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The Existence of Positive Psychological Environments and Their Impact on Regional Entrepreneurship

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Abstract. Studies of individual entrepreneurs consistently find that certain positive psychological traits are prevalent in entrepreneurial people and that these traits are particularly important determinants of an individual's ability to recognize opportunities as well as their propensity to exploit them. This evidence, in conjunction with the stylized fact that entrepreneurial activities are clustered in geographic space, leads to a few worthy questions. Are individuals that possess these traits heterogeneously distributed in geographic space? If so, does the distribution of these characteristics represent the psychological environment of a place and does it have important influences on the amount of entrepreneurship occurring in it? In this paper, I seek to answer these questions in order to provide an appreciation of the relationship between psychological environments and regional entrepreneurship; using Bayesian Model Averaging. The results suggest that regional psychological environments vary considerably across geographic space and that these differences indeed have important influences on the incidence of entrepreneurship.

1. Introduction

Research into the determinants of entrepreneurship has been extensively studied by academics in many disciplines. Within this literature, two alternative approaches to identifying these determinants have frequently been used. The first approach has been to systematically study individual entrepreneurs in an effort to identify characteristics or tendencies common to these individuals. The second approach explores disparities in structural economic characteristics in order to explain variation in entrepreneurial activities, which result from differences among these various regional characteristics and economic circumstances. Both approaches have revealed considerable insights into how and why entrepreneurial activities emerge. However, the impacts of psychological traits as determinants of regional levels of entrepreneurship are unknown. This is largely due to the fact that regional scientists have overwhelmingly disregarded the possible manifestation of individual positive psychological traits at the regional-level.

The literature focusing on individual entrepreneurs has used survey data to identify sets of characteristics that are commonly associated with successful and/or nascent entrepreneurs. Many studies have found that factors such as: social networks, (Saxenian, 1999; Sorenson, 2003; Johannisson, 1988; Larson, 1991) work experience, educational attainment (Evans and Leighton, 1990) and familial history (Dunn and Holtz-Eakin, 2000; Blanchflower and Oswald, 1990) have important influences on an individual's decision to engage in entrepreneurship. As well, many studies of entrepreneurially oriented people suggest that individual differences in psychological traits play a large role in an individual's tendency to engage in entrepreneurship.

Risk aversion is a particular trait that has been widely studied. The evidence consistently demonstrates that entrepreneurs are risk prone individuals (Kilstrom and Laffont, 1979; Brockhaus, 1980; Van Pragg and Cramer, 2001). The fundamental argument behind this trait's importance is that a high tolerance for risk makes an individual more willing to bear the burden of "Knighterian" uncertainty, which is fundamentally associated with engaging in entrepreneurship. Self-efficacy, or a strong belief in ones ability, is another trait that has been show to play a large role in an individual's willingness to engage in entrepreneurial activities (Markman et al., 2002). Still yet, other research suggests that individuals exhibiting a strong desire to achieve and a high tolerance for ambiguity are more likely to be entrepreneurial than are other individuals (McClelland, 1961; Schere, 1982).

The regional approach to entrepreneurship research essentially leaves aside individual characteristics, focusing instead on regional structural factors driving entrepreneurial activities. This body of literature argues that opportunities are not homogeneously distributed across space and, as a result, structural differences, and not individual differences, are driving regional variation in rates of entrepreneurship. This research has focused primarily on factors such as: transport costs, human capital concentrations, employment characteristics, industrial structures, research and development activities, diversity and financial capital availability (see for example Bartik, 1989; Reynolds et al., 1994; Dunn and Holtz-Eakin, 2000; Acs et al., 2007). As well, others have found that population, employment and income growth are important determinants of regional entrepreneurship (Acs and Armington, 2002).

Quite recently, a minority of regional scientists have started to place more emphasis on factors that have an implicit psychological basis. For example, studies linking regional stocks of social capital, creativity and tolerance to entrepreneurship have been conducted. Coleman (1988; 1990) and Putman (1993) have argued that regional stocks of social capital facilitate trust and cooperation among regional agents. Other psychological factors, such as, creativity and tolerance have crept into regional analyses of entrepreneurial activities via occupation-based indicators. The authors of these studies have suggested that agglomerations of creative individuals along with a tolerant and open regional environment exert significant positive impacts on levels of entrepreneurial activities (Lee et al., 2004; Florida, 2002; Mellander and Florida, 2006).

The basic arguments underlying the importance of these factors are that higher levels of social capital make entrepreneurship relevant social networks denser and with stronger links between larger numbers of nodes, while creative and tolerant regional environments facilitate entrepreneurship by advancing lower barriers to entry and by making these regions more open to radical ideas or innovations. To a lesser extent, this latter body of literature has argued that "open" and "creative" environments contain larger stocks of individuals which are more apt to both demand and adopt new and innovative types of products. The probability for entrepreneurship, then, is higher in these types of places because a larger willingness to both produce and consume radical types of products exists within them. Essentially, there exist better markets for the types of products and processes often introduced by entrepreneurs in these places.

While the individual and regional level studies approach entrepreneurship from different perspectives, both seek to explain variation in entrepreneurial activities. As a result, their contributions are certainly not unrelated; in fact both do hint at the importance of psychological traits to entrepreneurial activities. The individual-level approach has found direct evidence that psychological characteristics are important determinants of entrepreneurship. The regional-level approach, on the other hand, has not yet explicitly examined psychological characteristics as a determinant of entrepreneurship. However, it has provided evidence that characteristics with strong psychological undertones have important influences on the propensity of entrepreneurial activities and that they are unevenly distributed in space. What these two approaches seem, then, to suggest in common is that psychological traits may not only be important at individual-level but also at the region-level.

In light of these arguments and findings, the research reported here adds to the existing entrepreneurship literature in four important ways. First, to the author's knowledge, this work is the first attempt at incorporating a measure of the regional psychological environment into an analysis of the determinants of regional entrepreneurship. Second, this work introduces the question of whether or not variation in positive psychological environments exists across U.S cities. Third, it explores whether or not variation in positive psychological environments explain some portion of the variance in regional-levels of entrepreneurial activities, regardless of whether or not entrepreneurial opportunities are homogeneously or heterogeneously distributed. Lastly, this research infuses the issue of model uncertainty into modeling regional entrepreneurship. This last issue deserves attention in its own right as it has been largely ignored in all previous research on entrepreneurship.

The arrangement of this paper is as follows. Section 2 will discuss the dataset and the definitions of the variables used in this analysis. Section 3 lays out the methodological approaches, including discussions of the statistical issues surrounding spatial dependence and model uncertainty. Section 4 provides the estimation results while Section 5 contains a discussion of the results and provides some conclusions.

2. Data

The effect of differences in positive psychological environments on entrepreneurship across metropolitan regions in the U.S. is investigated using a sample of Metropolitan Statistical Areas (MSAs). The dataset covers 173 MSAs due, in part, to a lack of reliable data for each explanatory variable covering the entire set of MSAs in the U.S. Specifically, the data used to create the psychological index was problematic as a small number of individual responses existed for many MSAs. As a result, the ability of these aggregate measures to adequately represent the entire population of these MSAs, at large, was questionable and so many MSAs were dropped from the analysis, resulting in a final dataset containing 173 metropolitan regions. Although this loss seems significant, the remaining 173 cities contained nearly 85% of the U.S. urban population, as many of the omitted metros were quite small.

The dependent variable utilized in this analysis is high technology single establishment firm formations, a variable frequently used as a proxy for entrepreneurship. 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. Year 2003 data was utilized, as it corresponds to the most recent available data, and was aggregated to the appropriate metropolitan definition using aggregations of relevant counties[1].

The Census defines a single establishment as a single location (in terms of a physical location) where business is conducted or where services or operations are carried out. A single-establishment birth is defined to be a single establishment having no payroll in the first quarter of an initial year with a positive payroll in the first quarter of a subsequent year. As a result, single establishment firm formations constitute entirely new agents of firm-level economic organization.

High technology single-establishment births were isolated for a number of important motives. First, it is well known that the high technology sectors of the U.S. economy are highly dynamic and transitory. These sectors embody the outcomes of the process of new knowledge commercialization, which incumbent firms were unwilling or were unable to commercialize (Acs and Plummer, 2004; Acs el al., 2007). Furthermore, these sectors are responsible for a large amount of the growth in aggregate U.S. output; rendering them crucial players in the growth processes of the evolving "knowledge economy". Second, the high tech sectors epitomize the "Schumpeterian" sense of entrepreneurship, where new economic knowledge is being introduced in a highly competitive and dynamic environment. Thus, the "Schumpeterian" process of "creative destruction" is most certainly at work in these rapidly evolving sectors of the U.S. economy. Third, these sectors of the economy exclude new establishments, such as: new coffee shops, dry cleaners, or pizza places. Including these types of firms in the definition of entrepreneurship clouds the investigation of the determinants of new firms engaging in "creative destruction" as these types of firms are, in large part, simply proportional to population growth and involve little to no new knowledge. While it is certainly the case that many non-high tech sectors of the U.S. economy, such as business services, are engaging in creative destruction, the inclusion or exclusion of these sectors should have little impact on the fundamental results. This is because the process of creative destruction is certainly captured by the high tech sectors and so this measure serves the purposes of this paper well enough on its own.

The definition of high technology was defined in a manner laid out by Varga (1998). Varga's (1998) criteria involved three sub-criteria: 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.) the total number of innovations per 1,000 employees. For standardization purposes, the number of high tech firm formations in each metro was divided by the Census's 2000 population figures for that metropolitan region.

A growing body of literature has emerged regarding positive aspects of human psychology. This literature has become known as "positive psychology" and takes the point of view that psychological research efforts have focused to heavily on the negative aspects of human psychology and that an adequate understanding of positive aspects of psychological orientation would provide much missing information about human beings. This approach has particularly interesting implications for entrepreneurship research efforts that, to date, have been unexplored.

Studies of individual entrepreneurs, such as those mentioned in the introduction, have provided arguments and evidence supporting the importance of psychological characteristics to entrepreneurial actions. As well, many economists have argued that social capital characteristics, such as: trust and cooperation have important implications for collective action (Coleman, 1988 and 1990; Putnam, 1993). Still yet, economists and scholars of urban environments have

[1] MSA definitions correspond to the 2005 Office of Management and Budget (OMB) definitions.

professed the importance of regional variation in human creativity, tolerance and ingenuity to regional economic outcomes (Florida and Gates, 2001; Florida, 2002; Lee et al., 2004).

While originating in different fields of research and for considerably different purposes, all of these efforts have a common theme; that human psychological disposition varies across regions and that this variation has important influences on general economic situations and circumstances. It would not, then, take to much imagination to conceive the argument that regional differences in psychological environments have important influences on levels of entrepreneurship. Much, it seems, could be added to understanding the determinants of entrepreneurship by linking the positive psychological environment with regional variation in entrepreneurship.

To do just that, data on positive psychological characteristics were obtained from the Positive Psychology Center in Philadelphia Pennsylvania. These data cover 24 strengths of character contained in the Values in Action Inventory of Strengths (VIA-IS). The strengths of Character are defined as positive traits reflected in thoughts, feelings, and behaviors that exist in various degrees and that can be measured as individual differences (Park et al., 2004). All of the data for constructing the character strengths were collected online at www.authentichappiness.org and www.positivepsychology.org/strengths along with associated geographic information represented by a 3-digit zip code location (Park et al., 2004).

Uniform tools exist to assess each of the positive traits in the classification, one of which is a 240 item self-reported questionnaire that asks individuals to report the degree to which statements reflecting each of these 24 strengths apply to themselves using a 5 point Likert scale (Park et al., 2004). Investigations have demonstrated acceptable reliability and validity for each of these 24 character strengths. For example, Peterson and Seligman (2004) conducted a validity study using the nomination known-groups procedure where individuals were asked to identify individuals they believed to possess a given strength to a notable degree. The nominated individuals were then asked to complete the questionnaire without being told why. People nominated as a paragon of a particular type of character strength tended to score higher on that strength than non-nominated individuals (Peterson and Seligman, 2004).

Table 1 contains the 24 character strengths and their associated synonyms and definitions that were used to construct the positive psychological environment (PPE) index. Park et al. (2004; 604) states 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 point was to provide descriptions of the 24 measures in a manner that would distinguish and describe exactly what the given attributes were attempting to measure.

A sample of 203,003 individual respondents was contained in the data concerning positive psychological characteristics. All respondents associated with the same 3-digit zip code were averaged to create an average of each personality category for every 3-digit zip code. The 3-digit zip codes were then assigned to metropolitan regions using a simple visual basic script run in ArcView 9.1. The script served to calculate the centroid coordinates associated with each 3-digit zip code. These coordinates were then overlaid on an ArcView shapefile containing the geographic boundaries associated with each metropolitan region contained in the sample. All centriods falling into any given metro boundary were used to create an average of each personality characteristic associated with the given metropolitan region.

The city-level averages of the 24 strengths of character were used to construct the positive psychological environment (PPE) index used to measure these factors. This index was created to measure latent unobservable variation in a generalized positive psychological environment over a sample of U.S. cities. It was fashioned by extracting a single principle component from the 24 strengths of character. A single component was utilized because the Eigen values associated with the various underlying factors revealed that one factor dominated the others. Every individual characteristic associated with a rotated loading greater than 0.50 was included in the index. The varimax rotated factor loadings were then used as weights in the calculation of this index[2]. Table 2 contains the varimax rotated factor loadings for each of the 24 psychological attributes. Larger values of the PPE index can be viewed as indicative of a more "positive" psychological environment. This is because the variables used to create it reflect positive attitudes and behaviors, many of which have been shown to be positively related to individual entrepreneurs. Furthermore, one would expect higher levels of personality traits, such as: creativity, hope, bravery, fairness, zest, honesty, social intelligence, etc. to exhibit positive impacts on high tech entrepreneurial activities.

[2] The varimax rotation searches for the linear combination of the original factors that maximizes the variance of the loadings.

Table 1. Definitions of personality variables

Variable	Synonym(s)	Description
Beauty	awe, wonder, elevation	Noticing and appreciating beauty, excellence, and/or skilled performance in all domains of life, from nature to art to mathematics to science to everyday experience.
Bravery	valor	Not shrinking from threat, challenge, difficulty, or pain; speaking up for what is right even if there is opposition; acting on convictions even if unpopular; includes physical bravery but is not limited to it.
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	interest, novelty-seeking	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; giving everyone a fair chance.
Forgiveness	mercy	Forgiving those who have done wrong; giving people a second chance; not being vengeful.
Gratitude	none given	Being aware of and thankful for the good things that happen; taking time to express thanks.
Hope	optimism, future orientation	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; making (not necessarily telling) jokes.
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, critical thinking	Thinking things through and examining them from all sides; not jumping to conclusions; being able to change ones mind in light of evidence; weighing all evidence fairly.
Kindness	generosity, care, 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 maintain 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 ones own or formally; obviously related to the strength of curiosity but goes beyond it to describe the tendency to add systematically to what one knows.
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, purpose	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.

Table 2. 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

It should be noted that every city associated with less than 100 respondents was omitted from the sample. Metropolitan areas associated with less than 100 respondents were omitted to mitigate problems with bias that may have resulted if too few respondents were used to represent the given city. Furthermore, the distributions of the individual psychological characteristics tended to approach a bell-shape when a minimum of 100 individual respondents was defined as the minimum acceptable value[3].

Figure 1 depicts the geographic distribution of the positive psychological environment index. Positive psychological environments are highest in the southeastern U.S. metropolitan areas. As well, there exists a cluster of cities in the south-central Midwestern region of the U.S. that exhibit high positive psychological environments. Notable pockets also exist in Southwest and Pacific coast metropolitan regions, where values on the PPE index are also relatively large.

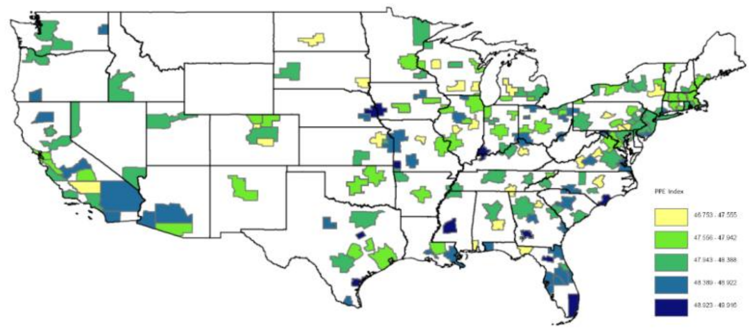

Figure 1. The geographic distribution of the PPE index

It is well known that variation in human capital has important implications for both economic growth and for the underlying entrepreneurship ushering in that growth. To adequately represent this variation, two measures of human capital are included in the analysis. These measures correspond to the traditional measures of human capital, which are based on educational attainment. The first measure corresponds to the percentage of the 25+ 2000 population in each metropolitan region having obtained at least a bachelors degree. The second educational attainment measure is the percentage of the 25+ 2000 population having obtained a graduate or professional degree.

Entrepreneurs, by definition, require an opportunity with which to exploit in the form of a new firm formation (Shane and Venkataraman, 2000). Therefore, some indicator of entrepreneurial opportunity should be included into this study of the determinants of entrepreneurship. The difficulty, however, is that opportunities cannot be directly observed until after they have been exploited. While this may be the case, it seems logical to assume that the regions with larger amounts of knowledge production ought to be associated with larger amounts of entrepreneurial opportunities. To sufficiently account for these opportunities, two measures of the knowledge are included into the analysis; one measuring the per capita knowledge and the other the growth of knowledge. Patents represent an accessible measure of the amount of codified knowledge existing in various places; therefore, patents are commonly used to measure the amount of knowledge in those places[4]. In this study, the growth

[3] Sensitivity analysis with respect to this minimum specification was carried out at several alternative thresholds (20, 50, 100, 150 and 200) and revealed that no notable differences in the mean parameter estimates or in the posterior distributions of those estimates existed.

[4] The author is well aware of the critiques associated with the use of patenting activities as a measure of knowledge, however, the alter-

of patenting activities over the period 1975-1999 was used to measure the growth of knowledge production, while year 2000 patents per 10,000 individuals was used to measure the amount per capita of knowledge available in any given region.

Many authors have suggested that diverse regions, or more specifically diverse cities, act as magnets of both talent and ideas (Jacobs, 1961; Lucas, 1988; Lee et al., 2004). The more diverse is the region, the more ideas and talent to draw from, thereby, facilitating more entrepreneurship in the form of new high technology firms. To adequately incorporate diversity into this analysis, two measures were used, both of which measure a particular variant of ethnic diversity. The first measure represents the percentage of the total 2000 population that is foreign born. The second measure corresponds to the percentage of the total 2000 population that is non-white. These measures are included to explain variation in entrepreneurship due to the impact of diversity.

The last sets of variables included in this analysis correspond to structural variables that reflect a region's economic dynamism. These variables are: the average annual growth in the share of regional economic output coming from high tech industries when compared to the national average 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. These variables were introduced to control for systematic variation in entrepreneurial activities that result from: differences in industrial structures (or industrial legacies), differences in income growth and differences in the growth of the labor force. Including these structural variables captures systematic regional variation in high tech entrepreneurial activities that is due to core structural differences. These control variables work to impede the PPE index from capturing variation in entrepreneurship that is really due to structural economic factors.

A log transformation was used on the dependent variable vector to produce a distribution that looked to be more normally distributed. Secondly, all of the explanatory variables were also studentized to accommodate the use of Zellner's g-prior (Zellner, 1986), for reasons described in Section 3.

natives are few and far in between. Therefore, patents are used in this paper in spite of the known weaknesses associated with doing so.

3. Method

There are two pertinent issues pertaining to the regression modeling of high technology entrepreneurship explored in this research. These issues are spatial dependence and model uncertainty. These issues are important because the existence of spatial dependence has been shown to cause bias in the resulting parameter estimates (LeSage and Pace, 2004) while model uncertainty creates a situation yielding suboptimal results for a number of reasons (Raftery et al., 1997). For one, considerable uncertainty over which specific variables to include into the regression model exists and estimates based on saturated models, containing many possible variables, does not address this issue in any consistently reliable theoretical framework. Secondly, simply introducing all of explanatory variables into the regression will result in the possibility of including irrelevant variables, which will tend to increase the dispersion of the estimated coefficients. This will make it difficult to identify the important variables influencing entrepreneurship. On the other hand, a strategy that relies on subsets of candidate explanatory variables will likely suffer from omitted variables bias if important variables are excluded.

As well, the considerable uncertainty regarding which explanatory variables are truly relevant in explaining variation in high tech entrepreneurship can lead to explanatory variable matrices suffering from collinearity, further reducing the precision of the coefficient estimates (Belsley et al., 1980). Collinearity also yields instability in regards to the parameter estimates because the inclusion or exclusion of any single explanatory variable can dramatically alter the coefficient estimates associated with any given explanatory variable.

To handle these issues, Bayesian Model Averaging is employed in the context of a spatial autoregressive regression framework. This modeling approach is especially advantageous for this study because it adequately addresses the considerable model uncertainty inherent in this analysis of the determinants of entrepreneurship, while at the same time, it accounts for suspected spatial autocorrelation of entrepreneurial activities.

3.1 Spatial dependence

Numerous regional-level studies of entrepreneurship have noted that entrepreneurial activities are clustered in space, resulting in outcomes that are spatially correlated (see for example Acs and Plummer, 2005 and Acs et al., 2007). The spatial clustering of these activities in previous empirical studies results in the expectation that spatial dependence may exist in the sample of data utilized in this paper, as entrepreneurial activities are modeled as the dependent variable.

It is unclear whether or not the use of non-contiguous metropolitan data, further exacerbated by the exclusion of certain metropolitan regions, as was discussed above, has resulted in a sample of data that is unaffected by the existence of spatial dependence. To handle this situation, the Bayesian Model Averaging strategy discussed in subsection 3.2 will be carried out in the context of a spatial autoregressive regression framework. It is important to note here, that this strategy will produce parameter estimates statistically equivalent to of the least-squares based approach should spatial dependence not be an important issue in this particular dataset (see Appendix B for details regarding the specification of the spatial weight matrix).

3.2 Bayesian model averaging

Considerable uncertainty exists regarding how relevant each of the candidate explanatory variables are in explaining variation in high tech entrepreneurship over the sample of metropolitan regions used in this paper. While many empirical studies suggest that the economic and human capital measures utilized in this paper, such as job growth or educational attainment are important predictors of high tech entrepreneurship, relatively little information exists to offer insights into which specific measures of educational attainment and diversity are appropriate. Furthermore, it is unclear whether or not the PPE index is truly relevant in explaining variation in the dependent variable. As a result, a considerable amount of model uncertainty exists with regard to the analysis carried out here..

Fortunately a literature exists to address these issues in a consistent framework that has been empirically verified. The literature is called Bayesian Model Averaging and involves comparing alternative sets of explanatory variables. This methodology overcomes the any problems associated with misspecification, collinearity and/or including irrelevant personality variables that this work might otherwise encounter. The basic theory was provided by Arnold Zellner (1971) and involves cases where there are a small number of alternative models to compare.

The 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. The priors for the models and parameters are then combined with the likelihood function, conditional on the parameters and models in order to produce a posterior distribution for each of the m alternative models under consideration. The posterior distributions are used to calculate posterior model probabilities for each of the m models, which are then used to compare the alternative model specifications.

While this procedure works well for cases with where m is small, its computational demands inhibit its application to cases where m is considerably larger, as is the case here. However, Madigan and York (1995) introduced a technique known as Markov Chain Monte Carlo Model Composition (MC^3) that enables the analysis to be carried out in cases where m is large, through a systematic sampling of the large model space. Work by Fernandez et al. (2001a and 2001b) and Raftery et al. (1997) then extend this work to applications of econometric regression modeling. Their approach is utilized in this paper (see Appendix C for explicit details).

4. Results

Several important findings were obtained via the particular methodological approach relied on in this paper. For one, the resulting posterior model probabilities lent empirical support for the preconception that a considerable amount of model uncertainty exists with regard to modeling the determinants of entrepreneurship. This was reflected by the fact that the most probable model was associated with a posterior model probability of only 0.25. This finding is interpreted as meaning that the most probable model only has a 25% chance of being the "true" data generating model. Furthermore, just under 1,000 unique models were found by the sampling scheme, yet only two of these were associated with posterior model probabilities greater than 0.01. This suggests that substantial uncertainty exists regarding which of the candidate explanatory variables are truly relevant in explaining variation in high tech entrepreneurship.

Table 3 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, where intervals that do not contain 0 indicate such significance. The estimates were obtained by estimating the set of unique models that were associated with posterior model probabilities greater than 0.001 or $1/10^{th}$ of 1 percent. The posterior probabilities correspond to 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), that is robust to the influence of outliers and heteroscedasticity. Each model was estimated with an intercept term included and with eight thousand draws (4,000 were omitted for burn in purposes). The set of model averaged estimates reveal several important findings. Beginning with spatial dependence, one can see that the coefficient estimate on the parameter, rho, is positive and statistically significant. This confirms the suspicion that entrepreneurial activities are correlated across space.

Table 3. Model averaged estimates

Variables	Coefficients	Lower 0.05	Upper 0.95
PPE index	0.0017	0.0002	0.0032
Tech. growth	0.0034	0.0012	0.0056
Foreign born	0.1058	0.0908	0.1209
Non-white	-0.0046	-0.0069	-0.0024
Pc. inc. growth	-0.0026	-0.0046	-0.0005
Job growth	0.1342	0.1164	0.1526
Pat. growth	-0.0358	-0.0482	-0.0232
Ba 25 +	0.4567	0.414	0.4994
Pat. 10k pop.	0.0137	0.0082	0.0195
Gp deg.	-0.1953	-0.2358	-0.1543
Rho	0.0845	0.0401	0.1271

Regarding the structural economic variables, these 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 the prevalence of high tech entrepreneurship. The two variables of ethnic diversity are both statistically significant as well, with foreign born being associated with a positive coefficient estimate while non-whites are associated with a negative estimate. In regards to the knowledge variables, the results suggest that the growth of patent activities over the period 1975-1999 is negatively associated with high tech entrepreneurship while the amount of knowledge per capita is positively related to it. Regarding human capital, the measure of the share of the 25+ 2000 population holding bachelors degrees is associated with a positive coefficient estimate while this share holding graduate and professional degrees is associated with a negative estimate. Lastly, the positive psychological environment index is positively related to high tech entrepreneurial activities.

5. Discussion and conclusions

Several important conclusions are suggested by the results of this ressearch. 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 what these coefficient estimates imply with regard to the determinants of high tech entrepreneurship.

5.1 Econometric considerations

5.1.1 Model uncertainty

With regard to the econometric conclusions, 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. This is particularly important because scholars of entrepreneurship underestimating the amount of uncertainty underlying their conclusions. The issue is critical because these models and their respective inferences are being used to formulate entrepreneurship policy without fully appreciating the sizeable uncertainty inherent in any particular model.

5.1.2 Spatial correlation and entrepreneurship

The results presented above have provided additional evidence that high tech entrepreneurship is a phenomena clustered in geographic space. This means that there exists sources of latent unobservable variation in entrepreneurial activities that are region specific. However, the intricacies of this particular dataset have rendered the impact of this variation rather small. The range of the possible values for the spatial dependence parameter is 0 to 1, where a 0 represents no spatial correlation and a 1 represents complete correlation[5]. Therefore, the coefficient estimate of 0.08 indicates that the spatial correlation that exists in this dataset is considerably small. Nevertheless, this finding should be interpreted with caution due to the non-contiguity based data used here, which was further exasperated by the exclusion of a large number of cities for reasons of data availability.

[5] In actuality the range of possible values is -1 to 1, however, the range -1 to 0 represents that case of negative spatial correlation. Negative correlation was ignored in this discussion because such correlation would indicate that the presence of entrepreneurial activities in one region would discourage its presence in neighboring regions. This seemed to be particularly absurd when considering the literature on entrepreneurship and so this case was ignored here.

5.2 Structural economic influences

In the rest of this discussion, attention will focus on the explicit explanatory variables that underlie the current model, beginning with the structural economic variables. Three structural economic variables deemed important in the entrepreneurship literature were investigated in this paper. These variables were: growth in high tech output as a share of total regional output, per capita income growth and total private employment growth. All of these variables were measured in terms of their growth rates. This was deliberate as it facilitates an "apples to apples" comparison of the magnitudes of their coefficient estimates.

Of these structural economic variables, employment growth has the strongest relationship with high tech entrepreneurship. The coefficient estimate on employment growth was positive, indicating that cities with growing numbers of employees are associated with growth in high tech entrepreneurship. It is not surprising to find that the coefficient estimate on the growth of the share of high tech output is positively related to high tech entrepreneurship. This finding suggests that a history of an expanding share of output in high tech sectors has a positive relationship with high tech entrepreneurship. This implies two things; one, that the commercialization of new high tech knowledge (which is fundamentally what new high tech entrepreneurship is) is considerably path dependent and two, that the returns to the expanding share of output in high technology that occurs in any given city may in fact be recycled in that city, spurring the formation of new high tech entrepreneurial firms. The surprising result is that income growth is negatively associated with high tech entrepreneurship. This evidence seems to suggest the following; that high tech entrepreneurial activity tends to occur in less expensive places, holding constant all of the other factors.

5.3 The influences of knowledge, human capital and diversity

Two commonly used measures of diversity were included to control for variation in the dependent variable that results from concentrations of diverse populations. The results indicate that higher concentrations of foreign born populations have a stronger relationship with entrepreneurial activities than do concentrations of non-white persons. This is evidenced by the fact that the mean coefficient estimate on foreign born populations is approximately ten standard deviations above zero, while the mean coefficient estimate on non-whites is only approximately two standard deviations above zero. Furthermore, concentrations of non-whites are associated with a negative impact on entrepreneurship, while the opposite is true with respect to concentrations of foreign born persons. These suggest an interesting possibility; that it's not racial diversity that is important to entrepreneurship (in fact the coefficient on racial diversity is negative), but rather that it's the diversity of the immigrant population that is important.

Two alternative measures of knowledge were included in this paper to control for the extent of entrepreneurial opportunity. The differences between these two variables are that the per capita level of patenting activities measures the amount of recent codified knowledge (3 years ago in this case), as a percentage of the population, whereas the other measures the growth of codified knowledge over the last 25 years. The fact that the coefficient estimate associated with the former is positive while the latter is negative suggests that higher percentages of recent codified knowledge is positively related to high tech entrepreneurial activities while growth in the amount of codified knowledge over the past quarter century is not. This further suggests that it is the level of the availability of new knowledge in a city that relates to high tech entrepreneurship and not the accumulation of knowledge in the past.

Two alternative measures of human capital were included to account for variation in entrepreneurship resulting from differences in levels of education. These were the shares of the 25+ 2000 population holding bachelors and graduate and professional degrees. The results indicate that 4 year degrees are positively associated with high tech entrepreneurship whereas advanced degrees have a negative association. This finding suggests two possibilities. One, that people who have obtained a graduate degree are less willing to leave their jobs to start new tech companies while those with bachelors degrees are more willing to do so. Perhaps the incomes that persons with advanced degrees are earning make them less willing to bear the "Knighterian" uncertainty associated with entrepreneurship. Second, this could mean that small cities with large universities or research laboratories create observations where large concentrations of persons holding graduate and professional degrees exist, yet these places do not have enough access to the other necessary preconditions for emergence of high tech entrepreneurship. Therefore, the global impact shows up as negative.

5.4 The influence of the psychological environment

Finally, focus will now be placed on the primary variable of interest; the positive psychological environment index. The results demonstrate that positive psychological environments do, indeed, exist and that these environments vary from place to place. Furthermore, the results indicate that this variation has important influences on high technology entrepreneurship, holding all other explanatory variables constant[6].

Many of the individual items included in the latent unobservable PPE index have precedence in the literature. The factors: honesty, leadership, teamwork, kindness and love all relate well to the concept of social capital (see Table 1). Therefore, the inclusion of these factors in the PPE index provides evidence supporting conclusions drawn in the existing literature on social capital. The results also provide evidence in support of the importance of creativity and tolerance to high tech entrepreneurship. The individual factors: creativity, judgment and fairness match up appreciably well to creativity and tolerance (see Table 1) as defined in the literature. For instance, the factor creativity obviously relates well to the definition of creativity as laid out in Florida (2002). In this research, 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 1). As a result, this factor appears to be almost synonymous with the definition of tolerance as it is used by Florida and Gates (2001). The implication is that tolerance and creativity are important psychological components of a region's psychological environment.

However, while social capital, creativity and tolerance are important components of the PPE index, the results suggests that there is more to the story than just these elements. Other factors are also found to be important measures of the latent positive psychological environment; some of which have only be examined in the individual-level context. Individual-level studies of entrepreneurs have found considerable evidence suggesting that risk tolerance, self efficacy and tolerance for ambiguity are important psychological characteristics of entrepreneurial individuals. The results presented in this research have shown that the factors: bravery, hope and perseverance capture important subcomponents of positive psychological environments. These particular findings, then, are especially interesting because the definition of the bravery factor 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, the results support the individual-level studies and provide evidence that the propensity of these characteristics in a particular population have a positive relationship with the amount of high tech entrepreneurship occurring in it.

Lastly, several of the remaining factors that this research has shown to contribute to positive psychological environments have been unexplored in all previous research on 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 tends to reflect an ability to relate to other people along with a general "excitement" for life. These factors are certainly related to the concept of social capital yet seem to go beyond the existing definition to include a more dynamic concept the might be better described as "human energy".

The central purpose of this research was to examine regional psychological environments as they pertain to entrepreneurship. The concept of positivity, while well documented at the individual-level, has never been explored at the regional-level. This research has demonstrated that important psychological characteristics manifest themselves at the level of the region through as an environmental factor, within which entrepreneurship emerges. Furthermore, this research has shown that they exhibit considerable variation across cities in the U.S and that constructs such as social capital, creativity and tolerance may be subcomponents of a more general socio-environmental determinant of entrepreneurship, which is described as the psychological environment here. As a result, this research has demonstrated that regional variations in psychological environments exist and that they have important influences on entrepreneurial activities.

While the evidence suggests that positive psychological environments have important influences on high technology entrepreneurship, it should be made clear that the environments are not, themselves, expli-

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[6] The relative size of this coefficient is rather small. However, it should be noted that the size of this coefficient is not comparable with the size of other coefficients. This is because the interpretation of the partial is complicated. The partial with respect to this variable reflects a change in a weighted average of Likert scales, thus, the small magnitude of this coefficient does not necessarily imply a small impact with regard to this variable. In other words, it is nearly impossible to compare the magnitude of a coefficient on a Likert scaled variable with to other continuously scaled variables.

cit producers of entrepreneurship. Rather, they likely work to enhance a regions propensity to identify and commercialize the entrepreneurial opportunities inherent in newly created knowledge. The psychological environments, then, are like "conductors" of entrepreneurial activity in that they increase the probability that new information translates into commercial innovation.

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Appendix A.
The Specification of the Spatial Weight Matrix

Typically, the specification is based on first order contiguity (also known as the Queens criteria). However, the current set of sample data is not contiguous, inhibiting this type of specification. 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. All $w_{i=j}$ are set equal to zero to prevent an observation from exhibiting dependence on itself. The matrix is then row standardized yielding a row stochastic matrix (since W is non negative). The purpose of obtaining a row stochastic weights matrix is that this type of weight matrix has nice numerical and interpretive properties (see LeSage and Pace (2004) for specific details). Once, W is specified in this manner, it will be used to represent the spatial relationships inherent in this analysis[7].

Appendix B.
Markov Chain Monte Carlo Model Composition

The MC[3] procedure starts with an initial randomly selected set of explanatory variables then deriving a proposal model to compare to the initial model through the use of three steps, where the use of each step is equally probable (i.e. each step has a probability of 0.33 of being used). These 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. 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 repeated. Madigan and York (1995) show that one can systematically walk though the large model space by repeating this procedure many times, essentially solving the

[7] A spatial weight matrix extracting the 5 nearest neighboring observations was used throughout this paper. This specification was used because evidence suggests that knowledge absorbed by high tech firms tends to be bound to an area approximately 50-75 miles from its source. The specification of W, here, is based on this empirical evidence (see Anselin, Acs and Varga, 2002).

problems associated with Bayesian Model Averaging in cases where m is large.

The key step in this process 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 relation 4.

$$\min[1, \frac{p(M_p \mid y)}{p(M_i \mid y)}] \qquad (4)$$

In relation 4, M_p represents the proposed model and M_i represents the initial model, both of which are based on the inclusion of different sets of explanatory variables. The terms in this ratio can be obtained by first combining the priors ($\pi(M)$ and $\pi(M,\beta,\sigma \mid M)$) with the likelihood function ($p(y \mid \beta,\sigma,M)$), to arrive at the joint probability for the models and parameters, shown in relation 5,

$$p(M,\beta,\sigma \mid y) = \pi(M)\pi(M,\beta,\sigma \mid M)p(y \mid \beta,\sigma,M) \qquad (5)$$

then by obtaining the joint posterior for the models and parameters shown in relation 6

$$p(M \mid y) = \iint p(M,\beta,\sigma \mid y)d\beta, d\sigma \qquad (6)$$

and analytically integrating β and σ out of the expression to arrive at a scalar expression for the numerator and denominator which are used in relation 4.

To arrive at the posterior model probabilities over the set of all unique models, it is necessary to save the log marginal density vectors for each unique model found by the sampling scheme. The models with posterior model probabilities that are greater than 0.001 were saved for use in constructing model averaged coefficient estimates, which account for the model uncertainty inherent in this application. To create these 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 0.001.

It should be noted here that work by LeSage and Parent (2007) demonstrates that the least-squares model comparison inferences will be adversely affected by spatial autocorrelation. As a result, the basic model averaging strategy outlined above will have to be augmented to account for spatial autocorrelation. This can be done by relying on the strategy laid out by LeSage and Parent (2007) in the context of a spatial autoregressive model. This strategy is conceptually the same strategy as was laid out above, with the addition of the parameter ρ to expressions 5 and 6 with one computational difference. The difference is that the parameter ρ cannot be analytically integrated out of expression 6 as were β and σ. To handle this problem, LeSage and Parent (2007) suggest storing the vectors of the log marginal values for both the current and proposed models over a grid of values for the parameter ρ. These vectors can then be scaled and integrated with respect to this parameter to produce the odds ratio shown in 4.

The last two issues with regard to the implementation of the model averaging strategies used in this paper involves the specification of the priors for the model parameters and diagnosis of convergence in the MC^3 sampling scheme. In accordance with the standard convention, Zellner's g-prior (Zellner, 1986) is utilized for the parameter β (Fernandez, Ley and Steel, 2001a and 2001b). A gamma prior is used for the parameter σ and following LeSage and Parent (2007), a beta prior is used for the spatial dependence parameter ρ. Fifty thousand draws were initially utilized and convergence in the sampling scheme was insured by carrying out the procedure twice and inspecting the results to see if the same results were obtained. Since the same results were, indeed, obtained the 50,000 draws were enough to ensure that the models with the most posterior support were among those sampled. Model averaged estimates can be obtained with confidence after ensuring that convergence in the sampling scheme has been attained.