many examples of economies that produce a considerable amount of knowledge yet fail to grow as rapidly as others producing similar amounts of knowledge. Furthermore, many economies that are seemingly adding a lot of new information to the system fail to grow at the same rate as others, if at all.

What accounts for this discrepancy? Emerging research suggests the knowledge production to absorption nexus may be to blame. This literature argues that newly created knowledge is only one piece of the puzzle and that there is a very real and considerable gap between newly created knowledge and that applied to economic production. Thus, the spillover of economic knowledge requires mechanisms or channels through which new knowledge is converted into economic knowledge. One particularly important mechanism which has been identified is that of entrepreneurship. The argument is that entrepreneurship is a process which commercializes newly created knowledge that was missed by other actors, most notably existing firms.

However, this theoretical perspective has not been adequately observed in empirical research. This chapter has argued that the reasons for this are that the empirical literature on entrepreneurship and regional productivity along with that on knowledge spillovers is notorious for presenting incorrect estimates on the size of knowledge spillover. Further, the empirical literature linking entrepreneurship to regional productivity fails to adequately measure productivity or use the correct spatial econometric specifications; due in large part to their failure to admit deficiencies inherent in measuring knowledge and entrepreneurship.

This research has relied on historical developments in economic production relationships (the production function and the growth accounting approach) along with recent improvements in applied spatial econometrics to empirically link entrepreneurship to

differences in regional total factor productivities. In so doing, it has shown that patent stocks and single establishment firm formation activities explain over 90% of the variation in regional total factor productivity differences. Further, it has presented evidence confirming earlier work that spillovers can be empirically identified by separating out the direct and indirect spatial effects using the spatial durbin regression model. The results demonstrate that entrepreneurship has a total impact on regional total factor productivity that is over five times larger than that of knowledge as measured by patenting activities. This result provides clear evidence that while knowledge production is necessary for steady-state economic growth; its commercial introduction has dramatically larger impacts on productivity in the real world. New knowledge must certainly be converted into useful economic knowledge in order to actually harness the efficiency gains that lie therein. Furthermore, entrepreneurship is an extremely important mechanism for bringing about this conversion.

CHAPTER 3 THE PRODUCTIVITY IMPACTS OF ENTREPRENEURSHIP ON AND OFF THE TECHNOLOGICAL FRONTIER

3.1. Introduction

Having empirically established a direct link between entrepreneurship and productivity at the regional-level in Chapter 2, an obvious next question is whether or not entrepreneurship enhances productivity in regional economies on both the leading and lagging end of the technological spectrum alike? This purely empirical question emerges in light of a few different existing theories that imply it. Additionally, it constitutes a logical successive step from that which was established in the preceding chapter.

At the very least, two established theories suggest that entrepreneurship will impact technological leaders differently than it will impact the laggards; those being innovation theory and technological gap theory. Furthermore, an emerging growth theory, neo-Schumpeterian growth theory, fundamentally posits the existence of two countervailing forces governing rates of economic growth, those being: technological innovation and technological diffusion. In this theoretical context, innovation is thought to emerge on the frontier and then diffuse to economies off the frontier. The basic equilibrium

sequence one where innovation emerges in frontier economies only to diffuse to technically lagging economies, where their introduction is materialized through existing firms.

Essential to all of these theories is the notion that economic expansion is driven by productivity enhancing innovation. Technological diffusion, on the other hand, works to diminish growth (internal regional specific growth that is) or at least decelerate it in the aggregate sense. This is because the diffusion of a given technology brings with it tremendous competitive pressures that erode away any positive economic profits that were obtained from the monopoly-like position the originating economy had over that specific technology.

Moreover, recent theoretical work in the realm of the neo-Schumpeterian growth theory proclaims that innovative entrepreneurship is the specific mechanism through which productivity growth is introduced in advanced economies (Acemoglu, Aghion, and Zilibotti 2006). At the same time, productivity increases in lagging economies are considered to be brought about principally through technological diffusion or imitation of the frontier technologies (Acemoglu, Aghion, and Zilibotti 2006; Ertur and Koch 2008). Technological innovation, in this type of model, is considered to be brought about by the bustle of selection made manifest by innovative entrepreneurs. On the contrary, technological diffusion is thought to be driven by investments channeled through established firms (Acemoglu, Aghion and Zilibotti 2006).

It is quite obvious that these theoretical arguments fundamentally involve technological interdependence between economies. In fact, technological interdependence fundamentally governs the dynamics of the model and leads to spatial regression models in a reduced form (Ertur and Koch 2008). Specifically, the interdependence facilitates the diffusion of technologies from leading economies to lagging economies which enhances laggard productivity and which is driven by channeled investments through existing large firms. Productivity gains in technologically leading economies results from innovative entrepreneurship (i.e. through the creation of new and innovative firms). As a result, these models imply that the technological state of any given regional economy relative to the technological frontier determines whether or not innovative activities are important channels for productivity growth in that economy.

If one were to concede that innovation, particularly meta-innovation, is indeed brought about by entrepreneurship (as is often theorized), then one could presume that entrepreneurship should drive productivity growth in economies on the frontier whilst productivity growth off the frontier should be brought about through the diffusion of technologies via existing organizations; in the form of foreign direct investment, or more generally, by investments made by existing firms based in other places. This in fact is exactly what the model proposed by Acemoglu, Aghion and Zilibotti (2006) implies. A critical premise of theories such as technological gap theory (Fagerberg 1987; Fagerberg and Verspagen 2002) or innovation theory (most commonly credited to

Schumpeter, 1911; 1939) is that innovation tends to emerge in rapid bursts at similar points along the temporal spectrum due to some cumulative accumulation process. These meta-innovations (a term derived from Paul Romer's concept of meta-ideas) then facilitate a plethora of follow-up incremental innovations which have a propensity to codify the original underlying meta-innovations. The codification then smooths the progress of their diffusion to lower cost labor markets where production is more profitable.

If it is true that these Kondratieff-like innovation long waves exist as well as if it is true that entrepreneurship is the primary mechanism bringing about meta-innovations, then the data should show that entrepreneurship drives productivity expansion in economies near the technological frontier while the same would not be true in economies far off the frontier. Within the context of a spatial model of the spatial durbin form, one would expect to observe large direct effects with regard to entrepreneurship in technologically advanced economies and small direct effects in technologically lagging economies. This reflects the fact that it is simply easier for laggard economies to absorb innovations from the frontier than it is for them to develop them themselves. Furthermore, it would not be very beneficial for economies near the technological frontier to absorb less productive technologies and so they must develop the innovations themselves in order to become more productive.

The point of contention with regard to the implications of these theoretical conjectures, as they apply to policy or to other real world application, is that they have yet to be either adequately confirmed or refuted in the empirical literature. This is not to say that a vast empirical literature involving both productivity (economic growth) and a technological frontier does not exist (see for example Fagerberg 1987; 1994; Dosi 1990; Fagerberg and Verspagen 2002). What it says is that what's missing is specific empirical confirmation of the direct theoretical link between entrepreneurship and the advancement of productivity in economies on the frontier. In other words, an empirical connection between the entrepreneurial driven growth of neo-Schumpeterian theory and productivity differences has not been established. Furthermore, the presumption that entrepreneurship is not at all responsible for diffusion and/or productivity gains in economies at a considerable distance from the frontier may prove to be false.

The purpose of this chapter is simple. It will test the efficacy of the application of these theories as they relate to entrepreneurship and productivity growth in a sample of regional economies. Consequently, the technological frontier will be defined as it pertains to the sample data and these theoretical claims will be tested in the context of differences in regional productivity. The layout of this chapter is as follows. Section 3.2 will discuss the dataset and the definition of the technological frontier that underlies the analysis. Section 3.3 will discuss the integration of the technological frontier within the spatial durbin regression model. Section 3.4 will present the results and Section 3.5 will provide the conclusions.

3.2 Data

To examine the different impacts of entrepreneurship and knowledge on regional total factor productivity in economies near and far from the technological frontier, the same pooled panel of data on the 49 continental U.S. states (again including DC as a state-level observation) covering the period 1997-2003 is utilized. U.S. states were used again because they constitute the smallest regional-level observations with reliable data on economic output. The same time horizon was used because of the change in industrial coding schemes that occurred in 1997. The lack of available data on single establishment firm formations after 2003 again limits the time horizon on the latter side. In addition, reliance on the same dataset facilitates an apples to apples comparison of these results with those of chapter 1. Once again Alaska and Hawaii were excluded from the dataset because of their isolation from the continental states. Finally, log transformations were again taken on all variables in order to yield elasticity inferences with regard to the parameter estimates.

Total Factor Productivity

Total factor productivity, as in the preceding chapter, will be estimated according to the augmented Solow model shown again in relation 3.1.

$$\text{tfp} = \ln(a) = \ln\left(\frac{y}{l}\right) - \alpha \ln\left(\frac{k}{l}\right) - \beta \ln\left(\frac{h}{l}\right) \quad (3.1)$$

To compute these values, gross state product (GSP) data was obtained from the Bureau of Economic Analysis (BEA) in year 2000 dollars. State-level physical capital stocks had to be estimated as they are not available at the state-level. To do this, the method of Garofalo and Yamarik (2002) was again utilized at the two-digit industry level. This methodology involves apportioning the constant dollar value of the national capital stock series to the state-level using the dollar value of GSP in constant dollars as is provided by the BEA. In other words, the national capital stock is multiplied by the ratio of state-level income in a given industry to the national income in that industry. The state-level industry estimates for the physical capital stock are then summed over all industries to arrive at the total state-level capital stock estimate. This procedure is summarized by equations 3.2 and 3.3.

$$k_{i,j}(t) = \left[\frac{y_{i,j}(t)}{Y_i(t)} \right] K_i(t) \quad (3.2)$$

$$k_i(t) = \sum_{j=1}^{19} k_{i,j}(t) \quad (3.3)$$

Where i denotes the specific industry and j denotes the particular state. Further, the uppercase letters denote national totals while the lowercase letters denote state-level values. The labor force was measured by state-level payroll expressed in year 2000 dollars. This data was provided by the Bureau of Labor Statistics (BLS). Human capital stocks were obtained from the U.S. Census Bureau and were measured as the total number of persons aged 25+ years who have obtained at least a bachelors degree. These data were then used to obtain least-squares estimates of $\hat{\alpha}$ and $\hat{\beta}$ as in chapter 1. Plugging the data and $\hat{\alpha}$ and $\hat{\beta}$ into equation 3.1 results in a $7n \times 1$ vector of $tfps$.

Knowledge

The stock of knowledge available to each state was again constructed using the total number of patents granted in each state as provided by the U.S. Patent and Trademark Office. It is well known that patents represent a problematic measure of the stock of knowledge available to regional economies. This is due to the fact that not all knowledge is patented and that which is tends to be produced in the private sector and is concentrated in certain types of industries. As a result, there likely exists a considerable amount of new knowledge that is not included in the stock of patents. Remember, however, that this type of deficiency is accommodated by the particular form of the spatial regression model that is implemented here; through the a priori assumption that the included variable measuring knowledge is likely omitting a significant amount of the true knowledge that is available to any regional economy. As a result, the unmeasured and omitted knowledge will not bias the coefficient estimates.

Entrepreneurship

There are a number of ways that scholars have measured entrepreneurship in previous research. The most common are: the number of self-employed individuals, the number of small firms, the number of small and medium sized firms (SME's), the total number of new establishments or the total number of new single establishments. Each of these methods of measuring entrepreneurship is associated with some strengths and some

weaknesses. For example, the number of self-employed individuals includes entrepreneurship at the earliest stage. On the other hand, this type of measure tends to be very coarse as it includes over 8.5 million Americans; most of which are not attempting to grow a new firm based on their exploitation of new knowledge (Glaeser 2007). The number of small firms, SME's and the total number of new establishments are likewise very coarse measures and so include many firms which are entirely replicative or are branches of some parent establishment. Furthermore, many of the small and medium sized firms are not at all new. Perhaps the best measure of entrepreneurship is the number of single establishment firm formations. This method excludes new branch plants and reflects the organization of a new company. As a result, it tends to best represent new forms of organizing labor and capital in the production of economic goods. Entrepreneurship is again measured by single establishment firm formations in this chapter.

The Technological Frontier

Measurement of the technological frontier is compulsory for an analysis of the contributions of entrepreneurial activities and knowledge production to regional productivity in economies at different points on the technological spectrum. Several methods for doing so have been employed in a large number of studies. This has resulted in the availability of a few alternative techniques for defining the technological frontier.

One technique is known as the stochastic frontier approach (SFA). This two step econometric approach, originally introduced by Aigner, Lovell and Schmidt (1977), works to erect a smooth parametric frontier that includes a stochastic component, or random error term, along with a systematic efficiency term (commonly referred to as the inefficiency term). The technique relies on regression analysis in the first stage and the residuals from the regression line in the second stage. The approach identifies the maximum amount of output that can be obtained from some given level of inputs (Kneller and Sevens, 2006). As such, it provides an estimate of the upper boundary on potential output and in so doing provides an estimate of the production possibilities frontier, which can then be used to define the technological frontier. While this technique's application is rather straight forward, it requires the imposition of several rather restrictive assumptions about the underlying technology that may or may not be true; such as the assumption of a temporally constant efficiency term (Jacobs, 2001).

Data envelopment analysis (DEA) is another possible approach with precedent in the literature. This approach is a non-parametric linear programming technique that relates inputs to outputs in production settings. It works to identify a piece-wise efficiency frontier without requiring a priori assumptions about the underlying technology. Aside from lacking prior assumptions on technology, DEA provides for inferences about where the sources of inefficiency lie in the individual observations (Sutter and Stough 2008). Specifically, DEA is capable of providing inferences on how much any specific input could be reduced without sacrificing output. In other words, DEA is capable of

identifying wasted resources or resources that are being used less efficiently than in other places. On the downside, DEA ascribes all signal (random or not) to the efficiency term. As one might expect, both DEA and SFA are widely applied in studies of individual firms and/or industries. Their application to the study of regional production, on the other hand, is considerably less common. Both methods are quite vulnerable to misspecification error as it relates to measurement error, omitted variables, the inclusion of irrelevant variables or the incorrect imposition of constant or variable returns to scale (Jacobs 2001). However, in spite of their differences, both approaches have consistently been shown to produce similar results (Bowlin et al. 1985; Thanassoulis 1993; Banker et al. 1986).

The last approach is a two step process that works to identify a technological leader that can be used to represent the technological frontier. This type of approach is commonly applied to the study of regional efficiency, such as in Griffith et al. (2004) and Kneller (2005), where they study the impacts of absorptive capacity on total factor productivity. This approach is also applied in Acemoglu, Aghion and Zilibotti (2006) to investigate the impact of barriers to entry in economies near and far from the technological frontier. This approach defines the most productive economy as the technological leader, using it as the numeraire in a measure of relative technical distance (Kneller and Stevens 2006). A possible extension would be to define the technological frontier using an average of several technically leading observations.

This approach does have critics who argue that assuming that the most productive observation is on the frontier and in fact solely defines the frontier is problematic (Jacobs 2001). However, in the context of this study, this criticism should not be a problem. It should not be a problem for one critical reason. The reason being that the central purpose of this chapter is not to precisely identify the technological leader or to provide extremely accurate inferences on the distances of particular economies from the frontier. Rather, the purpose here is to identify economies near the frontier without placing critical importance on the precise distances of any particular economy from it. Therefore, even if the chosen economy does not completely represent the technological frontier, it should certainly be a good enough proxy for the purposes here.

This approach, then, has considerable appeal for several reasons. For one, it provides an approach to establishing the set of economies with close proximity to the frontier with relative simplicity. Second, it renders making assumptions about the underlying technology unnecessary. Lastly, the manner with which the technological leader is identified, the augmented Solow model, is associated with a vast and highly rigorous precedent in the literature that clearly establishes which variables to include in the assessment. This methodology will be used to construct the technological frontier for these reasons.

With regard to the specifics, the technological frontier, as used in this chapter, will be constructed as follows. First the total factor productivities for all observations will be

estimated according to the augmented Solow model shown equation 3.1. The resulting vector of total factor productivities will then be sorted from high to low. The observation associated with the largest total factor productivity estimate will be used to represent the technological frontier. This approach is grounded in the notion that this specific economy is able to produce the most output relative to its inputs. The differences in levels of output, then, should be solely attributable to differences in the technologies applied to production.

3.3 Methodology

The central purpose of this chapter is to examine whether or not entrepreneurship directly influences productivity in economies near the technological frontier but not in economies far from the technological frontier. This hypothesis is implied in the model proposed by Acemoglu, Aghion and Zilibotti (2006) as well as by technological gap theory. An empirical analysis of these implications, then, would provide much to the existing literature.

A spatial econometric model known as the spatial durbin regression model will be used to conduct the analysis. This spatial framework is particularly relevant to this analysis for a number of reasons. For one, the theoretical neo-Schumpeterian growth model initially proposed by Aghion and Howitt (1998) and elaborated on in Howitt (2000), Acemoglu, Aghion and Zilibotti (2006) and Ertur and Koch (2007; 2008) reduces to this type of

spatial econometric model in an empirical application (Ertur and Koch 2008). This is extremely pertinent to this research as this type of growth model encapsulates aspects of both innovation and technological gap theories, as innovation in this type of model is driven by the creation of profit motivated new knowledge. Furthermore, this theoretical model contains avenues for the diffusion of newly created knowledge via structuralized technological interdependence, i.e. by technological gaps. Further, work by LeSage and Fischer (2008) demonstrates that even if one were to assume away the technological interdependence and rely on a non-spatial theoretical model, the same spatial econometric specification would still result if the observable variables were incompletely measured and if the subsequent unobservable portions of these variables exhibited spatial correlation (LeSage and Fischer 2008). This is a highly likely situation in light of the preceding chapter which shows this exact circumstance. Lastly, a spatial model of the spatial durbin variety facilitates the decomposition of the partial derivatives (de/dt_{fp} and dk/dt_{fp}) into their direct and indirect constituents. This enables an explicit focus on the direct effects of these variables, which is exactly the goal here.

To begin the analysis, a spatial durbin regression model of the form shown in equation 3.4 will be estimated.

$$TFP = \rho Wy + \alpha_1 e + \alpha_2 We + \alpha_3 a + \alpha_4 Wa + \varepsilon \quad (3.4)$$

In 3.4, TFP denotes a $7n \times 1$ vector containing logged values of total factor productivity for each observation for each of the seven years. The term, Wy denotes the spatially lagged dependent variable while terms We and Wa represent the spatially lagged

independent variables. The terms, $\rho, \alpha_1, \alpha_2, \alpha_3, \alpha_4$ correspond to the coefficients while ε reflects an *iid* error term.

As is indicated above, the decomposition of the total effects of entrepreneurship and knowledge into its direct and indirect components is critical. This decomposition is tantamount to decomposing the partial derivatives with respect to these variables into two categories; the own partial and cross partial derivatives. This is done according to equations 3.5 and 3.6.

$$\frac{dftp}{da} = (I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1} ((I_7 \otimes I_n) \hat{\alpha}_1 + (I_7 \otimes Wa) \hat{\alpha}_2) \quad (3.5)$$

$$\frac{dftp}{de} = (I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1} ((I_7 \otimes I_n) \hat{\alpha}_3 + (I_7 \otimes We) \hat{\alpha}_4) \quad (3.6)$$

Where $\frac{dftp}{da}$ denotes the response of *tfp* to changes in knowledge and $\frac{dftp}{de}$ represents the response of *tfp* to changes in entrepreneurship. The term I_7 denotes an identity matrix and W represents a row-normalized spatial connectivity matrix. The partial derivatives are interpreted as changes that lead to a move from one steady-state equilibrium to a new one (LeSage and Fischer 2008). The direct effects, or the own partial derivatives, constitute an average of the main-diagonal of the matrices shown in equations 3.5 and 3.6. The indirect effects constitute an average of the row sums of the off-diagonal elements of these matrices. As a result, the computation of the direct, indirect and total effects is rather straightforward. Lastly, the log-transformations that are taken on all variables in the model facilitate an elasticity interpretation of the partial derivatives shown in equations 3.5 and 3.6.

The remaining methodological issue is the incorporation of the technological frontier into the analysis. This was done as follows. First, the observation constituting the technological frontier was identified by isolating the maximum value of the total factor productivity vector. This will then be used as the denominator in a ratio of the total factor productivity for each observation relative to this value. The ratios were then sorted from high to low. A technological proximity threshold was then defined to differentiate between observations near and far from the technological frontier. Two alternative thresholds were specified; one that resulted in half of the observations being deemed near the frontier and one that isolated the top 20 percent. Five extraction matrices, based on these thresholds were then defined in order to extract all observations near and far from the technological frontier for both thresholds. This was done by placing values of 1 in positions to be included in the extraction and values of 0 in positions that are not to be extracted. The placement of the 1's and 0's depends on whether one is trying extract those observations near or far from the frontier. The extraction matrices were then multiplied by the two matrices of partial derivatives as is shown in equations 3.7 and 3.8, respectively; where $E_{1...5}$ represents the five extraction matrices.

$$dftp/da_{1...5} = E_{1...5}[(I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1}((I_7 \otimes I_n)\widehat{\alpha}_1 + (I_7 \otimes W a)\widehat{\alpha}_2)] \quad (3.7)$$

$$dftp/de_{1...5} = E_{1...5}[(I_7 \otimes I_n - \hat{\rho}(I_7 \otimes W))^{-1}((I_7 \otimes I_n)\widehat{\alpha}_3 + (I_7 \otimes W e)\widehat{\alpha}_4)] \quad (3.8)$$

Summary measures of the total, direct and indirect effects can then be estimated.

Specifically, the direct effects are estimated by averaging the main-diagonals elements of these matrices. The indirect effects are calculated by averaging the row sums of the off-

diagonal elements of these matrices. The total effects are the sums of the direct and indirect effects.

3.4 Results

Presentation of the results will follow accordingly. First, a series of specification tests pertaining to the spatial weight matrix will be presented. The sequence of alternative specifications of the matrix includes a set of 16 row-normalized spatial weight matrices that were used to represent the set of candidate connectivity structures. The weight matrix that is used in model estimation was selected using two metrics; the maximum log-likelihood function value based on maximum likelihood estimation and the maximum posterior model probability estimated via Bayesian MCMC methods. After these tests the regression results and model specification tests will be presented accordingly.

The pooled nature of the sample data has resulted in 343 observations that were stacked into a $7n \times 1$ vector of observations of the dependent variable and a $7n \times 2$ matrix of observations of the independent variables. The pooling thus affected the specification of the spatial weight matrix as the connectivity structure is only $n \times n$. To specify the spatial weight matrix for the pooled model, the spatial weight matrix had to be formed according to the expression shown in 3.9.

$$W_{7n} = I_7 \otimes W_n \quad (3.9)$$

Where n represents the 49 single year observations, I an identity matrix and \otimes denotes the kronecker product. This strategy is permissible because the spatial connectivity structure was constant over the time horizon used in this study.

Table 4. Weight Matrix Comparison Results

Number of Neighbors	Log-likelihood	Posterior model probability
1st order contiguity	262.0354	0.3182
1 NN	222.2959	0.0000
2 NN	243.7346	0.0000
3 NN	255.6039	0.0002
4 NN	260.8112	0.0486
5 NN	253.6972	0.0001
6 NN	260.4709	0.0592
7 NN	260.2232	0.0645
8 NN	262.3976	0.4925
9 NN	258.7449	0.0167
10 NN	245.3867	0.0000
11 NN	235.0169	0.0000
12 NN	232.5277	0.0000
13 NN	227.3723	0.0000
14 NN	222.3940	0.0000
15 NN	221.5681	0.0000

Table 4 contains the model comparison results pertaining to the specification of the spatial weight matrix. Sixteen different specifications were considered, ranging from a first order contiguity specification that selects border sharing observations through a specification that selects the 1-15 nearest neighboring observations based on the Euclidean distance between each state's centroid coordinates. The results demonstrate

that a spatial weight matrix selecting the 8 nearest neighboring observations fits the sample data the best in terms of both measures of fit. In terms of posterior model probabilities, this specification of the spatial weight matrix is more likely than all of the alternatives combined. As a result, this matrix will be used to define the spatial connectivity in the following model estimation.

Bayesian MCMC parameter estimates for the pooled spatial durbin model shown in relation 3.10 are presented in Table 5.

$$tfp = \alpha_0 i_n + \rho W tfp + \alpha_1 a + \alpha_2 W a + \alpha_3 e + \alpha_4 W e + \varepsilon \quad (3.10)$$

Once again, tfp represents logged total factor productivity, i_n denotes a vector of ones included to reflect to non-zero mean of the dependent variable, W is the spatial weight matrix, a is logged knowledge, e is logged entrepreneurship, ε is an *iid* error term, and α_0 through α_4 are the coefficients.

The results contained in Table 5 reveal a few things of note. For one, it shows that the excluded and included variables for entrepreneurship and knowledge are spatially correlated.

Table 5. Bayesian Spatial Durbin Model Estimates

Variable	coefficient	Std-Deviation	p-level
Constant	-0.5511	0.2566	0.0140
Rho	0.4970	0.0643	0.0000
Knowledge	0.0272	0.0175	0.0607
W-Knowledge	0.0677	0.0317	0.0165
Entrepreneurship	0.4952	0.0237	0.0000
W-Entrepreneurship	-0.1686	0.0534	0.0014

This conclusion is drawn, once again, by testing whether or not the common factor restrictions, shown in relations 3.11 and 3.12, hold.

$$-\alpha_1\rho = \alpha_2 \tag{1.19}$$

$$-\alpha_3\rho = \alpha_4 \tag{1.20}$$

From Table 5 one can see that $-\alpha_1\rho = -0.0135$. This value is considerable different from $\alpha_2 = 0.0272$. Further, the p-level associated with a t-test determining statistical significance is equal to 0.0000. Likewise, $-\alpha_3\rho = -0.2461$ is not equal to -0.1686 , the estimate of α_4 . Here again a t-test was implemented to ascertain whether or not these values were statistically significantly different from each other. The resulting p-value of 0.0445 provides this indication. Thus, one can confidently conclude that the common factor restrictions in 3.11 and 3.12 do not hold and, therefore, that the SDM approach is appropriate. The second thing to note is that the parameter estimates are equal to those provided in chapter 1. This confirms that enough MCMC draws were taken to assure that the sampling scheme has converged and that enough burn-ins were discarded.

Table 6 contains the mean direct and indirect effects of entrepreneurship and knowledge for all observations, for observations near the frontier and for observations far from the frontier as well as a 95% confidence interval computed around the means. These results are based on setting the frontier threshold such that half of the observations are deemed near the frontier and half are deemed far from the frontier.

The results show that the direct effect of entrepreneurship is approximately 0.5 in all cases. This suggests that a 1% increase in the number of single establishment firm

formations will lead to a 0.5% increase in regional total factor productivity regardless of distance from the technological frontier.

Table 6. Direct and Indirect Effects Near and Far from the Frontier - 50% Threshold

Entrepreneurship	Lower 0.05	Mean	Upper 0.95
All Direct Effect	0.4623	0.5016	0.5409
Near Direct Effect	0.4625	0.5017	0.5411
Far Direct Effect	0.4624	0.5015	0.5408
All Indirect Effect	0.4602	0.6620	0.8975
Near Indirect Effect	0.4597	0.6637	0.9016
Far Indirect Effect	0.4608	0.6594	0.8916
Knowledge	Lower 0.05	Mean	Upper 0.95
All Direct Effect	0.0061	0.0338	0.0611
Near Direct Effect	0.0062	0.0339	0.0614
Far Direct Effect	0.0060	0.0337	0.0612
All Indirect Effect	0.1054	0.1947	0.2949
Near Indirect Effect	0.1062	0.1965	0.2977
Far Indirect Effect	0.1041	0.1921	0.2909

While the estimate of the direct effect is largest for those places near the frontier and smallest for those far from the frontier, in no way are these differences statistically significant, as is evident by examining the 95% confidence intervals around the means. A similar pattern is evident in the indirect effects of entrepreneurship, where the indirect effect (or the spatial spillover effect) from neighboring observations is largest for those near the frontier and smallest for those far from the frontier. Once again, however, the differences are certainly not statistically significant.

The results in Table 6 also reveal that the direct effect of knowledge is approximately 0.03. Once again the direct effect is largest for those places near the frontier and smallest for those far from it, however, these differences are nowhere near statistical significance. The same is true of the indirect effects. It is also noteworthy to mention that the impact of entrepreneurship is much larger than knowledge for all places and that the direct effect of entrepreneurship is only slightly smaller than the indirect effect, whereas the indirect effect of knowledge is nearly 9 times larger than the direct effect.

In general, Table 6 suggests that the importance of entrepreneurship to total factor productivity is unaffected by the state of a regional economies technology. This due to the fact that the direct effect of entrepreneurship is nearly identical in economies both near and far from the technological frontier. As some might suggest, perhaps this is due to the fact that the technical threshold was too low. If one were to select only the top echelon of technological leaders, then perhaps differences in the direct effects would become apparent.

The result pertaining to this type of partitioning are contained in Table 7, where the near the frontier group contains only 20% of the observations; those closest to the technological frontier. These results present nearly identical results when compared with those in Table 6. In Table 7, the mean direct effect of entrepreneurship is again approximately equal to 0.5.

The result is again mildly larger for those near the frontier and slightly smaller for those far from the frontier. Once again, however, the 95% confidence intervals show that the differences are much smaller than that needed for anything close to statistical significance.

Table 7. Direct and Indirect Effects Near and Far from the Frontier - 20% Threshold

Entrepreneurship	Lower 0.05	Mean	Upper 0.95
All Direct Effect	0.4624	0.5016	0.5415
Near Direct Effect	0.4624	0.5017	0.5416
Far Direct Effect	0.4623	0.5014	0.5413
All Indirect Effect	0.4527	0.6633	0.9132
Near Indirect Effect	0.4521	0.6658	0.9192
Far Indirect Effect	0.4532	0.6608	0.9068
Knowledge	Lower 0.05	Mean	Upper 0.95
All Direct Effect	0.0064	0.0341	0.0613
Near Direct Effect	0.0065	0.0341	0.0613
Far Direct Effect	0.0063	0.0339	0.0612
All Indirect Effect	0.1033	0.1949	0.2978
Near Indirect Effect	0.1045	0.1974	0.3017
Far Indirect Effect	0.1022	0.1924	0.2938

The indirect effects of entrepreneurship are also nearly identical to those shown in Table 6. The direct and indirect effects of knowledge in Table 7 are also approximately equivalent to those in Table 6. In general this result suggests that the direct and indirect effects of entrepreneurship are unaffected by distance from the technological frontier.

3.4 Conclusions

Innovation theory has long posited that productivity differences, or differences in the efficiencies of combinations of labor and capital, emerge from differences in the propensity to apply new ways of doing things to old ones (Schumpeter 1911; 1939). In this context, innovation has often been credited to the cleverness of individuals and their propensity to engage in entrepreneurship. Technological gap theory suggests that regional economies at great distances from the technological frontier can catch-up to the leading economies by successfully adopting their innovative technologies (Fagerberg 1987; Verspagen 1993; Fagerberg and Verspagen 2002). Technological gap theory also recognizes that the absorption of innovative technologies requires significant effort and considerable amounts of capital investments.

In light of these ideas and their incorporation into theoretical growth models, recent theoretical work in modeling economic growth has led to models implying that entrepreneurship drives productivity growth (technical change) in economies on or near the technological frontier while channeled investments by existing organizations drives their diffusion (Acemoglu, Aghion, and Zilibotti 2006). These findings, then, have profound implications for the policy community at large. Yet at the same time, little empirical work has sought to test the efficacy of these implications.

This chapter has sought to undertake this issue by empirically examining the suggestion that entrepreneurship directly impacts regional total factor productivity in economies on and near the technological frontier while it does not in economies far from it. The

approach has been to estimate a reduced form of the model which takes on the form of a spatial durbin regression model. This model is both implied by the specific spatial-technological interdependencies inherent in the originating growth models as well as by non-spatial models exhibiting spatially correlated omitted variables. The results provided in this chapter suggest the following. One, that entrepreneurship has larger impacts on regional total factor productivity than do knowledge stocks, and two, that the direct affect of entrepreneurship is nearly identical in size in economies both near and far from the technological frontier. As a result, the analysis contained in this chapter does not support the theoretical implications of the discussed models. It appears that, in fact, entrepreneurship provides an identical productivity effect for both leading and lagging regional economies alike.

CHAPTER 4 PSYCHOLOGICAL CAPITAL AS A DETERMINANT OF REGIONAL ENTREPRENEURSHIP

4.1 Introduction

The preceding chapters have sought to examine the relationships between entrepreneurship, knowledge and productivity in a sample of U.S. states over the period 1997-2003. Before turning attention away from the economic impacts of entrepreneurship and to the determinants of it, it would be beneficial to begin by briefly taking stock of what has been learned thus far in order to motivate the topic more fully.

The analysis contained in Chapter 2 has shown that regional variation in knowledge stocks and entrepreneurship for the most part explains regional productivity differences in U.S. states. Of the two factors, the empirical data suggest that entrepreneurship has much larger impacts on these differences than do differences in stocks of knowledge. The impact of entrepreneurship on productivity is larger both directly and indirectly. This meaning that the productivity gains from endogenous entrepreneurship or the entrepreneurship created within the regional economy as well as the productivity gains from entrepreneurship in surrounding regions are considerably larger than that gained

from additions to the stock of knowledge as measured by patenting activities. In fact, the total cumulative effect of a 1% increase in the level of entrepreneurship has an effect on regional productivity that is over five times larger than the same increase in the stock of knowledge.

The investigation contained in Chapter 3 sought to test the efficacy of emergent Neo-Schumpeterian growth models as they pertain to entrepreneurship and the technological frontier. Specifically, the analysis carried out in this chapter sought to test the theoretical assertion that entrepreneurship is more important to leading frontier economies than it is to technically lagging regional economies. In general, the purpose of chapter to was to test the thesis.

The analysis did not support this assertion as the productivity augmentations provided by entrepreneurship and knowledge were statistically equivalent both near and far from the technological frontier. While these theoretical models appear highly eloquent and intuitively appealing, they lack support in the empirical data regarding U.S. states. As a consequence, the data does not directly support the theoretical idea that lagging economies would grow faster by enhancing barriers to entry or by creating conditions that favor established companies and their foreign direct investments.

To summarize, Chapters 2 and 3 have shown that entrepreneurship is an extremely important source of productivity growth in regional economies at all points on the

technological spectrum. These findings, then, imply that the process of entrepreneurship is highly important to dynamism or productivity growth in regional economies both near and far from the technological frontier. Given these results, understanding the determinants of entrepreneurship becomes critical to any policies based on entrepreneurial driven growth strategies.

4.2. The Determinants of Entrepreneurship

Taking the results of Chapters 2 and 3 as established, a critical question becomes; what factors determine the occurrence of entrepreneurship? To be sure, this question has been asked by countless scholars across a broad variety of scholarly disciplines. Within this vast literature however, two specific alternative approaches to identifying the important determinants have been utilized. The first approach has been to study individual entrepreneurs with the goal of identifying a set of characteristics common to these individuals. Thus, the focus is on individual differences between who is and who is not an entrepreneur. The second approach has focused on structural economic differences across various regional economies in an effort to explain variation in entrepreneurial activities due to differences in various supply-side or regional characteristics and economic conditions. This approach places emphasis away from individuals focusing instead on the environment within which they emerge. While different, both points of focus have revealed substantial insights into how and why entrepreneurial activities emerge.

The literature based on the study of the individual has emphasized individual-level characteristics that are shared by either successful and/or nascent entrepreneurs. These inquiries have identified several important determinants. One such determinant is the existence of critical social relationships with and between important players. These relationships have come to be described as social networks (Saxenian 1999; Sorenson 2003; Johannisson 1988; Larson 1991). Social networks are posited to be critically important because they lower the transaction costs of starting an entrepreneurial venture. This is due primarily to the establishment of high levels of trust between key players (Williamson 1991). Another and rather obvious characteristic of entrepreneurs is their relatively high levels of educational attainment (Evans and Leighton 1990). While this is certainly not always the case and many successful entrepreneurs defy this, high levels of education are a well established distinguishing characteristic of entrepreneurial individuals (Schultz 1959; Becker 1964; Evans and Leighton 1989; Bellu et al. 1990; Gimeno et al. 1997; Reynolds 1997).

Perhaps the most widely studied characteristics of individual entrepreneurs are their psychological attributes. In particular, risk tolerance is one psychological characteristic that has been widely ascribed to entrepreneurial individuals. The evidence consistently finds that entrepreneurs are risk tolerant individuals (Kilstrom and Laffont 1979; Brockhaus 1980; Van Praag and Cramer 2001; Stewart and Roth 2001). The basic theory concerning this distinguishing characteristic is that risk tolerant individuals are more willing to bear the burden of “Knightian” uncertainty that is deeply involved with

engaging in entrepreneurship. Other individual-level studies suggest that a strong sense of self-efficacy, or the unyielding belief in one's ability, plays a large role in who engages in entrepreneurial activities (Chen et al. 1998; Markman et al. 2002). Self-efficacy is important because entrepreneurs must overcome very real and substantial barriers with no established procedure on which to follow. As a result, they tend to overcome them simply by a strong individual belief in their ability to do so. Lastly, other research has found that individuals whom possess a strong need for achievement and a high tolerance for ambiguity are more likely to engage in entrepreneurship than are those who do not possess these traits (McClelland 1961; Budner 1982; Schere 1982; Begley and Boyd 1987; Collins et al. 2000).

The regional approach to entrepreneurship research has tended to leave aside individual characteristics, focusing instead on regional-level structural factors. This body of literature either implicitly or explicitly assumes that opportunities are objective and are not homogeneously distributed across geographic space. As a consequence, the structural differences are the important determinants of entrepreneurship and not the individual differences. This type of scholarly approach has focused primarily on factors that affect the creation of opportunities as well as the factors that decrease the barriers to their exploitation. It has identified low transport costs, high human capital concentrations, advantageous employment and industrial structures, extensive research and development activities, and abundant financial capital availability as critical factors (see for example Bartik 1989; Reynolds et al. 1994; Dunn and Holtz-Eakin 2000; Acs et al. 2008). In

addition, other scholarly work in this vein has argued that further basic structural factors previously linked to dynamic economies, like population, employment and income growth, are important determinants of entrepreneurship (Acs and Armington 2002).

In spite of the bifurcated history of the literature on the determinants of entrepreneurship, both types of determinants are likely to be important. While the individual entrepreneur cannot accomplish her goals in the absence of the right environment, one can hardly deny that entrepreneurial individuals tend to display clearly identifiable characteristics. As a result, the identification and exploitation of opportunities by entrepreneurs is very likely determined by a combination of both individual and environmental characteristics.

This has not gone completely unnoticed in the regional approach as some regional scholars have begun to place more emphasis on the regional manifestation of individual traits. In particular, psychological factors have begun to surface in regional analysis of entrepreneurial activities through the concepts of: social capital, creativity and tolerance. Coleman (1988, 1990) and Putman (1993), among others, have argued that regional stocks of social capital facilitate higher levels of trust and cooperation among regional actors. This supports the individual-level studies which have found them to be important ingredients of entrepreneurship (Saxenian, 1999). Other factors with definite psychological undertones, such as, creativity and tolerance, have crept into regional analyses of entrepreneurial activities; albeit through rather obscure and perhaps extraneous occupation-based indicators such as the creative class index. The arguments

for these latter factors have been based on the idea that agglomerations of creative individuals along with a tolerant and open regional environment make the economy more accepting of and willing to fund radical ideas (Andersson 1985; Lee et al. 2004; Florida 2002; Mellander and Florida 2007). These agglomerations have been ascribed to play the role of creative capital, which is separate and apart from human or social capital, yet is posited to exist as a stock that is available to the regional economy.

These social and psychological factors inexorably reside within the individual yet are made manifest at the level of the regional economy through agglomeration effects. As the individuals possessing higher levels of social capital accumulate in one place, it makes the regional social networks denser, by creating stronger links between larger numbers of nodes, while increased stocks of creative and tolerant individuals facilitate entrepreneurship by advancing lower barriers to entry within the entire region. Thus, these latter factors enhance regional economies by augmenting the general populous in ways that make it more open to radical ideas, innovations and firms.

While it is certainly true that the individual and regional-level investigative approaches to entrepreneurship have different points of view, both seek to explain variation in entrepreneurial activities and have contributed substantial amounts of understanding. The study of individual entrepreneurs has provided sizeable evidence indicating that certain psychological traits are central determinants of entrepreneurship. The regional economic advance, on the other hand, has demonstrated that many structural

characteristics within the regional environment are crucial factors facilitating entrepreneurship as well. Additionally, while the regional perspective has yet to fully address the issue of psychological characteristics, it has provided some early indications that psychologically based factors, such as: social capital, creativity and tolerance, have important influences on entrepreneurial activities at the regional-level as well.

Taking these perspectives together, it seems quite clear that the discovery and exploitation of opportunities by entrepreneurs is allied to both the person and their place (Schoonhoven and Romanelli 2001; Thornton and Flynn 2005). In other words, the nexus of person, place and the emergence of entrepreneurial endeavors in geographic space likely depends, to varying extents, on both psychological characteristics as well as on the structure of the environment within which it emerges.

Given these perspectives, it is likely the case that both psychological characteristics and structural variables are critical determinants of entrepreneurship. Yet there are significant holes in the literature as it pertains to these factors. The most prominent of these is the fact that the theoretically important individual psychological variables have not yet been explicitly included in regionally based empirical studies. As a result of this, we scholars have no basis on which to gauge how important they are to regional entrepreneurship if they are even important at all. Perhaps, it is the case, as some have already suggested, that it is really just the environment that drives the emergence of entrepreneurship in a given place. On the other hand, perhaps it is the case that individuals well equipped with entrepreneurially relevant psychological traits will manage to engage in entrepreneurship

regardless of the fact that their regional environment may not be endowed with the proper structural ingredients. To date, we simply do not know the answer to these questions. A second, and yet very related, gap in the literature involves how to think about individual psychological traits when considering regional systems of entrepreneurship. If these traits reside exclusively within the individual, does this fact prohibit their being relevant to regional entrepreneurship? Furthermore, how should we think about the psychological traits when considering regional economies and the role of entrepreneurship in them?

4.3. Psychological Capital

In his highly anticipated inaugural address, President Obama has this to say about the fundamental underlying sources of America's exceptionalism:

“Our challenges may be new, the instruments with which we meet them may be new, but those values upon which our success depends, honesty and hard work, courage and fair play, tolerance and curiosity, loyalty and patriotism -- these things are old. These things are true. They have been the quiet force of progress throughout our history. What is demanded then is a return to these truths.”

It is highly interesting that our new president ascribes the fundamental sources of American economic might to a set of psychological characteristics. This is interesting because the legacy of his presidency will likely rest on the performance of the economy

over his first term and very few economists seem to express this view explicitly in their scholarly research. So where does this statement come from? Was it simply a case of pandering? Was it included in his inaugural address because it fit the message that so captivated the minds of the electorate during his unanticipated rise from obscurity? I am not in a position to know the real answers to these questions, nor are they at all relevant to this research. However, the statement does hint at one thing; that people (either the president or his electorate) seem to believe that these values are somehow related to American economic success.

I bring this up to because it underscores the theoretical argument that I am going to make with regard to how individual-level psychological traits ought to be conceptualized with regard to regional entrepreneurship. The argument is that the individual psychological traits that have been empirically connected to those who engage in entrepreneurship manifest themselves as a stock of capital at the regional-level. Specifically, they are manifested in a stock of psychological capital. Regional economies that have larger endowments of psychological capital will have higher amounts of entrepreneurship, *ceteris paribus*, due to the positive impact this form of capital has on individuals, their perception of opportunity and their belief in their ability to exploit them.

Recent years have been subject to a steadily increasing amount of research on positive psychological traits (Luthans et al. 2007). Emerging from this research is a variety of classification systems for scientifically indentifying the traits that underlie positive

character strengths. One, in particular, is a 24 variable classification scheme devised by scholars such as Martin Seligman, Chris Peterson and a host of their affiliated colleagues. Together, their work posits the notion that positive psychological characteristics of human beings can be broadly captured by a 24 item set of character strengths. It should be noted, that their intention was not the creation of a very precise and rigid conceptualization of positivity, but rather it seems have been to create a flexible framework for thinking about positive attributes of human beings as well as a set of items on which to measure them (Luthans et al. 2007; Peterson and Seligman 2004).

While their work was initiated to better understand the role of positive character strengths in human well being, it has, perhaps unexpectedly, not gone unnoticed by a variety of other disciplines (Luthans and Youssef 2007). For instance, the concepts originating under the guise of positive psychology have been incorporated into a variety of literatures, from organizational behavior, organizational leadership, human resource management to appreciative inquiry, just to name a few (Luthans and Youssef 2007). The fundamental basis for this is that the existence of high levels of certain positive traits within an organization are thought to be critical to its success in today's competitive and global economy. Positive traits such as: curiosity, resiliency, creativity, among others, are increasingly being identified as critical inputs into successful organizations (Luthans et al. 2007; Luthans and Youssef 2007; Luthans et al. 2006). As a result of these developments, Luthans et al. (2007; 2006) coin the term psychological capital to refer to the stock of a specific set of traits that help facilitate organizational success.

It is in a very similar manner that the individual psychological traits, regarding entrepreneurship, should be conceived when thinking about regional entrepreneurship. In this way, the individual traits manifest themselves at the level of the region. The collection of individual positive traits, then, can be used to represent a stock of psychological capital that exists within any given regional economy much like it would within a firm.

4.4. Research Aims

The purpose of this chapter is threefold. First, to the author's knowledge, this dissertation is the first to attempt to assess the importance of psychological traits to entrepreneurship at the level of the functional region. Second, this chapter formally investigates the related matter of determining whether or not variation in psychological capital exists across various regions of the United States (an adequate variance in an explanatory variable is necessary for finding a significant impact in regression modeling). Third, it will provide additional evidence in support of psychological traits as important determinants of entrepreneurship that is not based on individual entrepreneurs.

The analysis will be arranged as follows. Section 4.5 will discuss the dataset and the definitions of the variables used analysis. Section 4.6 will lay out the methodological approach. This section will include a discussion of the potential spatial econometric regression approaches as well as a discussion of model uncertainty and its relevance to

the analysis. Section 4.7 will provide the estimation results while Section 4.8 will provide a discussion of the results.

4.5 Data

The effect of stocks of psychological capital on entrepreneurship across regional economies in the U.S. is investigated using a sample of Metropolitan Statistical Areas (MSAs). The departure from state level analysis is motivated by several factors. The first motivation has to do with the small number of observations that would result from a state-level analysis. At most, 50 observations could be constructed. This is due to the fact that the psychological variables are only available at one point in time. As a result of this, even a simple pooling of data for several years is not possible. Therefore, only one particular cross sectional series can be created. The reliance on a dataset comprised of only 50 observations would prohibit the construction of an adequate model explaining the complex process of entrepreneurship as the degrees of freedom would be severely stretched. A second problem has to do with the size of states as a unit of analysis. States are relatively large regional units. Furthermore, their populations are comprised of a wide spectrum of individuals. As such, an index of psychological capital would not be as meaningful when measured at this spatial scale. For example, the psychological characteristics of persons living in the cities within the states could be vastly different from those living in the rural areas. This fact would likely diminish the usefulness of the index of psychological capital that will be created. As a result, this chapter will shift

focus to U.S. cities in order to overcome these problems to the extent that is possible. A city-level analysis would tend to minimize these problems, more so than a state-level analysis would, and is possible here because the dependent variable has changed from total factor productivity (which was not possible to create at the city level) to entrepreneurship, which is available at the city-level.

The dataset covers 173 MSAs due to a lack of reliable data for each explanatory variable covering the entire set of MSAs in the U.S. Specifically, the number of individual observations underlying the psychological capital index was not adequately large for all of the U.S. cities, as a small number of individual responses existed for many of them. As a result, the capability of the aggregated index to tolerably represent the entire population of these MSAs at large was questionable and so many MSAs were dropped from the analysis. This resulted in a final dataset containing 173 metropolitan regions. While the loss of these MSAs may seem substantial, the cities were of the small variety.

Entrepreneurship

High technology single establishment firm formations will be used to represent the dependent variable, entrepreneurship. This type of specification is frequently used in the entrepreneurship literature as it captures well the Schumpeterian notion of “creative destruction” that brought about by entrepreneurs. These data were obtained for the U.S Bureau of the Census and were broken out by county and by five digit North American

Industrial Classification System (NAICS) codes. The data on this variable corresponds to 2003 as this was the most recent year included in the dataset. It was aggregated to the MSA according to the Office of Management and Budget 2005 MSA definitions.

With regard to this data, the Census defines a single establishment as a single physical location where business is conducted and/or where operations and services are undertaken. The birth of a single-establishment is defined to be a completely new establishment (no parent company) with no payroll in the first quarter of the initial year yet with a positive payroll in the first quarter of the following year. Therefore, single establishment firm formations are considered an entirely new unit of firm-level economic organization.

High technology single-establishment births were extracted from the complete set of firm births for several reasons. For one, the high technology sectors of the U.S. economy are widely considered to be the most dynamic and ephemeral. As a result of this fact, these sectors of the economy most closely involve the process of new knowledge commercialization, which incumbent firms were unwilling or were unable to carry out. In addition, the high technology sectors of the U.S. economy are responsible for an increasing share of the growth in aggregate economic output. This places them in a critically important role in the growth processes of the evolving global knowledge economy. Therefore, the main purpose of isolating these firm formations is that these sectors most closely epitomize the “Schumpeterian” sense of entrepreneurship. That

sense being where new economic knowledge is being introduced by individuals whom enter a highly competitive and vibrant economic environment. Creative destruction is most certainly at work in this sector of the U.S. economy. Finally, the high tech sector of the economy tends to exclude new establishments that are doing old things. For instance, the vast majority of new single establishment firm formations constitute firms like: restaurants, bars, and hobby shops. Counting these firms as entrepreneurial risks undermining the purpose here, as the start up of these types of firms are, for all intents and purposes, simply a function of population growth and they tend not to harness some new type of scientific knowledge or information.

The definition of high technology used for the extraction criteria was based on Varga (1998). This criteria involved firms classified in industries associated with:

- 1.) an above average research and development to industry sales ratio;
- 2.) an above average percentage of mathematicians, scientists, engineers and engineering technicians compared to total industry occupations and;
- 3.) a larger than average number of innovations per 1,000 employees.

The number of high tech firm formations in each observation was divided by the Census's 2000 population figures for that metropolitan region in order to standardize the variable.

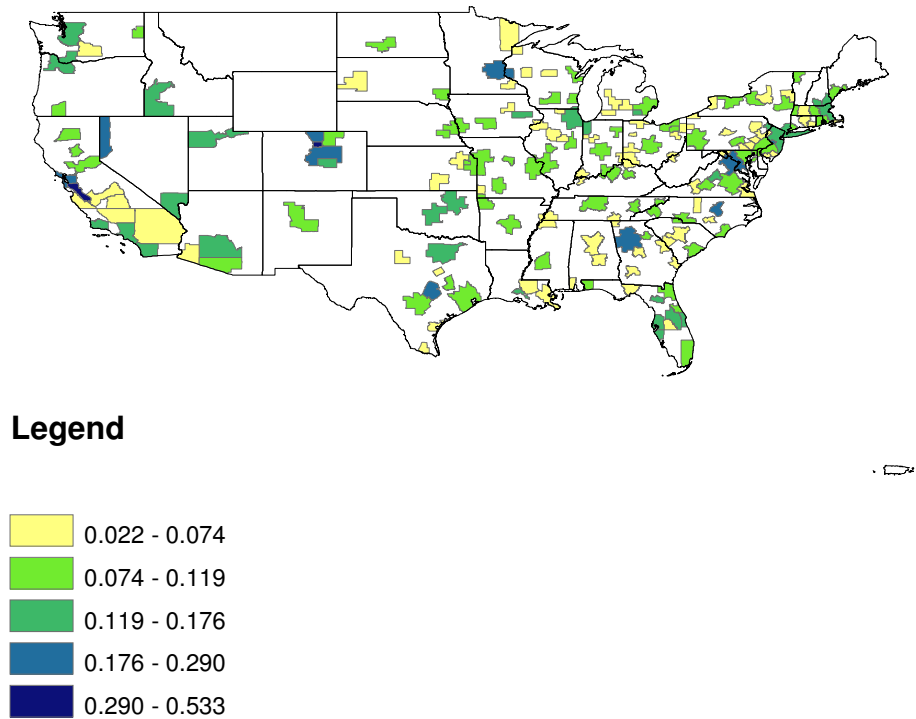


Figure 4. High Technology Single Establishment Firm Formations per 1,000 Persons

Figure 4 presents the geographic distribution of entrepreneurship, as measured by high technology single establishment formations, expressed per one thousand persons. This map shows that rates of entrepreneurship are highest in the San Jose-Sunnyvale-Santa Clara, CA and Boulder, CO metropolitan statistical areas. High rates of entrepreneurship are also found in the San Francisco-Oakland-Fremont, CA, Denver-Aurora, CO, Fort Collins-Loveland, CO, Austin-Round Rock, TX, Minneapolis-St. Paul-Bloomington, MN-WI, Atlanta-Sandy Springs-Marietta, GA, Raleigh-Cary, NC and Washington-Arlington-Alexandria, DC-VA-MD-WV MSAs. In general, rates of entrepreneurship tend to cluster spatially, with higher rate MSAs residing near other higher rate MSAs and

lower rates MSAs residing near lower rates MSAs. This is highly indicative of significant spatial dependence.

Psychological Capital

The data on psychological capital were obtained from the Positive Psychology Center in Philadelphia Pennsylvania. These data cover 24 strengths of character as defined in the Values in Action Inventory of Strengths (VIA-IS). The strengths of character are defined as positive traits that are reflected in individual thoughts, feelings, and behaviors. These strengths are thought to exist in various degrees and so can be measured as individual differences (Park, Peterson and Seligman 2004). The variables were measured by a series of online surveys found at www.authentic happiness.org and www.positivepsychology.org/strengths (Park, Peterson and Seligman 2004). In addition to the 24 strengths of character, the data contained geographic information represented by the three digit zip code location of the respondents.

The set of 24 positive traits were created via a 240 item self-reported questionnaire. The questionnaire asked the individuals to report the degree to which statements reflecting each of these 24 strengths apply to themselves (Park, Peterson and Seligman 2004). It was scored according to a 5 point Likert scale. A host of scholarly work has demonstrated acceptable reliability and validity for each of these 24 character strengths. For instance, one study by Peterson and Seligman (2004) was based on a validity

approach that relied on the nomination known-groups procedure. Under this methodology, individuals were asked to identify individuals they believed to possess a given strength to a notable degree. These individuals were then asked to complete the questionnaire blindly. The results of this study showed that the people nominated as an archetype of a particular trait tended to score higher on that trait than did individuals who were not nominated as possessing that trait (Peterson and Seligman 2004).

Table 8 contains the 24 character strengths along with their definitions. These variables were used to create the measure of psychological capital utilized in this chapter. Park, Peterson and Seligman (2004; 604) state that, “the identification of each strength with a list of synonyms was a deliberate strategy that attempted to capture the family of resemblance of each strength while acknowledging that the synonyms are not exact replicas of each other”. The basic idea was to provide a broad portrayal of the 24 measures in an effort to distinguish and depict accurately what the given attributes are purported to measure without prohibiting overlap across the various dimensions.

The entire sample contained 203,003 individual respondents. These data were initially aggregated to the level of the three digit zip code by averaging the values for all 24 traits for each individual falling within every three digit zip code. After this had been done, the three digit zip codes were assigned to their respective MSA using a visual basic script run in ArcView 9.1.

Table 8. Definitions of the 24 Strengths of Character

Variable	Synonym(s)	Description
Beauty	Awe, wonder, elevation	Noticing and appreciating beauty, excellence, and/or skilled performance in all domains of life.
Bravery	Valor	Not shrinking from threat, challenge, difficulty, or pain; speaking up for what is right even if there is opposition.
Teamwork	social responsibility, loyalty, citizenship	Working well as a member of a group or team; being loyal to the group; doing ones share.
Creativity	originality, ingenuity	Thinking of novel and productive ways to do things; includes artistic achievement but in not limited to it.
Curiosity	novelty-seeking, openness to experience	Taking an interest in all of ongoing experience; finding all subjects and topics fascinating; exploring and discovering.
Fairness	none given	Treating all people the same according to notions of fairness and justice; not letting personal feelings bias decisions about others.
Forgiveness	Mercy	Forgiving those who have done wrong; giving people a second chance.
Gratitude	none given	Being aware of and thankful for the good things that happen; taking time to express thanks.
Hope	Optimism, Future Mindset	Expecting the best in the future and working to achieve it; believing that a good future is something that can be brought about.
Humor	Playfulness	Liking to laugh and tease; bringing smiles to other people; seeing the light side.
Honesty	authenticity, integrity	Speaking the truth but more broadly presenting oneself in a genuine way; being without pretense; taking responsibility for ones feelings and actions.
Judgment	open-mindedness	Thinking things through and examining them from all sides; not jumping to conclusions; being able to change one's mind in light of evidence.
Kindness	generosity, compassion	Doing favors and good deeds for others; helping them; taking care of them.
Leadership	none given	Encouraging a group of which one is a member to get things done and at the same time maintaining good relations within the group; organizing group activities and seeing that they happen.
Love	none given	Valuing close relations with others, in particular those in which sharing and caring are reciprocated; being close to people.
Learn	none given	Mastering new skills, topics, and bodies of knowledge, whether on one's own or formally.
Modesty	Humility	Letting ones accomplishments speak for themselves; not seeking the spotlight; not regarding oneself as more special than one is.
Perseverance	persistence, industriousness	Finishing what one starts; persisting in a course of action in spite of obstacles; "getting in the door"; taking pleasure in completing tasks.
Perspective	Wisdom	Being able to provide wise counsel to others; having ways of looking at the world that makes sense to oneself and to other people.
Prudence	none given	Being careful about ones choices; not taking undue risks; not saying or doing things that might later be regretted.
Self-regulation	self-control	Regulating what one feels and does; being disciplined; controlling ones appetite and emotions.
Social intelligence	emotional intelligence, personal intelligence	Being aware of the motives and feelings of other people and oneself; knowing what to do to fit in to different social situations; knowing what makes other people tick.
Religiousness	spirituality, faith	Having coherent beliefs about the higher purpose and meaning of the universe; knowing where one fits within the larger scheme; having beliefs about the meaning of life that shape conduct and provide comfort.
Zest	vitality, enthusiasm, vigor, energy	Approaching life with excitement and energy; not doing things halfway or halfheartedly; living life as an adventure; feeling alive and activated.

The script was used to calculate the geographic centroid coordinates associated with each of the three digit zip code regions. These coordinates of these centroid locations were then superimposed on an ArcView shapefile that represented the geographic boundaries of each metropolitan statistical area contained in the sample. All of the centroid coordinates falling within the MSA boundaries were averaged to arrive at the final value of each personality characteristic associated with the each MSA. The city-level averages were used to represent the 24 strengths of character underlying the index of psychological capital that will be used in the analysis. This index seeks to measure latent variation in regional psychological capital over the sample of U.S. metropolitan statistical areas.

The index was created using a data driven approach. This differs considerable from the theory driven approach of Luthans et al. (2007) where they focused on theoretical concepts of states and traits in order to arrive at their notion of psychological capital. Here, the construct is arrived at by extracting a single component from the 24 strengths of character variables using the principle components method. One factor was extracted in light of an examination of the eigenvalues, which indicated the presence of one dominant factor. Finally, every individual trait associated with a rotated loading greater than 0.50 was included in the final index.

The weights for the index were based on the varimax rotated factor loadings. The varimax rotation works by searching for the linear combination of the original factors that

maximizes the variance of the loadings. Table 9 contains these loadings for each of the 24 psychological attributes.

Table 9. Varimax Rotated Factor Loadings

Characteristic	Loading
Beauty	0.398
Bravery	0.750
Love	0.672
Prudence	0.547
Teamwork	0.599
Creativity	0.529
Curiosity	0.407
Fairness	0.666
Forgiveness	0.493
Gratitude	0.795
Honesty	0.793
Hope	0.789
Humor	0.563
Perseverance	0.682
Judgment	0.530
Kindness	0.731
Leadership	0.825
Learning	0.207
Modesty	0.426
Perspective	0.741
self control	0.620
social intelligence	0.695
Spirituality	0.479
Zest	0.738

Larger values of the psychological capital index can be viewed as indicating higher levels of psychological capital because the Likert scale was constructed with values ranging from 1 to 5, where lower values indicate less possession of the particular trait.

Every MSA containing less than 100 individual survey respondents was excluded from the analysis. This was done to mitigate small sample bias that may result when a small number of individual respondents form the basis of the psychological capital index for that entire MSA.

Figure 5 illustrates the geographic distribution of the psychological capital index. Stocks of psychological capital appear to be the largest in the southeastern U.S. metropolitan areas. As well, a cluster of cities in the south-central Midwestern region of the U.S. exhibit large stocks of psychological capital. Several Southwest and Pacific coast metropolitan regions also exhibit large stocks of psychological capital.

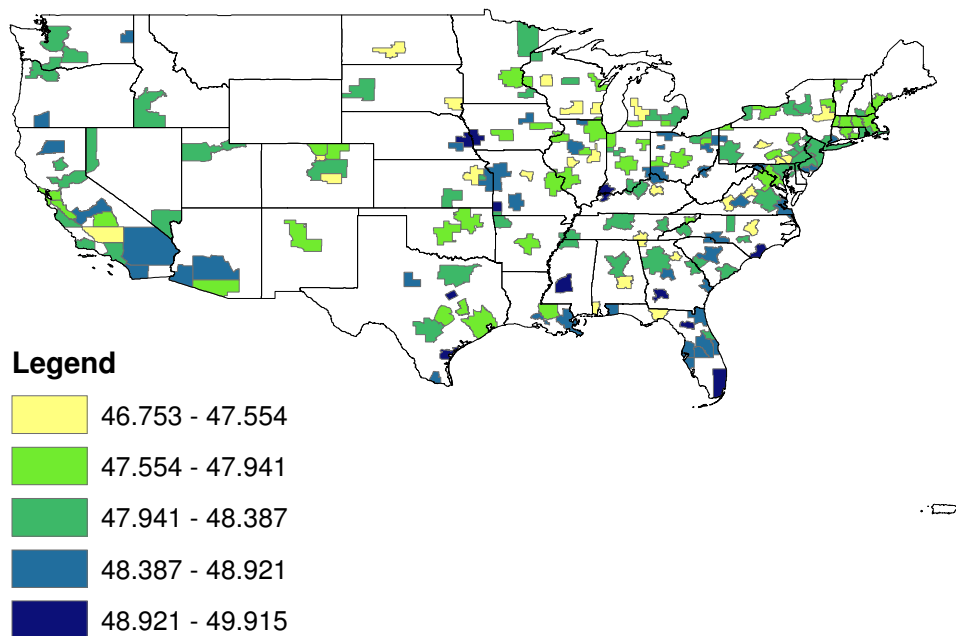


Figure 5. Psychological Capital Index by MSA.

Human Capital

It is well known that human capital is an important determinant of entrepreneurship. To take this into account, human capital is included into the analysis. The measure used here corresponds to the traditional measure of human capital used in the literature. It is based on educational attainment. Specifically, human capital is measured in this chapter by the percentage of the 25+ 2000 population in each MSA having obtained at least a bachelors degree. This proxy, therefore, measures human capital purely by variation in the number of college graduates. Figure 6 presents distribution of human capital across U.S. MSAs in 2000.

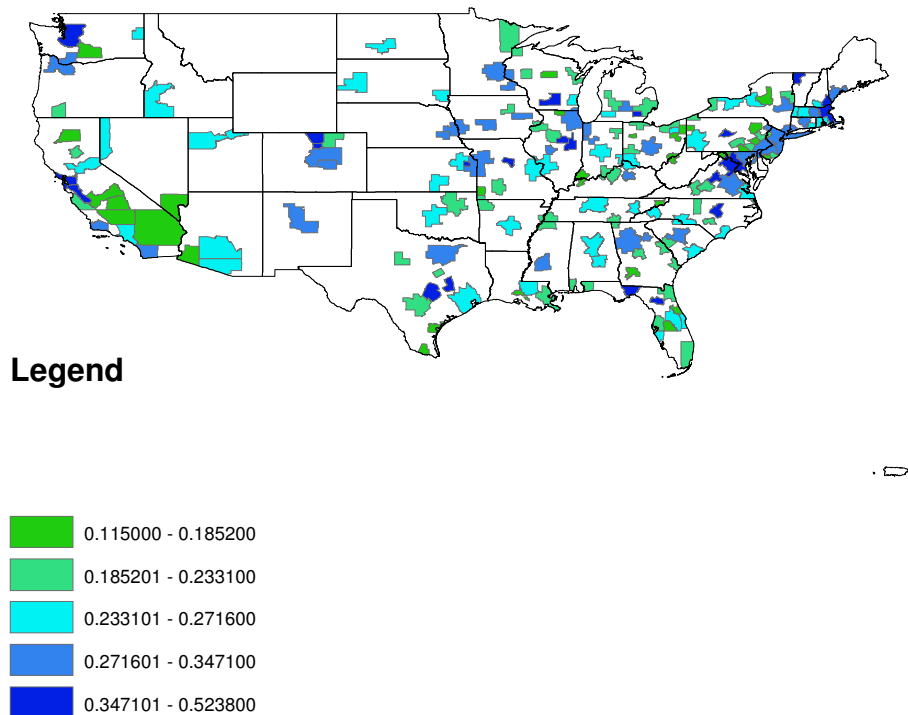


Figure 6. Human Capital by MSA 2000.

Knowledge

Entrepreneurship, by definition, is a process of the exploitation of opportunities by individuals through the formation of a new business (Shane and Venkataraman 2000). As a consequence, the extent of entrepreneurial opportunities is an important source of variation amounts of regional entrepreneurship. However, entrepreneurial opportunities are difficult to measure. This is because, in reality, they cannot be observed until after they have been exploited. A logical way to overcome this problem, and one that is often used in empirical studies, is to assume that the regions exhibiting larger stocks of knowledge are the same ones that contain larger amounts of entrepreneurial opportunities; given that opportunities stem from the creation of new knowledge. The analysis presented in this chapter accounts for the extent of entrepreneurial opportunity by measuring variation in stocks of knowledge as measured by patents.

Patents have been used to represent knowledge in a wide variety of research applications. Despite its limitations, patents constitute a well documented and readily accessible measure of the amount of codified knowledge existing in various places. However, patents are a widely criticized indicator for knowledge. This criticism is due to the fact that not all knowledge is patented and that which is does not necessarily represent any entrepreneurially significant information. Furthermore, patent counts contain little information in regards to the value or significance of the knowledge the underlies the specific patent. On the other hand, patents do measure explicit additions to the stock of

knowledge and have been used rather successfully as an approximate measure of the amount of knowledge contained in various places. For the purposes here, entrepreneurial opportunity will be measured as the total number of year 2000 patents per 10,000 individuals. This proxy represents the amount per capita of knowledge available to the residents of the given regional economy and so is a rough approximate of entrepreneurial opportunity.

Figure 7 presents the distribution of patenting activities across U.S. MSAs. Patenting activities per person are largest in the San Jose-Sunnyvale-Santa Clara, CA, Boise, ID and Rochester, MN MSAs.

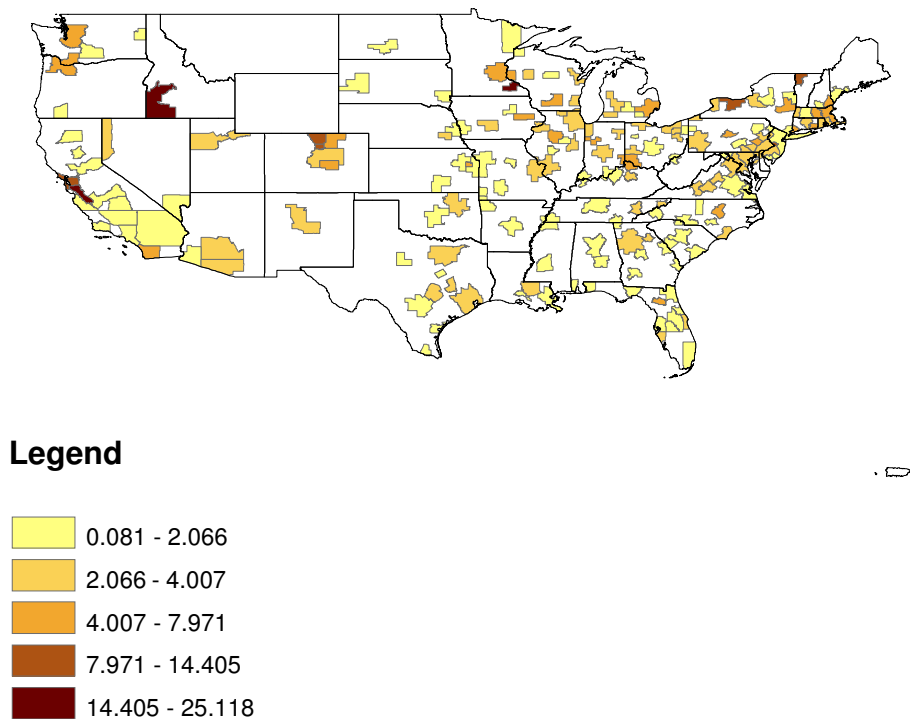


Figure 7. Patents per 10,000 Persons by MSA 2000

High concentrations also exist in San Francisco-Oakland-Fremont, CA, Rochester, NY and Boulder, CO. The small number of dark shaded MSAs is indicative of the considerable right hand skew of patenting activities. Generally, patenting activities are higher in Northwest, Great lakes and Northeastern cities and lower in the Southeast and plains MSAs.

Structural Economic Environmental Variables

The literature on the determinants of entrepreneurship overwhelmingly finds that the environment within which entrepreneurial activities emerge has tremendous impacts on the formation of these activities. In light of this, the last set of included explanatory variables correspond to structural environmental variables that reflect the underlying economic conditions within each functional region. Specifically, the average annual growth in the share of regional economic output coming from high tech industries over the period 1990-2000, the percentage change in per capita income over the period 1990-2000, and the percentage change in total private employment over the period 1990-2000 were included to account for such environments.

Including growth in high tech industries in to the model will measure differences in levels of high tech entrepreneurship due to variation in industrial structures across the regions. As such, it will account for differences in levels of entrepreneurship due to the presence of industries that are at the entrepreneurial stage of their industrial life cycle. Differences

in income growth will account for variation in entrepreneurship due to variation in personal incomes. Lastly, variation in employment growth will represent the conditions of the regional labor market. The purpose of including these structural variables, aside from their scholarly precedent, is to capture systematic regional variation in entrepreneurial activities that is due to structural economic differences. Including these variables will help avoid falsely attributing variation in economic environmental factors to the psychological capital variable.

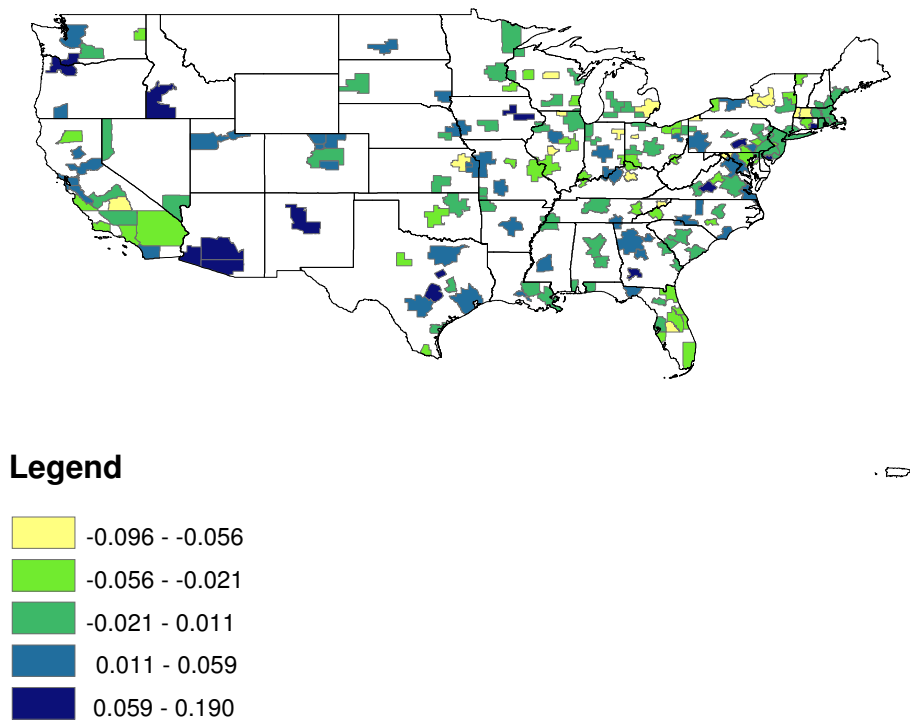


Figure 8. Growth in the Share of Regional Output in High Technology Sectors by MSA 1990-2000

Figure 8 presents the distribution of growth rates in the shares of regional output coming from the high tech sector over the period 1990-2000. This figure shows that MSAs with growing shares of high tech output are fairly even spread across the U.S. However, cities in the northwest and central southwest have for the most part been subject growing shares of output coming from high tech sectors. Other regions have cities with growing and shrinking shares of output in high tech.

Figure 9 displays the distribution of growth in per capita incomes over the period 1990-2000.

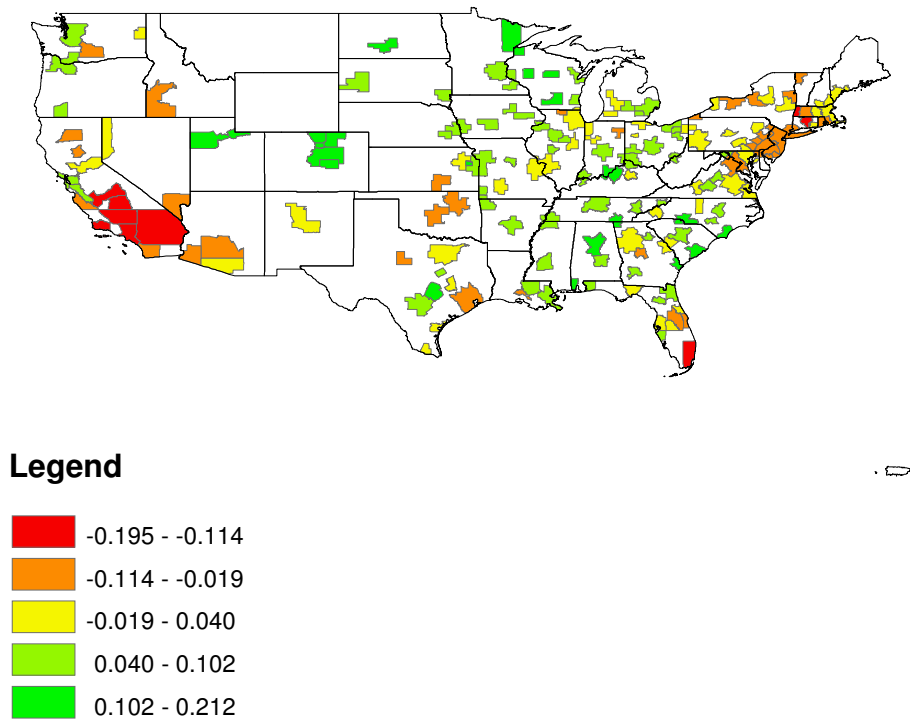


Figure 9. Growth in Per Capita Income Growth by MSA 1990-2000.

From this figure, one notices that per capita incomes tended to fall in MSAs located in the Northeast and Southwest, while they tended to grow in the Midwest, Southeast and Plains MSAs. Southern California's MSAs were, for the most part, subject to declines ranging from 10 to 20 percent.

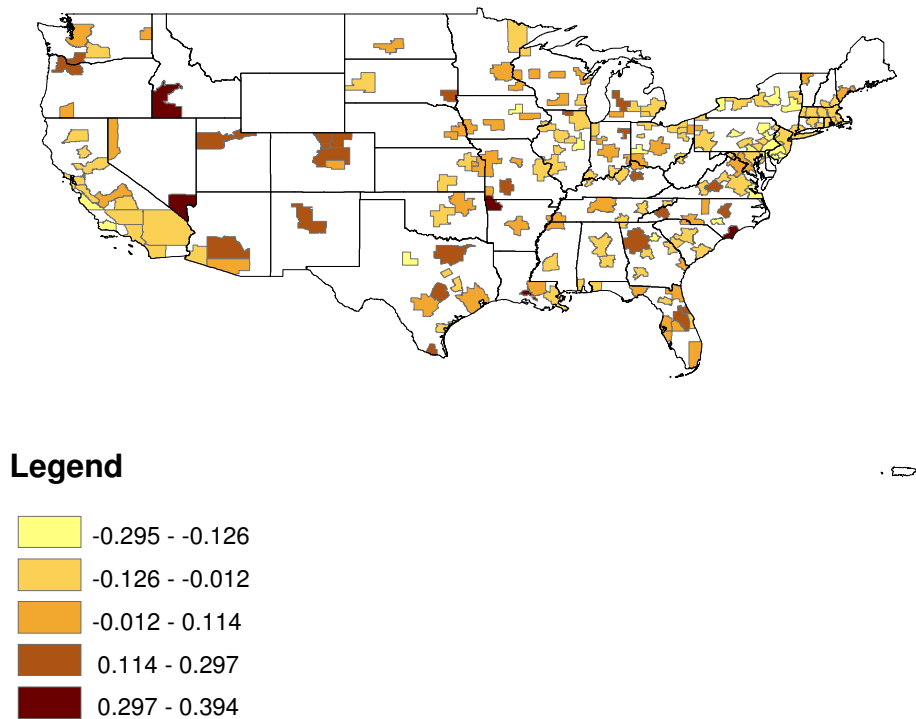


Figure 10. Growth in Total Private Employment by MSA 1990-2000.

Figure 10 presents the distribution of total private employment growth across the MSAs retained in the sample data over the period 1990-2000. Employment growth was largest in MSAs located in the Mountain west region. Employment declines tended to be

concentrated in the Northeast and Midwest. MSAs located in California also tended to fair on the negative side of the growth picture.

4.5.1 Data Transformations

Two data transformations were taken on the dependent and independent variables entering the model. First, the observations of the dependent variable were logged to produce a distribution that better reflected the assumed normality of this distribution. Second, all of the explanatory variables were studentized by subtracting their mean and dividing by their standard deviation in order to standardize the unequally scaled nature of the explanatory variables (in particular, the psychological capital index, which is Likert scaled) as well as to accommodate the use of Zellner's g-prior later on.

4.6. Methodology

The literature on the determinants of entrepreneurship is wide ranging no doubt. However, taken as a whole, models of the determinants of entrepreneurship can for the most part be condensed into one containing three types or suites of variables. One type pertains to the characteristics of individuals. These variables correspond to determinants such as the skills and aptitudes of individuals and are usually measured by human capital. A second type of variables constitutes determinants pertaining to the extent of entrepreneurial opportunity. Entrepreneurs exploit opportunities and as a result, models

of the determinants of entrepreneurship tend to include a set of variables accounting for variation in these opportunities. Finally, environmental or structural economic factors are widely considered to be important determinants of entrepreneurship. Thus, models of entrepreneurship have a propensity to include variables reflecting these environmental determinants.

In light of this, the current chapter shall begin with the model of the determinants of entrepreneurship that is shown in matrix form in equation 4.1. In this expression, entrepreneurship (E) is expressed as the dependent variable. The matrix X is used to denote an $n \times k$ explanatory variable matrix including the three previously mentioned suites of determinants, which are expressed as I , O and En and represent the individual, opportunity and environmental characteristics. The final line of 4.1 is used to denote the traditional assumption that the data generating process includes a random component governed by a univariate normal distribution with a mean of 0 and constant variance σ^2 .

$$\begin{aligned} E &= X\beta + \varepsilon \\ X &= [I, O, En] \\ \varepsilon &\sim N(0, \sigma^2) \end{aligned} \tag{4.1}$$

Since the primary purpose of this chapter is to examine the impact of stocks of psychological capital on entrepreneurial activities, the model shown in 4.1 can be augmented to contain this additional variable. This is shown in equation 4.2 by adding the additional psychological capital term (Pc) to the explanatory variable matrix presented in 4.1.

$$X = [I, O, En, Pc] \tag{4.2}$$

Psychological is included as an additional term for a number of reasons. For one, while psychological capital might seem on the surface to be an environmental factor, one could plausibly argue that it resides in the individual on the first level and in the region only as a higher level group construct. As a result of this, it remains unclear where it would be grouped at this point. Furthermore, this type of ambiguity is, in essence, irrelevant in the context of regression modeling as each explanatory variable enters the regression model as an individual term. Therefore, 4.2 is used here simply to drive home the point that this variable represents an extension of the literature on the determinants of regional entrepreneurship and is not a reflection of the fact that it is a determinant that is unclassifiable with the others.

4.6.1 Econometric Issues

Having expressed the basic qualitative features of the model, attention will turn to a discussion of the pertinent econometric considerations and the details concerning such matters. There are two pertinent issues pertaining to regression modeling of the determinants of entrepreneurship that this chapter explores. These issues involve both spatial dependence and model uncertainty. They are important issues to consider because the existence of spatial dependence is often explicitly acknowledged in the empirical literature on entrepreneurial activities while model uncertainty is implicitly present.

The presence of spatial dependence is an important issue because it indicates that data generating process governing entrepreneurial activities is likely to be considerably more complex than that implied by 4.1. This makes it plausible to assume that some form of spatial dependence is involved in the true data generating process. This fact, if it is true, would create a situation where OLS estimation techniques will present biased, inconsistent and/or inefficient estimates, depending on the nature of the actual data generating process (LeSage and Pace 2009).

Uncertainties over the specific form of the spatial dependence in the data generating process, the most appropriate specification of the spatial weight matrix, as well as, over which explanatory variables to include in the resulting regression models results in a situation where considerable model uncertainty is present in this application. Model uncertainty creates a situation yielding suboptimal results for a number of reasons (Raftery, Madigan and Hoeting 1997). For one, uncertainty over the form of the spatial dependence in the data generating process renders uncertainty in regards to which form of spatial econometric regression model is appropriate for estimation. Furthermore, uncertainty over which specific variables to include in the explanatory variable matrix exists (especially with regard to the psychological capital variable) and estimates based on saturated regression models containing all possible variables does not address this issue in any consistent theoretical framework. Simply including all of the potential explanatory variables into the model increases the possibility of including irrelevant variables. This will create a situation that is apt to increase the dispersion of the estimated

coefficients. This becomes a problem because an increase in dispersion makes it difficult to identify the important variables influencing entrepreneurship. In contrast, a strategy utilizing subsets of the set of candidate explanatory variables will likely suffer from omitted variables bias in cases where important variables are excluded. As well, uncertainties regarding which explanatory variables are truly relevant in explaining variation in entrepreneurship may lead to explanatory variable matrices suffering from collinearity, which would further reduce the precision of the coefficient estimates (Belsley, Kuh and Welsch 1980).

4.6.2 Spatial Dependence

Studies of entrepreneurship noting that these activities are clustered in geographic space are plentiful (see for example Acs and Plummer 2005 and Acs et al. 2008). This fact results in the expectation that the underlying data generating process involved in this application will contain some form of spatial dependence. However, the form of this dependence structure, while initially unknown, will be instrumental in specifying the appropriate spatial econometric model to estimate.

4.6.3 Uncertainties Involving the Appropriate Spatial Econometric Specification

As stated above, entrepreneurial activities tend to exhibit spatial clustering. As such, models examining the determinants of entrepreneurship tend to rely on spatial

econometric model specifications to compensate for this fact. In particular, several spatial econometric specifications are often used for this purpose. The most widely used one is the spatial autoregressive model shown in equation 4.3, which reflects the assumption of the data generating process shown in equation 4.4 (LeSage and Pace 2009).

$$y = \rho W y + X\beta + \varepsilon \quad (4.3)$$

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \varepsilon \quad (4.4)$$

In this type of specification spatial dependence is assumed to exist only in the dependent variable. An alternative specification is the spatial error model shown in equation 4.5, which is based on the assumption of the data generating process shown in equation 4.6 (LeSage and Pace 2009).

$$y = X\beta + u \quad (4.5)$$

$$u = \rho W u + \varepsilon \quad (4.5)$$

$$y = X\beta + (I_n - \rho W)^{-1} \varepsilon \quad (4.6)$$

This spatial error specification differs from that in 4.3 in that the spatial dependence exists only in the disturbances. Still yet, one might specify a spatial model of the spatial durbin form as was used in chapters one and two. This type of specification is shown in equation 4.7.

$$y = \rho W y + X\beta + WX\delta + \varepsilon \quad (4.7)$$

The spatial durbin model is used when spatial dependence exists in both the dependent and independent variables as is reflected in the data generating process governing this model shown in equation 4.8.

$$y = (I_n - \rho W)^{-1} (X\beta + WX\delta + \varepsilon) \quad (4.8)$$

Given the availability of these types of spatial econometric models, one is faced with considerable uncertainty over which is appropriate. This answer to this question depends on the true data generating process. However, one does not know the nature of this process a priori and so is left in a state of considerable uncertainty over which type of model to employ.

4.6.4 Uncertainty in the Specification of the Spatial Weight Matrix

Assuming one has determined the appropriate spatial model to estimate, one is next faced with the issue of spatial connectivity or rather the form of the spatial weight matrix. The standard or most common specification is one based on first order contiguity. This is not possible here because the data is not contiguous. An alternative strategy is to specify this matrix such that it extracts the m nearest neighbors to any y_i . Under this specification, the individual elements of W , denoted w_{ij} , correspond to a value > 0 if y_j is contained in the set of nearest neighboring observations and to a value of 0 if y_j is not contained in this set. Additionally, all $w_{i=j}$ are set equal to zero to prevent an observation from exhibiting dependence on itself. The matrix is then row standardized in order to arrive at a row stochastic matrix, which has advantageous numerical and interpretive properties (LeSage and Pace 2004).

Once again, the issue of uncertainty rears its head. This time, the uncertainty involves how to specify the form of the spatial connectivity through the spatial weight matrix.

Each and every application of a spatial model involves a spatial weight matrix, which is used to reflect the connectivity structure among the observations. Yet at the same time, each and every application may differ in regards to how the observations are connected. As a result, a considerable amount of uncertainty exists regarding the structure of spatial connectivity among the sample observations.

4.6.5 Uncertainty in the Specification of the Explanatory Variable Matrix

The final form of uncertainty involves which variables to include in the specified regression model. This form of uncertainty is due to the considerable ambiguity that exists in regards to the relevance of each of the candidate explanatory variables in explaining variation in entrepreneurship over the sample of metropolitan regions used in this chapter. While many empirical studies suggest that the individual, opportunity, and structural economic variables utilized in this chapter are important predictors of entrepreneurship, relatively little information exists to offer insights into whether or not psychological capital is truly relevant in explaining these activities at the regional level. Therefore, further uncertainty over which variables to include in the model exists in addition to the uncertainties associated with the fore mentioned sources.

4.6.6 Solving the Uncertainty Problems with Bayesian Model Comparison

This section of this chapter sets up and describes the model comparison procedures that will provide a solution to the problems associated with model uncertainty in regards to: the identification of the appropriate form of the spatial model, the identification of the appropriate spatial weight matrix and the relevance of psychological capital as an important explanatory variable. The approach will rely exclusively on Bayesian methods for this purpose. This approach is especially advantageous as it provides a unified approach to dealing with all of the problems with model uncertainty that are encountered in this chapter.

The basic theory was initially provided in Arnold Zellner's "An introduction to Bayesian Inference in Econometrics" (1971). In this work, Zellner deals with cases where there are a small number of alternative models to compare. The basic process begins with the specification of prior probabilities for each of the m models as well as prior distributions for each of the model parameters (Parent and LeSage 2007). In this expose, $\pi(M_i), i = 1 \dots m$ will represent the prior probabilities for each M_i while $\pi(\theta)$ represents the prior distributions for the parameters. The priors for the models and parameters are then combined with the relevant likelihood function (denoted here as $p(y|\theta, M)$), conditional on the data, the parameters and the models in order to produce the joint probability for the models, parameters and data. This takes the general form shown in equation 4.9.

$$p(M, \theta, y) = \pi(M)\pi(\theta|M)p(y|\theta, M) \quad (4.9)$$

The joint posterior distribution for alternative models and parameters values, shown in equation 4.10, is produced via application of Bayes Theorem.

$$p(M, \theta | y) = \frac{\pi(M)\pi(\theta|M)p(y|\theta,M)}{p(y)} \quad (4.10)$$

The posterior distributions can then be used to calculate posterior model probabilities for each of the m models, which are used to compare the alternative model specifications (LeSage and Parent 2007). These probabilities take the form shown in 4.11.

$$p(M|y) = \int p(M, \theta | y) d\theta \quad (4.11)$$

This technique can be implemented as a solution to model specification uncertainty and spatial connectivity uncertainty as these comparisons involve relatively few alternative models to consider.

In the case of variable uncertainty, however, the computational demands necessary for carrying the entire procedure often inhibit its application, as the number of alternative models m are often relatively large. It should be noted that this may not necessarily be the case here as the model will contain only 6 candidate explanatory variables. In this case, there will only be 64 candidate models (2^k , where k is the number of parameters) to compare. However, the technique introduced by Madigan and York (1995), known as Markov Chain Monte Carlo Model Composition (MC^3), enables the process to be carried out in cases where m is both large and small through a systematic sampling of the full model space. The MC^3 approach, then, suites both types of applications and will be used here for this reason. Other work by Fernandez, Ley, and Steel (2001a and 2001b) and Raftery, Madigan, and Hoeting (1997) extend this process to applications of econometric regression modeling and Parent and LeSage (2007) further extend it to the case of spatial econometric regression modeling.

The MC³ procedure starts with an initial randomly selected set of explanatory variables. It then derives a proposal model to compare to the initial model through the use of three steps (when implementing the reversible jump algorithm), where the use of each step is equally probable (i.e. each step has a $0.\bar{3}$ probability of being used). The three steps are a birth step, a death step or a move step. The birth step adds an explanatory variable to the model, the death step removes an explanatory variable from the model and the move step randomly switches an included variable with an excluded variable. It is important to make one distinction here. In the case of the spatial durbin model, the spatial lag of a given explanatory variable is forced to enter the model in every case where it appears. This is done to prevent spatial lags of an explanatory variable from appearing in a model without the explicit explanatory variable itself. Note that this will also simplify the beta interpretation formulas as well.

The initial model is then compared to the proposed model through the use of a procedure known as the Metropolis-Hastings step. The Metropolis-Hastings step is used to compare the two alternative models where either the initial model or the proposed model is accepted. If the proposed model is accepted, it becomes the initial model and the process is repeated. If the initial model is accepted, it remains the initial model and the process is again repeated. Madigan and York (1995) show that one can systematically walk through the large model space by repeating this procedure many times, essentially solving the problems associated with Bayesian Model Comparison in cases where m is large.

A key step in the algorithm is the comparison of the initial and proposed models in the Metropolis-Hastings step. This comparison involves the calculation of the odds ratio, shown in 4.12.

$$\min \left[1, \frac{(M_p|y)}{(M_i|y)} \right] \quad (4.12)$$

In the odds ratio shown in 4.12, M_p represents the proposed model and M_i represents the initial model, which are based on models with alternative candidate explanatory variables. The terms in this ratio can be obtained by combining the pertinent priors with the relevant likelihood function, to arrive at the joint probability for the models and parameters according to 4.9. Bayes' theorem is then used to produce the joint posterior for both models and parameters according to 4.10. Posterior model probabilities can be obtained by integrating the parameters out of the joint posterior of both the models and parameters. These probabilities are then used to represent the odds ratio shown 4.12.

To compute the posterior model probabilities over the complete set of all unique models, it is necessary to save the log marginal density vectors for each unique model found by the sampling scheme. In this chapter, only models with posterior model probabilities above the probability threshold of 0.001 will be stored for use in constructing model averaged coefficient estimates. To create the model averaged estimates, each of the saved models are estimated, including an intercept term. The coefficient estimates associated with these models are then multiplied by their specific posterior model probabilities and summed to create a weighted average across all models with posterior model probabilities that are greater than the probability threshold level of one tenth of

one percent. It should be pointed out that a strategy of averaging the coefficient estimates using the posterior model probabilities is deemed Bayesian Model Averaging. This differs slightly from Bayesian model comparison in that it averages the coefficient estimates in addition to just comparing the alternative model specifications.

4.6.6.1 The Priors and Log-marginal Posterior for the Spatial Autoregressive Model

To arrive at the log-marginal posterior for the spatial autoregressive model, which is necessary for model comparison, one must begin with the likelihood function for this model's parameters $\theta = (\alpha, \beta, \sigma, \rho)$. This takes the form shown in 4.13 (Parent and LeSage 2007; LeSage and Pace 2009).

$$L(\theta; y, X, W) \propto (\sigma^2)^{-n/2} |I_n - \rho W|^{1/2} \exp \left\{ -\frac{1}{2\sigma^2} ((I_n - \rho W)y - \alpha i_n - X\beta)' ((I_n - \rho W)y - \alpha i_n - X\beta) \right\} \quad (4.13)$$

Following Fernandez, Ley and Steele (2001), Parent and LeSage (2007) as well as LeSage and Pace (2009), a g-prior of the form shown 4.14 will be placed on the non-intercept explanatory variable parameters β , with $g_i = 1/n$, where n is the number of observations. This specification is due to the fact that in this application $n > k^2$, where k is the number of variables in the explanatory variable matrix, X .

$$\pi_b(\beta | \sigma^2) \sim N[\beta_0, \sigma^2 (gX'X)^{-1}] \quad (4.14)$$

An uninformative prior will be placed on the intercept term, α , which is forced to appear in every model since the dependent variable is not studentized (Parent and LeSage 2007).

An inverted gamma prior, shown in 4.15, is used for σ^2 with the hyper-parameters ν and \bar{s}^2 set = 0 so as to impose diffuseness on the prior distribution (Parent and LeSage 2007).

$$\pi_s(\sigma^2) \sim \frac{\nu}{\tau(\nu/2)} (\sigma^2)^{-\frac{\nu+2}{2}} \exp\left(-\frac{\nu\bar{s}^2}{2\sigma^2}\right) \quad (4.15)$$

Lastly, the zero-centered beta prior, shown in 4.16, will be placed on the parameter ρ , with the hyper-parameter $a_o = 1.01$. This will produce a highly uninformative prior that very evenly distributes the prior density mass across most values in the possible range (-1 to 1). This value of the hyper-parameter will also down-weight the prior emphasis placed on the end of the range of possible values. The down-weighting will eventually reach zero at the end points (LeSage and Pace 2009).

$$\pi_r(\rho) = \frac{1}{\text{Beta}(a_o, a_o)} \frac{(1+\rho)^{a_o-1} (1-\rho)^{a_o-1}}{2^{2a_o-1}} \quad (4.16)$$

Following the process presented in section 4.6.6, the application of Bayes' theorem will produce the joint posterior distribution for the spatial autoregressive model. This distribution is shown in 4.17 both generally (the first line) and with all the terms explicitly inserted (the remaining lines) (Parent and LeSage 2007).

$$\begin{aligned} p(M, \beta, \sigma, \rho | y, X, W) &= \iiint \pi_b(\beta | \sigma^2) \pi_s(\sigma^2) \pi_r(\rho) p(y | \alpha, \beta, \sigma^2, \rho) d\beta d\sigma^2 d\rho \quad (4.17) \\ &= \tau \left(\frac{\nu}{2}\right)^{-1} \left(\frac{\nu\bar{s}^2}{2}\right)^{\nu/2} (2\pi)^{-(n+k)/2} |gX'X|^{1/2} \iiint |I_n - \rho W| \frac{1}{\sigma^{n+\nu+k+2}} \exp\left\{-\frac{1}{2\sigma^2} \left[\nu\bar{s}^2 + \right. \right. \\ & \left. \left. ((I_n - \rho W)y - X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho(\frac{1}{n}\sum_i(Wy)_i)) i_n)'((I_n - \rho W)y - \right. \right. \\ & \left. \left. X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho(\frac{1}{n}\sum_i(Wy)_i)) i_n) + \beta' gX'X\beta + \right. \right. \\ & \left. \left. (\beta - (X'X)^{-1}X'(I_n - \rho W)y(p))' (X'X)(\beta - \right. \right. \\ & \left. \left. (X'X)^{-1}X'(I_n - \rho W)y(\rho)) \right] \right\} \frac{1}{\text{Beta}(a_o, a_o)} \frac{(1+\rho)^{a_o-1} (1-\rho)^{a_o-1}}{2^{2a_o-1}} d\beta d\sigma^2 d\rho \end{aligned}$$

The expression in 4.17 can be analytically integrated with respect to β and σ due to special properties of the normal and inverted gamma probability density functions (Parent

and LeSage 2007). The integration results in an expression of the log marginal posterior, shown in 4.18, that now depends only on ρ .

$$\begin{aligned}
 p(M, \rho | y, X, W) = & \frac{\tau\left(\frac{n+v-1}{2}\right)}{\tau\left(\frac{v}{2}\right)} (v\bar{s}^2)^{\frac{v}{2\pi} - \frac{n-1}{2}} \left(\frac{g}{1+g}\right)^{k/2} |I_n - \rho W| \left[v\bar{s}^2 + \frac{1}{g+1} \left((I_n - \right. \right. \\
 & \rho W)y - X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho\left(\frac{1}{n}\sum_i(Wy)_i\right)) i_n \Big)' \left((I_n - \rho W)y - \right. \\
 & X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho\left(\frac{1}{n}\sum_i(Wy)_i\right)) i_n \Big) + \frac{g}{g+1} \left((I_n - \rho W)y - \right. \\
 & X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho\left(\frac{1}{n}\sum_i(Wy)_i\right)) i_n \Big)' \left((I_n - \rho W)y - \right. \\
 & X((X'X)^{-1}X'(I_n - \rho W)y) - (\bar{y} - \rho\left(\frac{1}{n}\sum_i(Wy)_i\right)) i_n \Big) \Big]^{-n+v-1/2} \frac{1}{\text{Beta}(a_0, a_0)} \frac{(1+\rho)^{a_0-1} (1-\rho)^{a_0-1}}{2^{2a_0-1}}
 \end{aligned} \tag{4.18}$$

To compute the posterior model probabilities $p(M|y, X, W)$ for model comparison purposes, ρ must be removed from 4.18 in order to reduce this to the necessary scalar term (Fernandez, Ley and Steele 2001; Parent and LeSage 2007). To do this one must numerically integrate this parameter out of the expression, as analytical integration is not possible. Following the recommendations of Parent and LeSage (2007), this will be done by storing the vectors of the log marginal values over a grid of values for the parameter ρ . These vectors can then be scaled and integrated with respect to this parameter using a series of clever tricks in order to produce the respective posterior model probabilities (see Appendix A in Parent and LeSage 2007 complete details).

4.6.6.2 The Priors and Log-marginal Posterior for the Spatial Error Model

Since spatial error model takes the form shown in 4.19, the residuals take the form shown 4.20.

$$\begin{aligned} y &= \alpha i + X\beta + u \\ u &= \lambda W u + \varepsilon \end{aligned} \quad (4.19)$$

$$e = (y - X\beta - \alpha i)(I_n - \lambda W) \quad (4.20)$$

This results in the same likelihood function for the spatial error model's parameters that was shown in 4.13. It is shown again in 4.21 with the term λ used in place of ρ .

$$L(\alpha, \beta, \sigma, \lambda | y, X, W) \propto (\sigma^2)^{-n/2} |I_n - \lambda W|^{1/2} \exp \left\{ -\frac{1}{2\sigma^2} ((y - X\beta - \alpha i)(I_n - \lambda W))' ((y - X\beta - \alpha i)(I_n - \lambda W)) \right\} \quad (4.21)$$

The priors for the spatial error model are specified in the same manner as they were in section 4.6.6.1 for the spatial autoregressive model with one slight difference. This difference has to do with the formation of the g-prior placed on the parameter, β . For the spatial error model y is redefined $\tilde{y} = y - \lambda W y$ and X is redefined $\tilde{X} = X - \lambda W X$ (Parent and LeSage 2007). The g-prior, being based on the covariance matrix erected from $\tilde{X}'\tilde{X}$, then becomes that shown in 4.22 (Parent and LeSage 2007).

$$\pi_b(\beta | \sigma^2) \sim N[\beta_o, \sigma^2 (g\tilde{X}'\tilde{X})^{-1}] \quad (4.22)$$

Combining the priors with the likelihood function in 4.21 and analytically integrating the parameters β and σ out of the expression results in the marginal posterior distribution shown in 4.23 that depends only on λ (LeSage and Parent, 2007).

$$\begin{aligned} p(M, \lambda | y, X, W) &= \frac{\tau\left(\frac{n+v-1}{2}\right)}{\tau\left(\frac{v}{2}\right)} (v\bar{s}^2)^{\frac{v}{2\pi}} - \frac{n-1}{2} \left(\frac{g}{1+g}\right)^{k/2} |I_n - \lambda W| \left[v\bar{s}^2 + \frac{1}{g+1} \left(\tilde{y} - \tilde{X}((\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y}) - (\bar{y} - \lambda\left(\frac{1}{n}\sum_i(Wy)_i\right))i_n \right)' \left(\tilde{y} - \tilde{X}((\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y}) - (\bar{y} - \right. \right. \end{aligned} \quad (4.23)$$

$$\lambda \left(\frac{1}{n} \sum_i (Wy)_i \right) i_n + \frac{g}{g+1} (\tilde{y} - (\bar{y} - \lambda \left(\frac{1}{n} \sum_i (Wy)_i \right) i_n))' (\tilde{y} - (\bar{y} - \lambda \left(\frac{1}{n} \sum_i (Wy)_i \right) i_n)) \right]^{-n+v-1/2} \frac{1}{\text{Beta}(a_o, a_o)} \frac{(1+\lambda)^{a_o-1} (1-\lambda)^{a_o-1}}{2^{2a_o-1}}$$

The spatial dependence parameter (λ) can once be removed from the expression using numerical integration. This will convert 4.23 into the scalar term $p(M|y, X, W)$ that is used to calculate the posterior model probabilities necessary for Bayesian model comparison (Parent and LeSage 2007).

4.6.6.3 The Priors and Log-marginal Posterior for the Spatial Durbin Model

The likelihood function for the spatial durbin model takes the form shown in 4.24.

$$L(\alpha, \beta, \sigma, \rho; y, X, W) \propto (\sigma^2)^{-n/2} |I_n - \rho W|^{1/2} \exp \left\{ -\frac{1}{2\sigma^2} ((I_n - \rho W)y - \alpha i_n - XWX\beta)' ((I_n - \rho W)y - \alpha i_n - XWX\beta) \right\} \quad (4.24)$$

The priors for all parameters except for β remain the same as in sections 4.6.6.2 and 4.6.6.3. Once again, a g-prior will be used on the regression coefficients (β) so that the prior information will not exert excessive influence on the posterior conclusions vis-à-vis alternative model specifications based on different sets of candidate explanatory variables. The prior on the non-intercept regression coefficient parameter β for the spatial durbin model is shown in expression 4.25. This differs from that shown in 4.14 in that X is replaced by XWX .

$$\pi_b(\beta|\sigma^2) \sim N[\beta_0, \sigma^2 (gXWX'XWX)^{-1}] \quad (4.25)$$

Combining the priors with the likelihood function, shown in 4.24, and applying Bayes' Rule results in the marginal posterior distribution of the spatial durbin model shown in 4.26.

$$\begin{aligned}
 p(M, \alpha, \beta, \sigma, \rho | y, X, W) &= \iiint \pi_b(\beta | \sigma^2) \pi_s(\sigma^2) \pi_r(\rho) p(y | \alpha, \beta, \sigma^2, \rho) d\beta d\sigma^2 d\rho \\
 &= \tau \left(\frac{v}{2}\right)^{-1} \left(\frac{v\bar{s}^2}{2}\right)^{v/2} (2\pi)^{-(n+k)/2} |gXWX'XWX|^{1/2} \iiint |I_n - \\
 &\rho W| \frac{1}{\sigma^{n+v+k+2}} \exp \left\{ -\frac{1}{2\sigma^2} \left[v\bar{s}^2 + ((I_n - \rho W)y - XWX((XWX'XWX)^{-1}XWX'(I_n - \right. \right. \\
 &\rho W)y) - (\bar{y} - \rho(\frac{1}{n}\sum_i(Wy)_i)) i_n)'((I_n - \rho W)y - XWX((XWX'XWX)^{-1}XWX'(I_n - \\
 &\rho W)y) - (\bar{y} - \rho(\frac{1}{n}\sum_i(Wy)_i)) i_n) + \beta' gXWX'XWX\beta + \\
 &(\beta - (XWX'XWX)^{-1}XWX'(I_n - \rho W)y(p))' (XWX'XWX)(\beta - \\
 &\left. \left. (XWX'XWX)^{-1}XWX'(I_n - \rho W)y(\rho)) \right] \right\} \frac{1}{\text{Beta}(a_o, a_o)} \frac{(1+\rho)^{a_o-1} (1-\rho)^{a_o-1}}{2^{2a_o-1}} d\beta d\sigma^2 d\rho
 \end{aligned}
 \tag{4.26}$$

As in the preceding subsections, the spatial dependence parameter (ρ) can be removed from 4.26 using numerical integration in order to convert it into the scalar term $p(M|y, X, W)$ that is used to calculate the posterior model probabilities (LeSage and Parent, 2007).

4.7 Results

The results will be presented as follows. First, Bayesian model comparisons will be carried out with respect to the spatial econometric model specification. This set of results will be based on the complete computation of posterior model probabilities for all three model specifications with the explanatory variable matrix and spatial weight matrix held

constant. In so doing, the results will provide evidence that can be used to determine the spatial econometric model specification that best fits the sample data. Following this will be the results associated with model comparison as it pertains to the specification of the spatial weight matrix. Once again, the posterior model probabilities for weight matrix specifications under consideration will be fully computed. In this comparison the model specification that is identified in the first step will be held constant as will the explanatory variable matrix. Therefore, only the spatial weight matrix will vary in the comparison. Finally, after the most appropriate spatial econometric model and spatial weight matrix has been identified, they will be held constant and only the explanatory variable matrix will be permitted to vary over the alternative model specifications.

In a slight departure from the preceding comparison strategies, posterior model probabilities and model averaged estimates will be calculated using the Markov Chain Monte Carlo Model Comparison (MC^3) strategy laid out in section 6.6 in the context of Bayesian Model Averaging in the identified spatial econometric setting. It should be noted that given the relatively small number of candidate explanatory variables under consideration, posterior model probabilities could be computed for each alternative model specification. However, Matlab code for carrying out Bayesian Model Averaging using the MC^3 approach is readily available (www.spatial-econometrics.com) and will arrive at the same posterior conclusions and model averaged estimates given an adequate number of iterations in the sampling process (LeSage and Parent, 2007; LeSage and Pace, 2009). As a result, this approach will simply be used to abridge the coding requirements.

Table 10 contains model comparison results pertaining to the alternative model specifications that are based on different data generating processes. The set of results were obtained by including all of the candidate explanatory variables discussed in section 5, an intercept and a row-standardized spatial weight matrix that extracted the five nearest neighboring observations. Thus, only the model specification varied in the comparison. The right hand column contains the posterior model probabilities. Examination of the table reveals that the largest posterior model probability is associated with the spatial autoregressive specification. In fact, this model received nearly 98% of the posterior support.

Table 10. Spatial Model Specification Comparison Results

<u>Models</u>	<u>Posterior Probability</u>
Spatial Error Model	0.000
Spatial Durbin Model	0.023
Spatial Autoregressive Model	0.977

This result is rather surprising given the theoretical motivation in favor of the spatial durbin model provided in chapter 1. To elaborate, it is surprising because the spatial autoregressive regression model constitutes a very special nested case of the spatial durbin model, that case being when the parameter δ in expression 4.7 is equal to zero. This special case will only arise when one of two conditions hold; when there exists no omitted variables or when the omitted variables are not correlated with the included explanatory variables (LeSage and Pace, 2009; LeSage and Fischer, 2007). Given the

fact that it is highly unlikely that all of the important variables have been included (despite the fact that this model includes variables for all three suites of theoretically important variables) and that the data supports the inclusion of a spatially lagged dependent variable (which provides an explicit indication that omitted variables exist), one must conclude that the omitted variables must not be correlated with the included variables else posterior support would have suggested that the spatial durbin model was the most appropriate specification.

However unlikely these results may seem from a theoretical spatial econometric perspective, the data overwhelmingly favors the spatial autoregressive model. Given the unanticipated character of this result, one could proceed in two ways. On the one hand, the posterior information presented in Table 10 could be ignored in light of the convincing theoretical arguments in favor of the spatial durbin model. This way of proceeding would conceivably raise the risk of inflating parameter inefficiency but would not risk introducing bias and inconsistency. This is because the posterior inference suggests a data generating process of the spatial autoregressive form and the estimates provided by spatial durbin estimation under this data generating process are known to be inefficient in this case (LeSage and Pace, 2009).

Alternatively, one could follow what the posterior evidence suggests and assume a spatial autoregressive data generating process. This would risk introducing some amount of parameter bias and inconsistency if the data generating process was truly spatial durbin in

spite of the posterior evidence. In light of these tradeoffs and the overwhelming posterior support for the spatial autoregressive data generating process, it seems more fitting to set aside the theoretical arguments in favor of the spatial durbin model in order to pursue the data generating process indicated by the data; that being to assume a spatial autoregressive data generating process and to proceed with that type of model specification and associated estimation routine.

Table 11 contains results associated with the spatial weight matrix specification testing procedure. These results were based on the calculation of posterior model probabilities for 20 alternative specifications of the row standardized spatial weight matrix holding the spatial econometric specification (spatial autoregressive) and the explanatory variable matrix constant.

The results reveal that a spatial weight matrix extracting the two nearest neighboring MSAs best fits the sample data. This specification is associated with a posterior model probability of 0.195, which is nearly three times larger than any of the alternatives. The remaining posterior mass is spread fairly evenly across the alternative specification. The dominance of the two nearest neighbor specification of the spatial weight matrix is shown in figure 11 as is the even spread of the remaining posterior mass.

Table. 11 Spatial Weight Matrix Comparison Results

Spatial Weight Matrix	Posterior Probability
1NN	0.011
2NN	0.195
3NN	0.069
4NN	0.051
5NN	0.067
6NN	0.066
7NN	0.075
8NN	0.044
9NN	0.041
10NN	0.035
11NN	0.036
12NN	0.029
13NN	0.036
14NN	0.029
15NN	0.029
16NN	0.030
17NN	0.034
18NN	0.038
19NN	0.050
20NN	0.037

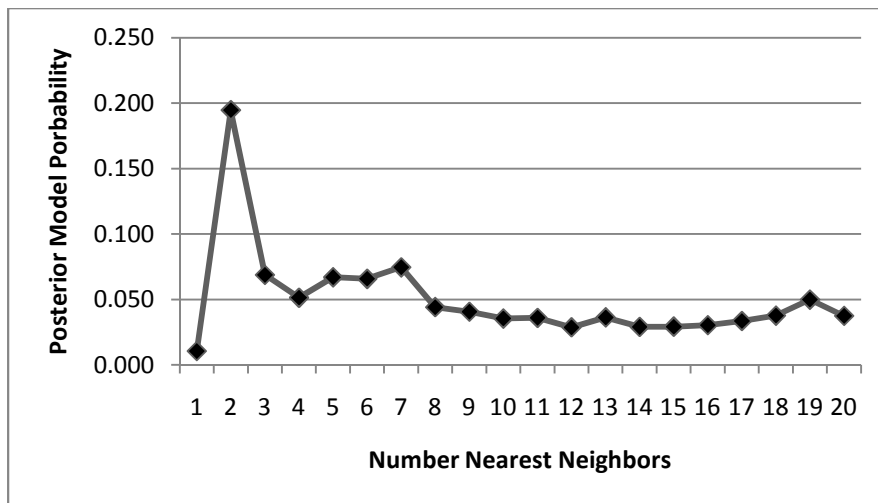


Figure 11. Plot of Posterior Support for the Spatial Weight Matrix Specification Tests

Table 12 contains the set of model averaged estimates. Column 2 contains the mean coefficient estimates, while columns 3 and 4 contain the upper and lower bounds of a 95% confidence interval computed around the means. The 95% confidence interval was computed to provide inferences regarding the statistical significance of the respective coefficient estimates. An interval containing a zero between the upper and lower bounds indicate a lack of statistical significance with respect to the given variable.

Two separate runs of 200,000 draws were used to investigate convergence in the sampling scheme. These runs were implemented with different sets of randomly selected initial explanatory variable matrices. The convergence tests resulted in model averaged estimates that were identical out to thousandths place for all parameter estimates and in a few cases the parameter estimates were identical to the ten thousandths decimal place. Both runs sampled 64 of the possible 64 models and both resulted in 17 models with posterior model probabilities greater than 0.001. Furthermore, both runs revealed identical representations of the top 10 models, which accounted for over 94% of the posterior mass. As well, the top 10 model had posterior model probabilities identical to the third decimal place. This evidence provides a clear indication of having taken enough draws to ensure convergence.

The subsequent model averaged estimates were created by estimating the complete set of unique models that were associated with posterior model probabilities greater than $1/10^{\text{th}}$ of 1 percent with these probabilities constituting the weights underlying the averaged

estimates. Each individual model was estimated via a Bayesian heteroscedastic variant of the spatial autoregressive regression model, initially introduced by LeSage (1997). Additionally, each model was estimated with an intercept term and spatially lagged dependent variable included and by taking 15,000 MCMC draws with 5,000 omitted for burn in purposes.

Table 12. Model Averaged Estimates

Variable	Mean Coefficient	Lower 0.05 CI	Upper 0.95 CI
Psychological Capital Index	0.0039	0.0011	0.0068
High Tech Industry Growth	0.0101	0.0044	0.0158
Pc Income Growth	-0.0248	-0.0366	-0.0128
Employment Growth	0.1701	0.1466	0.1939
Education Attainment	0.3043	0.2840	0.3244
Patents Per 10K	0.0164	0.0086	0.0240
P	0.1317	0.0931	0.1703

The set of model averaged estimates reveal several important findings. Beginning with the spatially lagged dependent variable, one can see that the coefficient estimate on the parameter, ρ , is positive and statistically significant. This confirms the suspicion that a spatial model was in fact necessary for this application (an issue that was omitted from the model specification tests).

Turning attention to the explanatory variables and beginning with the environmental factors, the results indicate that growth in high tech as a share regional output is positively related to high technology entrepreneurship as is total private employment

growth. Per capita income growth, on the other hand, appears to be negatively related to high technology entrepreneurship. The measure of individual factors, education attainment, confirms the positive influence indicated in the literature. In regards to the measure of entrepreneurial opportunity, the results suggest that it is positively related to entrepreneurial activities. Lastly, the psychological capital index is associated with a positive and statistically significant coefficient estimate. This result indicates that aggregate psychological capital has a relevant positive influence on entrepreneurial activities in U.S. cities.

4.8. Discussion and Conclusions

Several important conclusions are provided in this paper. This final section will discuss each of the individual results in considerable detail. The discussion will focus on how the coefficient estimates ought to be interpreted as well as discuss more fully their relevance to the scholarly literature on the determinants of entrepreneurship.

First, considerable model uncertainty was shown to exist between the alternative model specifications. This finding suggests that many empirical studies purporting to explain the determinants of entrepreneurship may be relying on models that have small probabilities of being correctly specified. In particular, the issues of the specific form of spatial model to estimate as well as how to specify the spatial weight matrix are often overlooked. Variable selection uncertainty, to the author's knowledge, has never been

addressed in this literature by using formal Bayesian logic despite the considerable theoretical reasons for doing so (i.e. it constitutes a formal way to accommodate all of these issues in addition to its ability to handle more the conventional issue of parameter uncertainty). This is an important issue to address here because model uncertainty is known to inflate parameter estimates as well as increase the dispersion around the estimates. This makes it hard to identify the impacts of various variables with any precision or accuracy. For instance, the psychological capital variable was not associated with a statistically significant effect in the author's exploratory work based on saturated spatial models, nor was per capita income growth. After dealing with model uncertainty, however, it was revealed that the standard deviations shrank considerably, providing more precision, and a finding of their relevance was made.

The results provide additional evidence that entrepreneurship is a phenomenon clustered in space. This means that there exist latent unobservable sources of variation in entrepreneurial activities that are region specific and have important influences on its prevalence in various places. Ignoring this would be tantamount to suffering from omitted variables bias and as such would lead to biased and inconsistent parameter estimates. The coefficient estimate of 0.132 indicates that the spatial correlation that exists in this dataset is moderately weak. However, this finding should be interpreted with caution due to the exclusion of a large number of cities for reasons of data availability.

The rest of this discussion will focus on the classes of explanatory variables defined in section 6 beginning with the structural economic or environmental variables. Three structural economic variables, deemed important in the entrepreneurship literature, were used to represent and control for these factors. The variables were: growth in high tech output as a share of total regional output, per capita income growth and total private employment growth. Of these variables, employment growth has the largest impact on high tech entrepreneurship by far. The coefficient estimate on employment growth was positive, indicating that cities with growing numbers of employees were the ones associated with growth in high tech entrepreneurship. The coefficient estimate on the growth of the share of high tech output was also found to be positively related to high tech entrepreneurship. This parameter estimate suggests that a history of an expanding share of output in high tech sectors has a positive impact on high tech entrepreneurship. This implies two things; that the commercialization of new high tech knowledge is considerably path dependent and two, that an expanding share of output in high technology, relative to the whole economy, spurs still more formation of new high technology entrepreneurial firms. The unanticipated result is that income growth was found to be negatively associated with entrepreneurship. What this might suggest is that entrepreneurial activity tends to occur in less expensive places, *ceteris paribus*, or that rising incomes give rise to complacency in the populous, which makes them less likely to take on entrepreneurial uncertainty.

Entrepreneurial opportunity is seen as one of the most critical determinants of entrepreneurship within the theoretical literature. In fact, very few models of entrepreneurship feel at liberty to omit it and rightly so. The evidence contained in this analysis confirms the theoretical relationship by finding that patenting activities have a positive relationship with entrepreneurial activities. However, this impact is considerably smaller than that associated with educational attainment (the sole individual factor) and two of the environmental factors. This result suggests that opportunities are not as critical as many have posited or that patents are not a great indication of the presence of entrepreneurial opportunity.

Finally, focus will now be placed on the primary variable of interest in this chapter; the psychological capital index. The results demonstrate that psychological capital does vary across U.S. cities and that it has important positive impacts on entrepreneurial activities. This finding is critical to understanding the determinants of entrepreneurship because it suggests two important things. First, it puts forward the notion that individual psychological capacities are important determinants of who engages in entrepreneurship, despite one's level of education or access to opportunities. Second, it suggests that these individual capacities may constitute a neglected form of capital that is both available and relevant to regional economies. This finding opens the door to a plethora of additional future research on if it is possible as well as how to create, retain and build this form of capital in an effort to spur entrepreneurially-driven innovation.

Many of the individual factors that have been identified as being related to the latent and unobservable variable, psychological capital (see Table 9), have precedence in the literature and it is worthwhile to discuss this more fully here. First, the factors: honesty, leadership, teamwork, kindness and love all seem to support the social capital construct as an important determinant of entrepreneurship (see Table 8). This is because they are empirically supported here through their relatively large rotated factor loadings assigned to them through the application of the principle components method. Therefore, this provides evidence supporting the conclusions drawn in the existing literature on social capital as an important determinant of entrepreneurship.

The factor analytic approach also provides evidence supporting the importance of creativity and tolerance to high tech entrepreneurship. The individual factors: creativity, judgment and fairness match up palpably well to creativity and tolerance (see Table 8) as espoused by their main scholarly proponents. For example, the factor creativity obviously relates well to the definition of creativity as laid out in works such as Florida's (2002) "The Rise of the Creative Class". Additionally, the factor, fairness, is designed to measure the following: treating all people the same, not letting personal feelings bias decisions about others, giving everyone a fair chance (see Table 8). According to this definition the factor, fairness, is nearly synonymous with the definition of tolerance espoused in this same work (among numerous others).

However, while social capital, creativity and tolerance are important determinants of high tech entrepreneurship, this chapter indicates that there is more to the story than just these elements. Other factors are also found to be linearly related to the latent index of psychological capital. Some of which have precedence only in the individual-based studies of entrepreneurship. In particular, individual-level studies of entrepreneurs have found considerable evidence suggesting that risk tolerance, self efficacy and a high tolerance for ambiguity are important determinants of entrepreneurial activities. However, these traits as entrepreneurial determinants are still contested and have certainly not been investigated with regard to regional stock variables. The results provided in this chapter have shown that the factors: bravery, hope and perseverance explain variation in psychological capital. These findings support these assertions because the definition of the bravery strength corresponds well to the individual-level definitions regarding risk aversion and tolerance for ambiguity, while factor definitions pertaining to hope and perseverance correspond well to the definition of self efficacy. In light of this, it is apparent that this chapter supports the discussed individual-level studies in an alternative setting as well as it provides further indication that the proclivity of these traits within a regional population has a positive association with the amount of high tech entrepreneurship occurring in it.

Lastly, several of the remaining factors that this research has expressed as underlying regional psychological capital have been unexplored in all previous research regarding the determinants of entrepreneurship. These factors are: zest for life, gratitude, humor,

perspective, self control and social intelligence. These factors capture variation in characteristics, such as: enjoying other people and one's life, an ability to control one's emotions, being gracious and exhibiting knowledge regarding what makes other people "tick". This set of psychological characteristics capture an unexplored area of psychological disposition that seems to reflect an ability to relate to other people and approach life with enthusiasm and an energy for human experience. These factors, while related to the concept of social capital, go beyond the existing definition emphasizing trust and cooperation to embrace a more dynamic concept that are best described as human energy or thirst for experience.

To summarize, the intention of this chapter was to estimate a commonly implied model of the determinants of entrepreneurship with the addition of psychological capital as an explanatory variable. The results are suggestive of the fact that psychological capital is a very real determinant of regional entrepreneurship and that it varies enough across cities in the U.S. to render it deserving of more research. Furthermore, this chapter provides empirical evidence that several factors found to be important at the individual-level are at work at the regional-level as well and possibly constitute an entirely neglected form of capital relevant to regional entrepreneurship.

CHAPTER 5 CONCLUSIONS

Higher levels of entrepreneurship within regional economies are widely considered to be related to any increases in economic that occur in them. As such, public policies encouraging higher levels of regional entrepreneurship are commonly considered to be growth inducing policies. The purpose of this dissertation has been to examine three critical issues related to the economic outcomes of and the inputs into regional entrepreneurship using recent advances in spatial econometrics. The specific goal of this effort was threefold: 1.) to more precisely identify the impact of entrepreneurship on regional variation in total factor productivity; 2.) to examine the theoretical argument that entrepreneurship enhances productivity in economies near the technological frontier while it does not do so in economies that are farther from it; 3.) to examine the relevance of psychological capital as an important, yet to date neglected, determinant of regional entrepreneurship.

This dissertation was, therefore, organized into three principle parts. The first part set out to analyze the impact of entrepreneurship on regional total factor productivity with respect to knowledge stocks in all economies contained in the sample data. The

conclusions of this effort are summarized in section 5.1. Part two, constituting Chapter 3, took a look at whether the impacts of entrepreneurship were a function of the distance of the given place from the technological frontier. The conclusions stemming from this chapter are contained in section 5.2. Part three, presented in Chapter 4, changed emphasis away from a focus on the economic outcomes to a focus on the input or rather the determinants of entrepreneurship. More specifically, this chapter sought to extend the most prominent model of the determinants of entrepreneurship, which focuses on individual, opportunity and environmental characteristics, to include psychological capital. The primary focus of this chapter was to describe why psychological capital may be a relevant regional determinant of entrepreneurship, create an index purporting to measure it and to assess its relationship with regional variation in entrepreneurial activities. The conclusions with regard to these issues are summarized in section 5.3. Finally, section 5.4 will briefly discuss how the conclusions impact entrepreneurship policy.

5.1 Overall Impacts

Theories of economic growth have overwhelmingly identified knowledge as the fundamental driver of economic expansion. However, there are many examples of economies that produce large amounts of knowledge yet fail to grow as rapidly as others producing similar amounts if at all. Many have sought to explain why this is so. What they have come to suggest is that newly created knowledge is only one piece of the

puzzle and that there is a very real and considerable gap between newly created knowledge and that applied to economic production. Thus, the spillover of economic knowledge requires mechanisms or channels through which new knowledge is converted into economic knowledge. One channel that has been identified is that of entrepreneurship. The argument is that entrepreneurship works to commercialize new knowledge, leading to productivity increases and, through that, economic growth.

However, this theoretical perspective has not been adequately observed in empirical research. Chapter has argued that the reasons for this are that the empirical literature on entrepreneurship and regional productivity along with that on knowledge spillovers is notorious for presenting incorrect estimates on the size of knowledge spillover. Further, the empirical literature linking entrepreneurship to regional productivity fails to adequately measure productivity or use the correct spatial econometric specifications; due in large part to their failure to admit deficiencies inherent in measuring knowledge and entrepreneurship.

This chapter has relied on historical developments in economic production relationships along with recent improvements in applied spatial econometrics to empirically link entrepreneurship to differences in regional total factor productivities. In so doing, it has shown that patent stocks and single establishment firm formation activities explain over 90% of the variation in regional total factor productivity differences. It presented evidence confirming earlier work that spillovers can be empirically identified by

separating out the direct and indirect spatial effects using the spatial durbin regression model. The results demonstrate that entrepreneurship has a total impact on regional total factor productivity that is over five times larger than that of knowledge as measured by patenting activities. This result provides clear evidence that while knowledge production is necessary for steady-state economic growth; its commercial introduction has dramatically larger impacts on productivity in the real world. As a result, this evidence suggests that entrepreneurship is an extremely important mechanism for bringing about productivity growth.

5.2 Impacts Near and Far From the Technological Frontier

Technological gap theory suggests that regional economies at great distances from the technological frontier can catch-up to these leading economies by successfully adopting their innovative technologies while those on the frontier have to invent new ones in order to stay ahead (Fagerberg, 1987; Soete and Verspagen, 1993; Fagerberg and Verspagen, 2002). The theory also recognizes that the absorption of innovative technologies requires significant effort and considerable amounts of capital investments. In light of these ideas and their incorporation into Neo-Schumpeterian growth models, recent theoretical work in modeling economic growth has implied that entrepreneurship drives productivity growth in economies on or near the technological frontier while channeled investments by existing organizations drives their diffusion (Acemoglu, Aghion, and Zilibotti, 2006). These findings, then, have profound implications for the policy community at large.

However, little empirical work has sought to test the efficacy of these implications with empirical data.

Chapter 3 has undertaken this gap in the literature by empirically examining the suggestion that entrepreneurship directly impacts regional total factor productivity in economies on and near the technological frontier while it does not in economies far from it. The approach has been to estimate a reduced form of the full model, which takes on the form of a spatial durbin regression model. This model is implied by the specific spatial-technological interdependencies inherent in the underlying growth models as well as by non-spatial models exhibiting spatially correlated omitted variables. The results suggest that entrepreneurship has a direct effect on productivity growth that is nearly identical in size in economies both near and far from the technological frontier as based on the sample of U.S. states. As a result, the analysis contained in this dissertation does not support the theoretical implications of the discussed models. It appears that entrepreneurship has nearly identical impacts on productivity in leading and lagging regional economies.

5.3 Psychological Capital as a Determinant of Entrepreneurship

Certain psychological traits have long been identified in individuals that engage in entrepreneurship. A very similar set of psychological traits have also recently been identified as critical factors of successful organizations and have been described as a

form of psychological capital (Luthans et al., 2007; Luthans and Youssef, 2007; Luthans et al., 2006). In light of these developments, Chapter 4 sought to extend a common mode of the determinants of entrepreneurship to examine the possible manifestation of psychological capital at the city level.

The results demonstrated that psychological capital varied across U.S. cities and that it had a positive impact on the level of entrepreneurial activities occurring in them. This finding is critical to understanding the determinants of entrepreneurship because it suggests two important things. First, it suggests that these individual capacities may collectively constitute a neglected form of capital that is both available and relevant to regional economies. Second, it supports previous research that put forward the idea that individual psychological capacities are important determinants of who engages in entrepreneurship, despite one's level of education or access to opportunities. The results of Chapter 4 are especially exciting because they open the door to future policy relevant research topics as: if it is possible as well as how to create, retain and build this form of capital in an effort to spur entrepreneurially-driven innovation.

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