THREE ESSAYS ON LOCATION ASPECTS IN BIOTECHNOLOGY ENTREPRENEURSHIP

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by
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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled

THREE ESSAYS ON LOCATION ASPECTS IN BIOTECHNOLOGY ENTREPRENEURSHIP

Presented by Christos Kolympiris

A candidate for the degree of Doctor of Philosophy

And hereby certify that in their opinion it is worthy of acceptance.

Professor Nicholas Kalaitzandonakes

Professor Thomas G. Johnson

Professor Peter G. Klein

Professor Douglas J. Miller

Professor Douglas D. Moesel

To my wife Natasa…

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THREE ESSAYS ON LOCATION ASPECTS IN BIOTECHNOLOGY ENTREPRENERUSHIP

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ABSTRACT

Despite its success, as measured by financial growth, innovative outcomes and number of firms entering the industry, biotechnology remains a risky and capital intensive industry partly due to market uncertainties and complex regulatory regimes. Given its knowledge intensive character, biotechnology is also a fertile ground for entrepreneurial activities including firm creation. In such an environment characterized by high risk and rewards coupled with the potent role of knowledge, established and newly founded biotechnology firms are in a constant race to secure funds mainly from venture capital firms and government agencies while reaping knowledge, know-how and expertise from spatial externalities.

This dissertation analyzes three key issues in entrepreneurship research pertaining to funding, spatial externalities and location attributes of the biotechnology industry in the United States. The first issue is whether spatial externalities help biotechnology firms increase their much needed venture capital funds and Essay 1 analyzes that issue. The second issue regards the effect of funds from the National Institutes of Health, which is the largest source of R&D expenses in biotechnology, on local firm births and Essay 2 is concerned with the issue in question. The third issue, examined in Essay 3, emanates

from the rise of entrepreneurial university and its role as a local growth engine. The Essay examines those factors related to decisions by academic faculty, who are in the core of the entrepreneurial university, to start their biotechnology firms locally as a means of local economic development.

Essay 1 employs a spatial autoregressive model that associates the total venture capital (VC) amount raised by a given biotechnology firm with the corresponding amount of neighboring firms. The empirical results indicate that biotechnology firms improve their venture capital funding through collocation with biotechnology and venture capital firms, perhaps due to knowledge spillovers. We find that the potential spatial externalities associated with VC fund accumulations decay with distance. The positive effects associated with neighboring VC funds stop at about 20 miles, and the positive effects from neighboring VC firms end at about 10 miles. After controlling for the VC funds raised by neighboring biotechnology firms, we find that the agglomeration of neighboring biotechnology firms does not have a separate positive effect on the origin firm's VC funding level. Also, VC funding is significantly determined by the source of the VC funds and by firm-related factors such as the firm's age. However, the region-specific characteristics used in this study do not have a significant impact on VC funding levels.

Essay 2 employs a Poisson count data model of the number of biotechnology firm births per year in a given Metropolitan Statistical Area (MSA) conditional on the total dollar amount provided to the MSA's universities, incumbent private firms and research institutes/ hospitals from previous years' grants awarded from the National Institutes of Health (NIH). The empirical results suggest that while federal monies are expected to

generate new local firms, there are significant differences in the transforming capacity across different types of institutions. The capacity of private firms to transform federal research funds to new local biotechnology firms outweighs the corresponding capacity of universities, while federal funds directed towards research institutes and hospitals do not appear to translate to local firm births.

Essay 3 employs an ordered logit model to analyze the effects of regional, institutional and personal characteristics on academic entrepreneurs' decision to start their biotechnology firms locally. The empirical results indicate that scientific labor availability, agglomeration of biotechnology firms, age, and founder's academic institution effects are important determinants of an academic entrepreneur's firm location choice. Contrary to expectations we find that an academic entrepreneur's eminence does not have explanatory power on firm location choice. The results with regard to venture capital availability are mixed since we find that while local agglomeration of venture capital firms decreases the probability of local firm creation, the presence of large venture capital firms increases that probability. While many explanations are possible, we attribute the finding in question to venture capital anchoring effects where large venture capital firms attract newly founded firms close to them.

ESSAY 1: Spatial Collocation and Venture Capital in the US Biotechnology Industry

1. Introduction

Biotechnology is a leading growth industry in the United States based on the rate of new firm creation, the pace of technological innovation, and the rate of revenue growth. There was only one major biotechnology firm (Genentech) in 1977(Ernst and Young, 2009) , but today there are more than 1,500 biotechnology firms in the U.S. whose combined sales approached $100 billion in 2008 (Datamonitor, 2009). Furthermore, the U.S. continues to rank first in biotechnology innovation as measured by intellectual property protection, education level of the workforce, research and development (R&D) intensity, quality of the business climate, and research foundations (Scientific American, 2009).

Despite its impressive growth over the past 30 years, biotechnology remains a risky and capital intensive industry. For example, the R&D cost for the development of a new drug product averages $802 million (DiMasi, Hansen, & Grabowski, 2003) due to the complex science and the strict regulatory environment while the potential commercial success for any given product is highly uncertain (Haussler & Zademach, 2007). Due to this high-risk and high-reward environment, dedicated biotechnology firms (DBFs) are in a constant race to secure funds from venture capital firms (VCFs), government agencies, and other sources. The importance of venture capital (VC) funding on a DBF's success has been highlighted in the literature (Carpenter & Petersen, 2002; Champenois, Engel, & Heneric, 2006; De Bettignies & Brander, 2007). The purpose of this paper is to examine

some key questions about VC funds accumulated by DBFs and the spatial relationships between the DBFs and their VCFs. First, are the VC funding levels among neighboring DBFs positively correlated such that an increase in VC funding for one DBF is expected to spillover to neighboring DBFs? Second, do DBFs attract more VC funding as the number of DBFs located in close proximity increases (while holding their VC funding levels constant)? Third, do DBFs attract more VC funding as the number of VCFs located in close proximity increases (perhaps due to network externalities that create efficiency gains)?

The benefits of spatial collocation among DBFs has been established in the literature (e.g., Powell et. al, 2002) , and the collocation of DBFs and VCFs has been observed in some metropolitan areas. However, the possible spatial effects on VC funding in the biotechnology industry have not been thoroughly analyzed in the existing literature. In this paper, we attempt to enhance our understanding of these spatial relationships by addressing the questions mentioned above. Specifically, we address the first question by examining the spatial correlations among VC funding levels for firms that are located in close proximity. We also examine the spatial extent of these collocation externalities by identifying the distance at which the spatial correlations become statistically insignificant. We address the second question by estimating the marginal effects of an increase in the number of neighboring DBFs on the VC funding level accumulated by a given DBF. We address the third question by estimating the marginal effects of an increase in the number of neighboring VCFs on the VC funding level accumulated by a given DBF. These questions are expressed as four distinct

hypotheses that we test using a fitted spatial autoregressive (SAR) model of the VC funds raised by the DBFs in our data set.

The paper is organized as follows: in the next section, we review the relevant literature and present the four main research hypotheses for this paper. In section 3, we specify the spatial econometric model used to test our research hypotheses, and we describe our data sources in section 4. We then discuss the estimation and test results in section 5, and we offer concluding comments in section 6.

2. Literature Review and Research Hypotheses

2.1. Positive Externalities

Over the past several years, a large number of studies have demonstrated the existence of positive externalities emanating from the spatial collocation of dissimilar or similar firms[1] (e.g. Cooper and Folta, 2000 ; Rocha and Sternberg, 2005 ; Amin and Wilkinson). These positive externalities are often termed agglomeration economies and are separated into two types: localization and urbanization economies. Localization economies describe the gains from locating close to firms with similar characteristics (e.g., firms in the same industry, firms sharing a common organizational or financial structure, or firms of similar age and size), and we focus on these externalities in the next subsection. Urbanization economies describe the gains from locating close to heterogeneous firms, and these may arise from complementary use of shared resources as well as experimentation with novel strategies and forms of organization.

[1] There are also contributions to this literature that challenge the existence of such positive spatial externalities (see Håkanson, 2005; Breschi and Lissoni, 2001)

Localization economies are often described in terms of knowledge exchange, information flows, innovation enhancement, ease of project collaboration, and fostering of entrepreneurship (see Bönte, 2004 ; Bathelt et al., 2004 ; Jonsson, 2002 ; Kirat and Lung, 1999 ; Boschma and Wenting, 2007 ; and Gertler (2003) for examples and see Breschi and Malerba, 2001 for a discussion). In the biotechnology industry, the effects of spatial collocation of DBFs, VCFs, universities, research centers, and other industry participants have been mostly studied in the context of efficiencies in knowledge creation (Coenen, Moodysson, & Asheim, 2004; Gittelman, 2007; McKelvey, Alm, & Riccaboni, 2003; Moodysson & Jonsson, 2007). A plausible spatial benefit that has not received much attention in the literature is the increase of VC funds for the collocating DBFs. This increase can either be conceptualized as a positive externality *per se* or as the indirect outcome of other externalities. For example, it is possible that collocating DBFs realize spatial externalities and become more efficient, which helps them to attract more VC funds.

2.2. Localization Economies

Spatial externalities[2] in the biotechnology industry have received considerable attention due to the knowledge-intensive nature of the industry and the persistent spatial clustering of DBFs in metropolitan areas. A handful of studies on clusters and regional development have emphasized the importance of tacit knowledge[3] (Adams & Jaffe, 1996; Feldman, 1999; Fontes, 2005; Jaffe, Trajtenberg, Henderson, & Henderson, 2005; Zander & Kogut, 1995) as a means for imitation (Aldrich & Wiedenmayer, 1993; Hannan &

[2] See Rocha (Rocha, 2004) for a detailed discussion of the literature that describes and analyzes the externalities that may accrue from spatial collocation.

[3] There are also contributions to the literature that raise doubts about the importance of tacit knowledge (see Breschi and Lissoni, 2001 ; Håkanson, 2005).

Freeman, 1989; Meyer & Rowan, 1977; Stuart & Sorenson, 2003; Thornton, 1999), learning, and performance benchmarking (Maskell, 2001). The transmission of tacit knowledge is facilitated by spatial proximity through information dissemination (Hedstrom, Sandell, & Stern, 2000; Herrigel, 1983; Liebeskind, Oliver, Zucker, & Brewer, 1996; Piore & Sabel, 1986; Saxenian, 1994; Sorenson & Stuart, 2001), relationship formation (Blau, 1977; Bossard, 1932; Enright, 1991; Festinger, Schachter, & Back, 1963; Gordon & McCann, 2000; Kono, Palmer, Friedland, & Zafonte, 1998; Park, 1926; Porter, 1998a, 1998b; Rosenfeld, 1997; Sternberg, 1991; Zipf, 1949), direct observation, participation, or shared experience. Tacit knowledge may be generated from scientific, assembled, or idiosyncratic sources (Jensen & Meckling, 1976), but it is not easily communicated through formal channels in any form. To overcome these difficulties, people with shared research experiences may develop communication codes, shared meanings, and language in order to create epistemic proximity (Steinmueller, 2000), which is easier to develop under spatial collocation (Fontes, 2005).

There are other ways in which firms can capture the benefits of localization economies through spatial collocation. For example, spatial proximity among similar firms also contributes to the integration of diverse knowledge bases in order to innovate (Dahlander & McKelvey, 2005; Liebeskind, et al., 1996). Also, localization economies may be conducive to growth (Beaudry, 2001; Henderson, 1997), innovation (Acs, Fitzroy, & Smith, 1999; Beaudry & Breschi, 2003), and the mitigation of the free rider problem (Beal, 2001; Beal & Gimeno, 2001). Beaudry (2001) for example found that UK firms in the aerospace industry located in clusters of same firms grew faster and Henderson (1997) studied five capital good industries and found evidence of own

industry externalities. All in all, localization economies are instrumental in boosting a firm's performance as measured by innovation, growth, the ability to learn and replicate, the integration of knowledge, and network building.

The geographic scope of spatial benefits such as information dissemination has received less attention from researchers. In the literature that analyzes spatial spillovers, the spatial externalities are assumed to accrue among agents located within close proximity of each other, and the spatial externalities are assumed to wane as the distance between agents increases until they eventually cease to exist. However, the estimates of the distance over which spatial externalities span have not been uniform across studies. Delaney (1993) found that "most biotechs use information sources (within a 50-mile radius of the firm)" while Orlando (2004) found that spillovers from industrial R&D can carry for up to 200 miles for firms in the same industry. Rosenthal and Strange (2003) studied six industries and concluded that agglomeration externalities decay drastically in the first few miles and then attenuate at a slower pace.

Given these considerations, it is possible that collocating DBFs realize spatial externalities and become more efficient, which helps them to attract more VC funds. Accordingly, we hypothesize that:

H1: VC funding levels of spatially proximate DBFs are positively associated with each other.

H2: The association between the VC funding levels for any two DBFs declines as the distance between the DBFs increases.

2.3. Spatial Externalities Among Biotechnology Firms

While researchers have studied the existence and magnitude of the externalities that may arise among spatially proximate firms, the notion that agglomeration benefits increase with the number of firms located in a region has been explicitly addressed only by a few studies such as Arthur (1990) and Wallsten (2001). The existence of these agglomeration benefits is implicitly maintained in many studies (Stuart & Sorenson, 2003), and the general view in the literature is that a larger number of collocating firms is associated with higher learning opportunities, higher potential for network building, and better chances for organizational change. Otherwise, firms located in less dense regions must establish relationships with firms located elsewhere[4] (Cooke, 2001; Echeverri-Carroll & Brennan, 1999; Gilding, 2008; Rees, Lagendijk, & Oinas, 2005; Saxenian & Hsu, 2001). Thus, the presence of a larger number of related firms in close proximity to a DBF is expected to increase the localization externalities discussed previously because spillovers among DBFs can be stronger in regions with a higher density of biotechnology activities.

Given these considerations, the collocating DBFs would tend to realize larger spatial externalities and become more efficient in areas where firm density is higher, which could help them attract more VC funds. In this context, we hypothesize that:

H3: The level of VC fund accumulation for a DBF increases with the number of other DBFs located in close proximity to the DBF.

It should be noted that H3 is distinct from H1, which refers to spatial correlations among the VC funding levels. Here, H3 refers to the impact of having more neighboring DBFs

[4] This is not to say that only firms located in spatially isolated regions establish distant relationships. Gilding (2008) describes how network effects and institutional cluster composition may determine whether distant relationships are complements or substitutes for local connections.

on the VC funds for a particular DBF while the VC funding levels of the neighboring firms are held constant.

2.4. Spatial Externalities Among DBFs and VCFs

VC financing is a crucial element of success and sustainability in any industry (Carlsson, 1995; Stankiewicz & Carlsson, 1991), including biotechnology (Eliasson, Eliasson, & Carlsson, 1997; Valentin, Jensen, & Dahlgren, 2008; Waxell & Malmberg, 2007). In particular, Carpenter and Petersen (2002) show that VC funds are especially critical for DBFs because government funds are typically not sufficient to cover their needs for capital. VC investments fill the void as they are typically directed towards high-return ventures associated with high degrees of risk (Amit, Brander, & Zott, 1998; Gompers & Lerner, 2001; Lam, 1991; Timmons, Bygrave, Wright, Sapienza, & Busenitz, 2003) such as the development of a new biotechnology product (Audretsch, 2001; Champenois, et al., 2006).

However, the contribution of VCFs to the funded DBFs extends beyond financial outlays and may include knowledge creation and dissemination as well as management or consulting services. For example, De Bettignies and Brander (2007) develop a theoretical model that shows VC funding occurs and survives only when VCF managerial contributions are productive, and other researchers have shown that these contributions improve value creation (Lam, 1991; Wijbenga, Postma, Van Witteloostuijn, & Zwart, 2003) and innovation efficiency (Kortum & Lerner, 2000; Langeland, 2007; Muller, Fujiwara, & Herstatt, 2004; Wonglimpiyarat, 2006)[5]. Local networks of VCFs can also

[5] For studies analyzing the potentially negative effects of VC financing, see Wasserman (2003), Gompers (1996), Lee and Wahal (2004), Zacharakis and Meyer (1998), and Fischer and Pollock (2004).

generate non publicly-available knowledge (Shane & Cable, 2002) due to their experience and involvement in multiple enterprises. In particular, VCFs help filter information, screen projects, and create and disseminate new knowledge that can benefit both the firms they fund as well as other proximate firms (Macmillan, Kulow, & Khoylian, 1998). This knowledge created by the VCFs is largely tacit, so the DBFs located in proximity to VCFs may have better access to it. As their knowledge base improves, these more efficient DBFs are expected to attract more VC funds. Evidence of this relationship between these possible efficiencies and capital accumulation gains is indirectly provided by the empirical work of Haussler and Zademach (2007) , who found that regions with a balanced presence of VCFs and DBFs exhibited the best financial performance. Hence, the collocation of VCFs and DBFs can improve a DBF's knowledge base through access, information (Powell, et al., 2002), and ease of communication (Doran & Bannock, 2000; Green, 1991)[6]. Given these considerations, we hypothesize that:

H 4: The level of VC fund accumulation for a DBF increases with the number of VCFs located in close proximity to the DBF.

In testing the above stated hypotheses there are some empirical issues that must be handled with care. If H3 and H4 are true, then the neighboring firms for a particular DBF are also expected to achieve higher VC funding levels, which may hamper our ability to accurately measure the marginal effects associated with VC funding levels among neighbors under H1 and H2. Further, a model designed to test all four hypotheses

[6] In contrast, Dahlander and McKelvey (2005) criticize claims of the potential importance of spatial effects among VCFs and DBFs.

must include the VC funding levels for neighbors (H1 and H2) as well as the counts of neighboring DBFs (H3) and VCFs (H4). Given these variables may be highly correlated if all four hypotheses are true, the model estimation procedure may be subject to potentially harmful collinearity, which may inflate the estimator variance and diminish the power of our statistical tests. To account for this potential problem, we estimate two versions of our model. First, we impose the null components of H3 and H4 (i.e., there are no effects associated with the counts of neighboring DBFs or VCFs) and only evaluate the evidence in support of H1 and H2 (Model 1). Then, we estimate a second version of the model without these restrictions so that we can test all four hypotheses (Model 2). The details of the model specifications are provided in the next section.

3. Methods and Procedures

We use a fitted spatial autoregression (SAR) model to examine the empirical support for the four main hypotheses. Following Anselin (2006), the general form of the SAR model is

$$y = \sum_{i}^{R} \rho_i W_i y + X + \varepsilon \qquad (1)$$

$$\varepsilon \sim N(O, \sigma^2 I)$$

where y is an $n \times 1$ vector of dependent variables, each W is an $n \times n$ spatial weight matrix that defines the neighbors for the observed dependent variables, and X is a matrix of control variables. In our application, the dependent variable is the natural logarithm of the total VC amount invested in the n DBFs (AMT). So, the spatial correlation

parameters $\rho_{i=1...R}$ measure the elasticity between the VC funds raised by the origin DBF and the average level of VC funds raised by DBFs within a specified distance range from the origin DBF.

Following Anselin (2001), a common alternative to the SAR model is the spatial error model (SEM) in which the spatial lags arise between the model error components rather than the dependent variable. In particular, both models are special cases of more general spatial regression models, and the SAR model may be converted to an SEM and vice versa. Due to this equivalence, Anselin (2001) notes in his section 3.1 that the SAR model is appropriate when the purpose of the modeling exercise is to focus on the existence and strength of the spatial relationships (i.e., as in H1 and H2), and the SEM is appropriate when the spatial structure is not of primary importance and we only want to adjust for its presence. For these reasons, we use the SAR models of the spatial relationships among the DBF funding levels to test our four main research hypotheses.

To test whether the spatial effects decay with distance under H2, the definition of neighbors in each W matrix[7] is based on sequential 10 mile intervals from the origin DBF. For example, the DBFs situated less than 10 miles from the origin DBF were considered as one set of neighbors, and the corresponding parameter ρ_1 measures the elasticity of the weighted average VC of these neighboring DBFs on the VC funds of the origin DBF. The second set of neighbors was composed of those firms 10.01 miles to 20 miles away from the origin DBF, and the corresponding parameter ρ_2 measures the

[7] If the distance between DBF i and DBF j falls within the distance range in question, then $w_{i,j} \in W$ equals 1. Otherwise, the weight matrix element equals 0. Then, the sum of each row in the matrix is normalized to one by dividing each $w_{i,j}$ by the row sum. Thus, the product of the elements in row i and the vector of observed dependent variables represents the average value of the dependent variable for all DBFs defined as neighbors to DBF i.

elasticity of the weighted average VC of those DBFs on the origin DBF VC accumulation. The same procedure was repeated to identify subsets of neighboring firms within 10-mile rings of all DBFs in the sample.

Under H1, we expect a positive sign for each ρ associated with a spatial ring that exhibits positive spatial effects among the VC accumulations for neighboring DBFs, and we expect the magnitude of the ρ's to decrease as we move farther away from the origin DBF under H2. We also use the estimated spatial correlation parameters to determine the threshold distance from the origin DBF where the spatial effects are effectively exhausted. In particular, this threshold distance is identified as the point where the subsequent ρs are statistically insignificant. For example, if the ρ_2 coefficient for the DBFs in the 10.01 mile to 20 mile range is statistically insignificant and the same holds for the subsequent ρ's, then we would conclude that the positive spatial externalities are exhausted at about 10 miles from the origin DBF.

For hypothesis H3, the relationship between DBF collocation and VC accumulation is represented by the number of neighboring DBFs (*NB*) residing in 10-mile increments from every DBF[8]. The first *NB* variable reflects the number of DBFs within 10 miles of the origin DBF, the second *NB* variable reflects the number of DBFs within 10.01 to 20 miles of the origin DBF, and so on. The regression coefficients for these variables measure the marginal effect (semi-elasticity) of an additional neighboring DBF in this distance interval on the origin DBF's VC fund accumulation. Under H3, we expect positive signs on these estimated coefficients, and their absolute magnitudes are

[8] The number of neighboring firms is a standard measure of density in the literature (see Baum and Mezias, 1992; Lomi, 2000 ; Sorenson and Audia, 2000).

expected to decrease as we move to spatial rings that are farther from the origin DBF. Similarly, H4 is represented with corresponding variables that count the number of VCFs (*VC*) in 10-mile intervals from every DBF. Under H4, we expect positive signs on these estimated semi-elasticity coefficients, and their absolute magnitudes are expected to decrease as we move farther from the origin DBF.

In addition to the variables that directly represent hypotheses H1-H4, we must also control for other firm-specific and location-specific effects that may affect the VC accumulation of individual DBFs. First, while VCFs and DBFs of all sizes are found to collocate (Powell, et al., 2002), local VC funds are often directed towards young firms that are seeking early-stage investments (Gupta & Sapienza, 1992; Harrison & Mason, 2000; Lemarié, Mangematin, & Torre, 2001; Plant, 2007; Powell, et al., 2002). Later-stage financing that is sought by more mature DBFs is typically larger in size and requires syndication from more (and often distant) VCFs. Accordingly, our model includes controls for the DBF's age in linear and quadratic form (*Age* and Age^2), and age is used as proxy for a DBF's size. We expect the coefficients for the age variable coefficients to be positive in the linear term and negative in the quadratic term (forming a concave marginal effect) so that firms rely less on VC funds as they become very mature and increasingly use alternative financing sources such as capital markets (Wonglimpiyarat, 2006). We also include the natural logarithm of the average distance of each DBF from its financing VCFs in the model (*VCDistance*). The variable represents the straight line distance from the location of each DBF to each financing VCF, and the weighted average assigns more weight to those VCFs that provided more funds. We expect the sign of the coefficient for this variable to be positive.

Second, we include two explanatory variables that could influence the level of VC funds obtained by individual DBFs. Government grants are generally awarded to firms with promising science and may serve as a signal of success potential that leads to higher VC funds accumulation (Lerner, 1999). We use a dummy variable (*SBIR*) that equals one if the DBF received Small Business Innovation Research (SBIR) grants (and equals 0 otherwise), and we expect a positive sign on the coefficient for this variable. We also include a dummy variable (*Foreign*) that equals 1 if the DBF received funds from non-US VCFs (and equals 0 otherwise). Non-US funds are viewed as a type of distant financing, which typically involves larger funding amounts. Thus, we expect a positive sign on the coefficient for this dummy variable.

Third, we include four explanatory variables that serve as proxy variables for region-specific effects on VC funding. The first is a dummy variable (*Tax*) that equals one if the DBF's state had an R&D tax credit from 1990 to 2007[9]. This proxy variable represents the local tax incentives that can strengthen the DBFs' financial position and subsequently attract more VC funds. We expect the sign of the coefficient for this variable to be positive. The second variable (*University*) measures the distance from each DBF to the nearest university. DBFs that are close to universities may benefit from potential knowledge spillovers, so we expect a positive sign for the coefficient on this variable. The third variable is an index that measures the relative cost of doing business in the DBF's state (*Business*), which serves as a proxy for the local macroeconomic

[9] We use a dummy variable to represent the local tax effect instead of the local tax rate because the financial statements of the DBFs in our sample are not available. Thus, we cannot calculate the effective tax rates for each firm.

environment[10]. We expect the coefficient for this variable to be positive because DBFs will face higher resource costs (i.e., labor, facilities) and require more funds in more expensive states. Finally, DBFs can become more successful and achieve higher VC accumulations if the local business climate (e.g., zoning ordinances) is more conducive to business activities. We account for this effect on VC funds by including a variable that counts the average total number of non-biotech establishments in the DBF's zip code from 1992 to 2007 (*Establishments*). We expect the sign of the coefficient for this proxy variable to be positive.

Finally, we recognize that the VC funding levels may depend on factors directly associated with the VCFs and their costs of doing business, and we include two variables to represent these effects. The first variable controls for syndication effects where closely located DBFs receive funds from the same distantly located VCF(s). Powell et al. [9] found that "New York money is restless moving around to Boston, San Diego…California money goes to Boston…" A detailed examination of our data revealed a similar pattern where VCFs of region i often provided large funding amounts to very closely located DBFs residing in region j, where j is typically quite distant from i. The variable is formulated as a cross-product or interaction variable and measures the sum of the distances between each firm's closest neighbors and their funding VCFs, and the variable is formed as

$$Cross = W_{NS} \times D \tag{2}$$

[10] Although the state level of aggregation for this variable might be too coarse to represent local factors, we were unable to identify other proxy variables that may capture such local effects and that were available for all of the observations in our sample.

where $Cross$ is the $n \times 1$ cross-product variable for each of the n firms, W_{NS} is an $n \times 1$ non-standardized W matrix that indentifies the firms located within a 1 mile radius from the origin firm, and D is the $n \times 1$ vector of the weighted distance for each firm from its financing VCFs. $Cross$ is increasing in both the number of firms in close vicinity and in the distance from funding VCFs, so it captures the potential increase of VC funds realized by firms closely surrounded by a large number of firms funded by distant VCFs. As previously explained, distant VC transactions typically involve higher funding levels, so we expect the coefficient for this variable to be positive.

The second variable accounts for potential cost efficiencies realized by VCFs when they invest in proximate firms. Proximity helps VCFs with monitoring the funded DBFs and reduces information asymmetries (Lerner, 1995) and other transaction costs. VCFs may then invite local DBFs they invest in to locate close to each other and gain from these cost efficiencies. Hence DBFs located close to other DBFs funded by the same VCFs can accumulate more VC funds because the VCFs prefer to invest in proximate firms. To account for this effect, we include a variable (*LocalVC*) that measures the number of DBFs located less than 10 miles from the origin DBF who were funded by VCF(s) located in the same radius that also funded the origin DBF. A priori, the expected sign for this coefficient is positive.

Before we provide a detailed discussion of the data used to estimate the model, we present the explicit forms of the two empirical model specifications that we use to test the four main hypotheses. Model 1 is:

$$\ln(AMT)$$
$$= a + \beta_{Age}(Age) + \beta_{Age^2}(Age^2) + \beta_{Cross}(\ln(Cross)) + \beta_{VC\_Distance}(\ln(VC\_Distance))$$
$$+ \beta_{SBIR}(SBIR) + \beta_{Foreign}(Foreign) + \rho_1(\ln(AMT_{010})) + \rho_2(\ln(AMT_{1020}))$$
$$+ \rho_3(\ln(AMT_{2030})) + \beta_{Localv\,c}(Localvc) + \beta_{Tax}(Tax) + \beta_{University}(University)$$
$$+ \beta_{Business}(Business)$$
$$+ \beta_{Establis\ hments}(Establishments) \quad (3)$$

and Model 2 is:

$$\ln(AMT)$$
$$= a + \beta_{Age}(Age) + \beta_{Age^2}(Age^2) + \beta_{Cross}(\ln(Cross)) + \beta_{VC\_Distance}(\ln(VC\_Distance))$$
$$+ \beta_{SBIR}(SBIR) + \beta_{Foreign}(Foreign) + \beta_{NB\_010}(NB\_010) + \beta_{NB\_1020}(NB\_1020)$$
$$+ \beta_{NB\_2030}(NB\_2030) + \rho_1(\ln(AMT_{010})) + \rho_2(\ln(AMT_{1020})) + \rho_3(\ln(AMT_{2030}))$$
$$+ \beta_{VC_{010}}(VC_{010}) + \beta_{VC_{1020}}(VC_{1020}) + \beta_{VC_{2030}}(VC_{2030}) + \beta_{Localvc}(Localvc) + \beta_{Tax}(Tax)$$
$$+ \beta_{University}(University) + \beta_{Business}(Business)$$
$$+ \beta_{Establis\ hments}(Establishments) \quad (4)$$

Model 1 is used to test hypotheses H1 and H2 under the restriction that the effects for hypotheses H3 and H4 are zero. Then, we use Model 2 to test all four hypotheses (H1-H4).

4. Data Sources and Presentation

We collected the total VC funding received by all firms in the biotechnology industry from 1990 to 2007 through Thomson's Financial SDC Platinum Database (SDC). This information was used to construct the dependent variable (*AMT*) and the average VC funds received by neighboring DBFs that are used to test H1 and H2. To form the

distance-specific explanatory variables, we converted the addresses of each DBF and VCF in the database to geographic coordinates (obtained from http://www.batchgeocode.com/) and calculated the distance between each DBF and between each DBF and VCF. The SDC database also provides the founding date of each DBF (to calculate each DBF's age) and whether or not a DBF had received non-US funds (to form *Foreign*). The dummy variable indicating whether or not each DBF had received SBIR grants (*SBIR*) was constructed from information obtained from InKnowVation, Inc.

The dummy variable for state-specific R&D tax credits (*Tax*) was obtained from each state government's taxation website. The distance to each DBF's nearest university (*University*) was compiled from address information provided by the Association of University Technology Managers, and the addresses were converted to geographic coordinates using the tools at http://www.batchgeocode.com/ . The cost of doing business index (*Business*) was collected from the Milken Institute website. Finally, the total number of establishments at each DBF's ZIP code (*Establishments*) was collected from the U.S. Bureau of the Census.

The final version of the database was restricted to all VC funding transactions without missing information on these variables, which yielded a dataset with 3,055 funding transactions between 728 US-located VCFs and 816 US-located DBFs. The database was also restricted to include DBFs founded after 1990 in order to focus on those DBFs that must rely on VC funding to some degree. Also, the VC funding amounts were retained as nominal values in the data set. Although we may prefer to compare real monetary values over this lengthy sample period, much of the VC funding data are only

available as aggregate amounts received since the founding of the firm, and we were unable to adjust the VC accumulations for inflation[11].

The map presented in Figure 1 indicates the location of the firms in our sample. Many of the DBFs and VCFs reside in East Coast and West Coast cities, especially San Francisco, San Diego, Los Angeles, Boston, and New York. However, some interior cities like Denver and Chicago are also populated with multiple VCFs and DBFs. This spatial pattern in the data illustrates the previously mentioned evidence of spatial clustering in the biotechnology industry.

Figure 1. Biotechnology and Venture Capital Firms in the Dataset

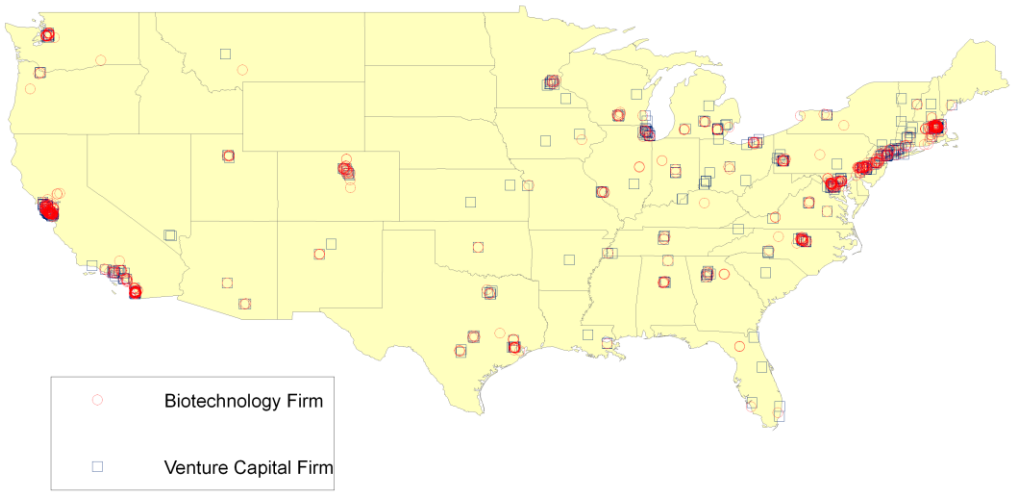


Table 1 presents descriptive statistics for the dependent and explanatory variables. Given the relatively large range of values for most of the variables, the sample is composed of firms with notable differences in total VC amount invested, age, and

[11] We did estimate the regression models for DBFs founded in different periods (1990-1995, 1996-2000, and 2001-2006), and these results are very similar to the results reported here.

distance from the VCFs. A significant portion of the DBFs had received SBIR grants (slightly more than 25 percent), and nearly 33 percent of the firms received foreign funds. Also, there are no considerable differences among the average VC amount accumulated by neighbor DBFs located at different distance ranges from the origin DBF. Due to these similarities, we do not expect other local or site-specific factors to affect the VC funding level. We also find that more VCFs and DBFs are located within 10 miles from the origin DBF, and the number of neighboring VCFs and DBFs decreases as the distance from the origin DBF increases. On average, each DBF has 2.91 DBF neighbors that are funded by the same local VCF if they are located in ZIP codes with more than 1,000 non-biotech establishments.

Also, the modal values for the number of DBFs in the 10 to 20 mile and the 20 to 30 mile rings from the origin DBF are zero, which shows that our dataset contains DBFs from more spatially disconnected regions. In contrast, some DBFs have neighbors in all of the distance ranges considered (up to 40 miles from the origin), and most of these cases are located in the more spatially connected areas such as San Diego or Boston. Given that all of these firms are included in the empirical analysis, we are able to account for the effects of proximity for firms with neighbors and without neighbors.

Table 1. Descriptive Statistics of the Variables Used in the Empirical Models. (816 Biotechnology Firms in the Sample)

Variables / Statistic	Mean	Median	Mode	Standard Deviation	Number of Biotechnology Firms with Neighbors at the Range [a]
AMT	35.43	19.40	0.08	43.60	
Age	8.50	8.00	7.00	4.35	
Cross	626.52	597.59	0.00	551.55	
VC_Distance	805.44	603.00	0.00	775.93	
SBIR					209
FOREIGN					268
NB_010	55.12	30.00	113.00	55.78	790
NB_1020	32.16	15.00	0.00	40.80	797
NB_2030	19.94	11.00	0.00	29.96	800
AMT_010	19.19	18.96	19.30	14.47	775
AMT_1020	19.26	18.33	18.45	15.95	697
AMT_2030	21.68	13.19	10.36	24.19	562
VC_010	26.45	11.00	18.00	32.77	752
VC_1020	17.60	7.00	1.00	29.20	687
VC_2030	12.04	2.00	0.00	23.61	553
Localvc	2.91	0.00	0.00	6.14	
Tax					783
University	13.75	6.59	0.65	26.78	
Business	112.47	123.13	123.13	14.24	
Establishments	1.29	1.12	2.83	0.80	

[a] In the case of FOREIGN, SBIR and Tax the figures reflect the number of Biotechnology Firms which had received non-US funds, SBIR grants and located at states with R&D tax credit respectively.

AMT	Total Amount Invested in Biotechnology Firm since Foundation (Million $)
Age	Age of Biotechnology Firm as of 2007 (Years)
Cross	Cross Regressive Variable (Miles)
VC_Distance	Weighted Average Distance of Biotechnology Firm from Funding Venture Capital Firms (Miles)
FOREIGN	Binary Variable Coded 1 if Biotechnology Firm had Received Funds from Non-US Venture Capital Firms
NB_010	Number of Biotechnology Firms 0 to 10 Miles from Origin Biotechnology Firm
NB_1020	Number of Biotechnology Firms 10.01 to 20 Miles from Origin Biotechnology Firm
NB_2030	Number of Biotechnology Firms 20.01 to 30 Miles from Origin Biotechnology Firm
SBIR	Binary Variable Coded 1 if Biotechnology Firm had Received SBIR Grants
AMT_010	Average VC Amount Invested in Biotechnology Firms Located 0 to 10 Miles from Origin Biotechnology Firm (Million $)
AMT_1020	Average VC Amount Invested in Biotechnology Firms Located 10.01 to 20 Miles from Origin Biotechnology Firm (Million $)
AMT_2030	Average VC Amount Invested in Biotechnology Firms Located 20.01 to 30 Miles from Origin Biotechnology Firm (Million $)
VC_010	Number of Venture Capital Firms 0 to 10 miles from Origin Biotechnology Firm
VC_1020	Number of Venture Capital Firms 10.01 to 20 miles from Origin Biotechnology Firm
VC_2030	Number of Venture Capital Firms 20.01 to 30 miles from Origin Biotechnology Firm
Localvc	Number of Biotechnology Firms 0 to 10 Miles from the Origin Firm who Were Funded by Venture Capital Firms that also Funded the Origin Firm and are Located within 0 to 10 miles Radius from the Origin Firm
Tax	Binary Variable Coded 1 if Biotechnology Firm is Located in State with an R&D Tax Credit
University	Distance of Biotechnology Firm from Closest University (miles)
Business	Index Increasing as the Cost of Doing Business in the Origin Firm's State Increases
Establishments	Average Total Number of non-Biotech Establishments in the Origin Firm's Zip Code from 1992 to 2007 (thousand)

The spatial nature of our dependent variable is shown in Figures 2a and 2b, which are maps of the DBFs in the dataset classified by the percentile of the total amount of VC funds invested. For example, the component of Figure 2b denoted as "Firms with VC Accumulation Between 60^{th} and 100^{th} Percentile" refers to those DBFs whose total VC amount invested exceeded the values accumulated by 60 percent of the other DBFs, and

the "Firms with VC Accumulation Between 10th and 30th Percentile" legend of Figure 2a refers to those DBFs whose total VC amount invested exceeded the amounts collected by at least 10 percent of the firms but no more than 30 percent of the other DBFs.

As seen in Figures 2a and 2b, the highest VC amounts invested occurred in clusters, with San Diego being the most homogeneous. In contrast, the East Coast clusters are more heterogeneous since both high and low VC funding amounts are observed. We also find strong visual evidence of spatial autocorrelation due to the large number of values with the same magnitude that are closely located. For example, the San Diego and Seattle clusters are almost entirely composed of DBFs with VC funds above the 60th percentile.

Figure 2a. Biotechnology Firms Classified According to Their VC Funds Accumulation

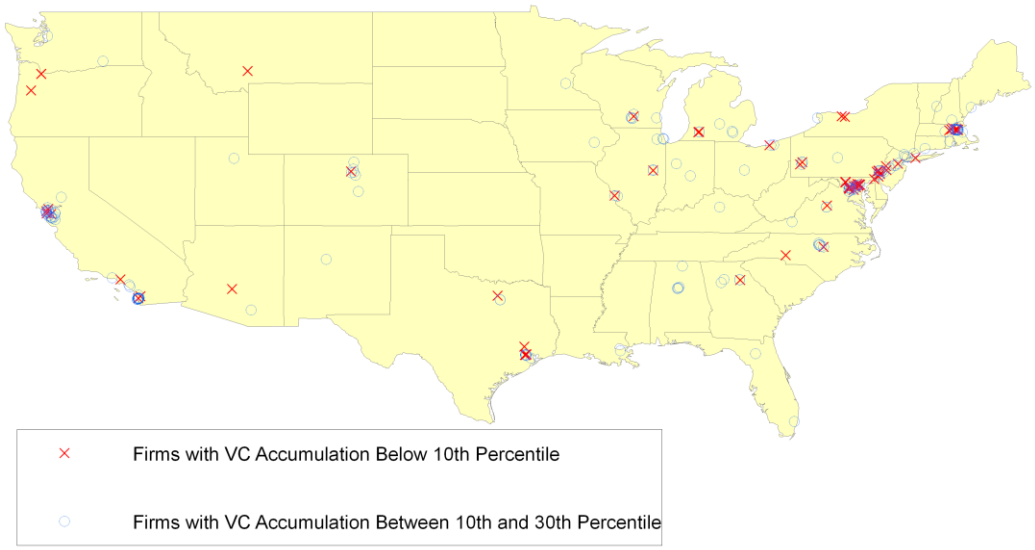
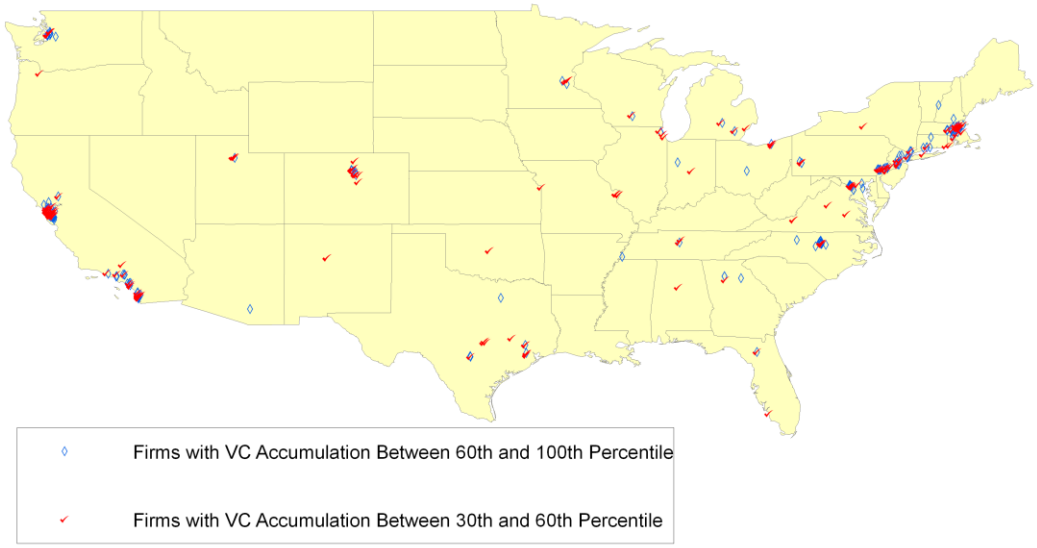


Figure 2b. Biotechnology Firms Classified According to Their VC Funds Accumulation



An alternative way to assess the spatial dependencies of the dependent variable is Moran's scatter plot (Figure 3), which is based on neighboring DBFs located less than 30 miles[12] from the origin DBF. The slope of the scatter plot reflects the global value of Moran's I statistic

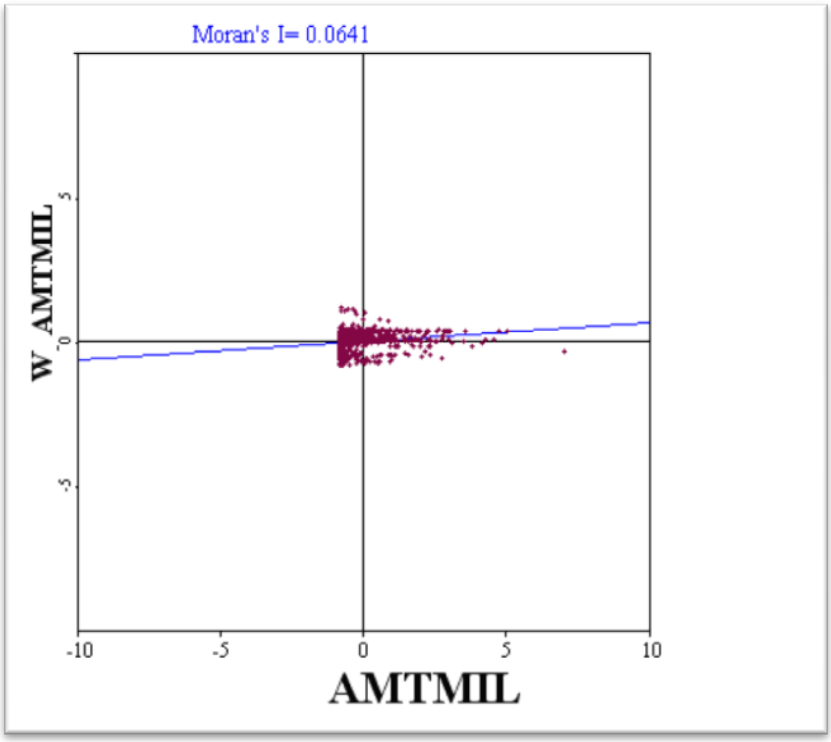
$$I = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) (x_j - \bar{x}) \Big/ \sum_{i=1}^{n} (x_i - \bar{x})^2 \qquad (4)$$

and the positive slope indicates that VC amounts invested in neighboring firms are positively related. Note that positive slope of Moran's I statistic can be generated by both high VC performance across neighbors and by poor funding performance across neighbors. That is, high VC funding amounts invested in neighbors are matched with high VC levels for the origin DBF (1st quadrant), and low VC funds invested in neighbors

[12] Figure 3 changes only slightly when the neighbor-defining threshold is different than 30 miles.

are matched with low VC funds for the origin DBF (3rd quadrant). Observations in the 2nd and 4th quadrant of Figure 3 represent cases for which the origin DBF's VC level does not follow the same pattern with the neighbors' VC levels: high VC amounts for the origin DBF are matched with low VC levels for the neighbors and the reverse. Most of these observations are either located in the heterogeneous East Coast clusters or they are fairly new DBFs with low VC accumulations surrounded by older and wealthier DBFs.

Figure 3. Moran's I of Total Amount Invested for Threshold Level 30.



5. Estimation Results

There are several plausible estimation methods for SAR models that are commonly used in practice, and these include maximum likelihood (ML), methods of moments, and instrumental variable estimators. Although software packages that can compute these

estimates are now available, we note that these tools are designed for standard SAR models with one set of spatial lags in Equation (1). In contrast, Models 1 and 2 have multiple sets or rings of spatial lags, and these cannot be readily handled by the existing spatial software tools. For this reason, we use the ordinary least squares (OLS) estimator for the parameters in Models 1 and 2.

Earlier authors in this literature noted that OLS was generally assumed to be biased and inconsistent due to the spatially lagged dependent variables on the righthand side of the models. However, Lee (2002) proved in his Theorem 1 that OLS is consistent if the number of neighbors can become infinitely large as the sample size increases, which is not always plausible in all spatial models but is true for our case (i.e., the number of neighboring firms within ten miles of an origin DBF is potentially unlimited). Also, Anselin (2006) argues that the OLS estimator is relatively robust to variations in the model assumptions and may have desirable asymptotic properties relative to the standard ML estimator of the SAR model, which is based on an explicit normality assumption. However, the Shapiro-Wilk statistics reported in Table 2 indicate that the normality assumption is not supported by our data. Finally, Franzese and Hays (2007) use Monte Carlo simulation experiments to show that the finite sample bias associated with the OLS estimator is reasonably small in moderately large samples (at least 50 observations) that have relatively small spatial correlation coefficients ($\rho < 0.3$). Our fitted SAR models meet both of these conditions, and we use the OLS estimator for these reasons. The ordinary least squares (OLS) estimates of Model 1 and Model 2 are reported in Table 2.

The Breusch-Pagan and White test results provide strong evidence of heteroskedasticity, so we adjusted the OLS standard errors with White's heteroskedastic-robust variance estimator. Also, Moran's I statistic is significantly positive, which provides evidence of spatial correlation in support of our SAR specification. As we explained at the end of section 2, the spatial lags of log-AMT and the neighbor count variables (*NB* and *VC*) may be highly correlated, and we report the collinearity diagnostics in Table 2. The explanatory variables in Model 1 have a condition number within the acceptable range (45.05), and the condition number for Model 2 is only a bit higher (64.71) as we add the *NB* and *VC* variables. Given the similarity of the estimates reported in Table 2, this degree of collinearity does not appear to have affected the estimation results. To verify this conclusion, we also estimated versions of the base regression model that only includes the *NB* or *VC* variables (without the SAR terms), and we found no substantial differences among those fitted models and the results reported in Table 2. For reasons of parsimony, we do not report these model estimates here. Given that the OLS estimation results are quite stable across these alternative model specifications, we focus on the estimates of Model 1 and Model 2 because these models are directly related to the main hypotheses, H1-H4. The detailed estimation results for Model 1 and Model 2 are described in the following subsections.

Table 2. OLS Estimates for Model 1 and Model 2. The Dependent Variable is the Natural Log of Venture Capital Funds Invested (Million $) in a Biotechnology Firm (DBF).

Variables / Specification	Model 1 Not Testing H3 and H4		Model 2 Testing All Hypotheses	
Intercept	-1.667	***	-1.835	***
	(0.491)		(0.588)	
Age (years)	0.221	***	0.208	***
	(0.048)		(0.048)	
Age^2 (years)	-0.010	***	-0.009	***
	(0.004)		(0.003)	
Log (CROSS) (miles)	0.028	*	0.031	*
	(0.017)		(0.018)	
Log (VC_DISTANCE) (miles)	0.258	***	0.255	***
	(0.037)		(0.038)	
SBIR (binary)	0.265	*	0.268	**
	(0.105)		(0.104)	
Foreign (binary)	1.183	***	1.205	***
	(0.095)		(0.096)	
Number of DBFs within 0 - 10 miles from origin DBF			-0.003	*
			(0.002)	
Number of DBFs within 10.01 - 20 miles from origin DBF			-0.001	
			(0.003)	
Number of DBFs within 20.01 - 30 miles from origin DBF			-0.004	
			(0.003)	
ρ_1	0.334	***	0.327	***
	(0.059)		(0.061)	
ρ_2	0.089	*	0.097	*
	(0.048)		(0.053)	
ρ_3	0.038		0.026	
	(0.036)		(0.040)	
Number of VCFs 0 - 10 miles from origin DBF			0.005	**
			(0.002)	
Number of VCFs 10.01 - 20 miles from origin DBF			0.004	
			(0.003)	
Number of VCFs 20.01 - 30 miles from origin DBF			0.003	
			(0.003)	
Number of DBFs funded by same local VCFs with origin DBF	0.036	***	0.037	***
	(0.006)		(0.007)	
R&D tax credit (binary)	(0.185)		-0.194	
	(0.218)		(0.221)	
Distance to closest university (miles)	(0.001)		-0.001	
	(0.003)		(0.003)	
Cost of doing business index	0.002		0.004	
	(0.004)		(0.006)	
Total establishments	0.022		0.042	
	(0.064)		(0.061)	
Number of Observations	815		811	
R-Square	0.514		0.517	
Adj R-Square	0.506		0.505	
Shapiro-Wilk Test	0.98	***	0.98	***
White's Test	306.30	***	390.10	***
Breusch-Pagan Test	107.30	***	112.10	***
Multicollinearity Condition Number	45.05		64.71	
Moran's I [a]	0.12	***	0.10	***

All Standard Errors in Parentheses are White's Standard Errors

[a] Calculation is based on a weight matrix with a 30 miles threshold level, and run with OLS.

*** .01 significance, ** .05 significance, * .10 significance

5.1. Model 1 (under the null restrictions for H3 and H4)

From the estimation results in the first column of Table 2, the ρ_1 coefficient for neighbors within 10 miles from the origin DBF is positive and significant at the 1% level, and the estimate implies that a one percent increase in the average VC amount raised by the DBFs within 10 miles of the origin DBF is expected to generate a 0.334[13] percent increase in the origin's DBF VC accumulation. Further, the estimated value of ρ_2 is positive but only significant at the 10% level, and a one percent increase in the VC amount raised by the DBFs 10.01 to 20 miles from the origin DBF is expected to generate a 0.089 percent increase in the origin DBF's VC accumulation. Beyond the 20 miles range, the estimated spatial elasticity is small in magnitude and statistically insignificant[14]. These results support H1 and H2 because the estimated spatial effects are positive and decay with distance from the origin DBF.

Regarding the firm-specific control variables, we find that a one percent increase in the average distance from the funding VCFs and the origin DBF (*VCDistance*) is expected to generate a 0.258 percent increase in the VC funds accumulated by the origin DBF. We also find that funding from distant VCFs is associated with higher VC amounts. Similarly, the age control variable was positive in the linear term and negative in the quadratic term, which suggests that a DBF's size (as represented by its age) has a concave relationship with total VC funding. In particular, the expected VC funds peak when the DBF reaches 10.7 years of age. The SBIR dummy coefficient is positive and

[13] At the mean of the dependent variable reported in Table 1 ($35.4 million), the expected VC funding for a DBF increases by roughly $118,000 as the average funding level of the neighboring DBFs increases by $354,000 (i.e., one percent of the mean).

[14] We also evaluated SAR models with spatial lags up to 60 miles from the origin DBF, and the estimated coefficients for these lags were consistently small and statistically insignificant.

significant at the 10% level, and the expected funding level is roughly 26.5 percent higher for DBFs that attain SBIR grants. The *Foreign* dummy coefficient is also positive and strongly significant, which supports our expectation that the presence of non-US funding sources is positively associated with total VC accumulation.

The coefficient for the cross-product variable (*Cross*) is positive but marginally significant and the estimated magnitude is quite small. If neighboring DBFs are financed from VCFs that are ten percent more distant, then the expected funding level for the origin DBF increases by approximately 0.28 percent. In contrast, the coefficient for the number of local DBFs receiving funds from the same local VCF (*LocalVC*) is positive and strongly significant, and the magnitude implies that having one more DBF within 10 miles of the origin DBF and that receives VC funds from the same local VCF is expected to increase the VC funding level for the origin DBF by roughly 3.6 percent. Finally, the estimated coefficients for the other control variables (*Tax*, *University*, *Business*, and *Establishments*) do not have significant explanatory power for VC fund accumulation in Model 1.

5.2. Model 2 (including all hypotheses)

From the second column in Table 2, we find that estimated SAR coefficients (ρ_1, ρ_2, and ρ_3) are very similar in magnitude and in statistical significance to the results for Model 1, and these results also support H1 and H2 because the spatial relationships are positive and decay with distance from the origin DBF. Note that two of the three estimates are a bit smaller (in absolute magnitude) for Model 2 than in Model 1, which is expected if some of the positive spatial correlation among the VC funding levels is captured by the *NB* and *VC* variables due to the agglomeration effects between DBFs and VCFs.

Regarding the evidence in support of H3 and H4, we find that the estimated impacts associated with having more neighboring DBFs or VCFs (while holding the level of neighboring VC funds constant) are somewhat divergent. In particular, the estimated coefficients for the three rings of neighboring DBFs (*NB*) are negative, small, and generally insignificant (one is significant at the 10% level). The estimated coefficients for the three rings of neighboring VCFs (*VC*) are all positive, but only the first ring (i.e., VCFs within 10 miles of the origin DBF) has a statistically significant coefficient at the 5% level. The estimate of this semi-elasticity coefficient implies that having one more VCF within 10 miles of the origin DBF increases the expected VC funding level by 0.5 percent ($177,000 at the mean of the dependent variable) while holding the neighboring VC funding levels constant. Thus, the estimation results for Model 2 do not support H3 but do provide support for H4, and the overall results imply that the key determinant of VC funding levels is the amount of funds attracted by neighbors rather than the number of neighboring firms. Finally, the estimated coefficients for the other firm-specific and region-specific control variables are very similar in magnitude and have the same degree of statistical significance observed in Model 1.

6. Concluding Comments

There has been an abundance of research regarding spatial externalities in the biotechnology industry. Several authors have shown that the biotechnology industry is a fertile ground for positive externalities stemming from spatial collocation of actors, but the connection between venture capital and spatial collocation among DBFs and between DBFs and VCFs has received less attention. The empirical results presented in this paper

indicate that there are spatial externalities associated with VC fund accumulations which decay with distance. The positive effects associated with neighboring VC funds stop at about 20 miles, and the positive effects from neighboring VC firms end at about 10 miles. After controlling for the VC funds raised by neighboring DBFs, we find that the number of neighboring DBFs does not have a separate positive effect on the origin firm's VC funding level. Also, VC funding is significantly determined by the source of the VC funds and by firm-related factors such as the DBF's age. However, the region-specific characteristics used in this study do not have a significant impact on VC funding levels.

Finally, we note that clusters among firms in a given industry have been defined in a number of ways in the existing literature, and the clustering factors used in other research include synergies among collocating agents, knowledge flows, and social ties. In nearly all cluster definitions, the starting point is the region in which the cluster is located. However, the particular definition of the spatial dimension varies considerably across studies, and Rocha's (2004) survey of the literature outlines the different approaches taken when defining cluster scope. He also notes that clusters have been defined as science parks, cities, regions, and even whole continents (Gertler, 1995; Massey, Quintas, & Wield, 1992; Saxenian, 1994). While the spatial scope for clusters is not the primary goal of the present work, our findings may help to inform further research on this issue.

7. References

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ESSAY 2: The Impact of Federal Funding on Local Biotechnology Firm Creation.

1. Introduction

Since its scientific onset after the breakthrough discovery of Boyer and Cohen in 1973 and the birth of the first biotechnology firm, Genentech, in 1977 the biotechnology industry has been a locus of academic research analyzing the location patterns of the industry. Put aside the financial growth of biotechnology firms and the benefits accruing to regions hosting them, the drastic increase in the number of biotechnology firms in the U.S. from 0 to over 700 in 1998 (Zucker, Darby, & Brewer, 1998) and to more than 1500 firms today (Ernst & Young, 2009) has prompted scholarly work explaining what makes certain regions attractive for newly established biotechnology firms.

It is well known that biotechnology firms (and other startups) cluster near research institutions (Audretsch, Lehmann, & Warning, 2005; Goetz & Morgan, 1995) as these new firms benefit from knowledge spillovers (Audretsch, et al., 2005; Goetz & Morgan, 1995), agglomeration economies (Stuart & Sorenson, 2003) presence of star scientists (Zucker, et al., 1998) and other channels contributive to firm births . While the causal connection between biotechnology firm births and proximity to research institutions is complex, research analyzing the effects of factors that might have originally lead to the spatial concentration and creation of means conducive to firm births is scarce. One such means is research funds availability. Until now the effect on local entrepreneurship of a marginal research dollar controlling for the existence of the institution-centered cluster at the first place has not been thoroughly analyzed.

Research funds availability is a necessary but not sufficient condition for knowledge creation that can lead to firm births. Funds recipients can be decisive in determining not only how knowledge is generated but also what the outcomes of knowledge are. Different types of institutions have distinct knowledge creation and dissemination mechanisms and as such they differ in their capacity in transforming knowledge to economic knowledge and more specifically to firm births. It is then straightforward to ask what types of institutions, to what degree and under which conditions are more able to transform research funds to new firms.

In this paper we analyze the abovementioned questions by examining the weight that federal research dollars carry on biotechnology firm births. We examine and contrast how existing private firms, universities and research institutes/hospitals have historically transformed research funds to biotechnology firms at the local level. We do so by estimating the association between the amount of federal grants awarded to MSAs' institutions and the subsequent firm birth rate at the MSAs in question. Previous research analyzing the capacity of a certain type of institution in transforming funds to firms while accounting for the corresponding capacity of other types of institutions is – at best – limited.

New biotechnology firms have traditionally originated from established private firms and from research taking place at research institutions. The gradual shift from the traditional Mertonian university (Merton, 1968) to the entrepreneurial university (Etzkowitz, 1998) which not only allows but also encourages commercialization of university research has given an additional boost for firms emanating from university research. While the importance of incumbent firms as means spawning new firms has not

lessen, biotechnology is also the most fruitful area for commercialization of university research particularly due to the immediate applications of basic biotechnology research (Argyres & Liebeskind, 1998; Orsengio, 1989; Shane, 2004).

The government's primary goal in providing funds towards biotechnology is knowledge creation but it is also important to analyze the most effective fund recipients in transforming funds to economic knowledge. Accessing the efficacy of federal monies in promoting biotechnology besides other federal efforts such as initiatives and fiscal policies is crucial because ineffective use of federal funds can discourage private support, waste taxpayers contributions and damage scientific progress. Further, understanding the causes of entrepreneurship is critical for local economic development and welfare since newly established firms have positive impacts in terms of knowledge creation, innovation enhancement and employment (Battelle, 2008; Kirchhoff, Newbert, Hasan, & Armington, 2007).

Our empirical analysis is based on fitted fixed effects count data models associating biotechnology firm births and federal funds from the National Institutes of Health (NIH). We employ a unique dataset that has not been used previously covering a 15 year time span which then allows to provide a comprehensive assessment of the effect of federal funds recipients on regional firm births. Given the fitted econometric models we test whether and to what degree federal monies awarded to universities, research institutes and private firms have translated to local firm births.

The paper is organized as follows: the next section reviews the relevant background literature and develops research hypotheses of the effects of federal monies on biotechnology firm births. Section 3 describes our econometric model and estimation

procedures, and section 4 reviews the data. Results are presented in section 5, followed by concluding comments and suggestions for further research.

2. Literature and Hypotheses

Our theoretical expectations stem from two strands of literature; the first strand is composed of studies analyzing firm births in certain regions typically without delineating the scientific origin of the newly established firms. In the literature in question the most common term describing newly formed firms is "startups". The second strand of literature consists of studies focusing on newly established firms spawning from other institutions such as universities and private firms. In this strand of literature the newly established firms are termed as "spinoffs" or "spinouts".[1]

2.1 Newly Established Firms and University Research

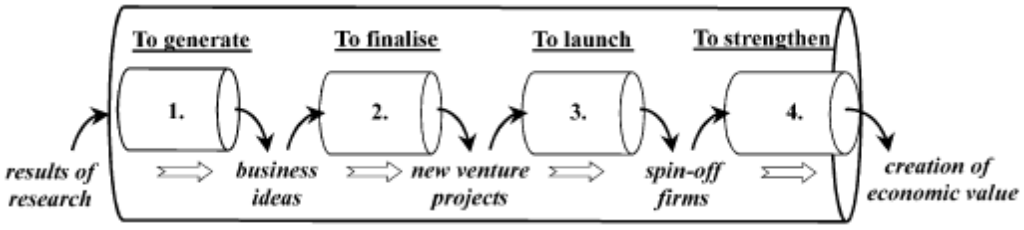
Biotechnology is the most prolific industry for university spinoffs (Shane, 2004) and since the bulk of universities' financial support comes from the federal government, federal funds become progressively more important especially as the entrepreneurial university gains ground. Not only universities compete simultaneously for funds from the same source but they are also in a race for more successful commercialization of their research in a field suited for such efforts.

Ndonzuau et al.'s (2002) model, reproduced as Figure 1 below, outlines the creation of spinoffs where financial resources are conceptually located at the beginning of the diagram where results of research are necessary in order to generate business ideas.

[1] We ignore here the distinction between spinoff and spinout – if it exists – (Pirnay, Surlemont, & Nlemvo, 2003).

Figure 1
The Global Process of Valorization by Spin-off

(Adopted from F.N. Ndonzuau et al.)



Previous research on university spinoffs has shown that, among others, access to public funding (Chachamidou & Logothetidis, 2008), research grants awarded to the university (Gideon D. Markman, 2004), access to more financial resources (Landry, Amara, & Rherrad, 2006), and increased R&D expenditures (Lockett & Wright, 2005; Powers & McDougall, 2005) are significant predictors of university spinoff activity. Chachamidou and Logothetidis (2008) studied nanotechnology spinoff creation at European universities and outlined the importance of public funds while Markman et al. (2004) found that the accumulation of research grants is conducive to firm births. [2] Landry et al. (2006) , Lockett and Wright (2005) and Powers and McDougall (2005) adopted a resource-based view and argued that institutions/researchers with more resources are more likely to spawn new firms. The empirical results from these studies showed that (a) Canadian researchers with more industry and state funds were more likely to start a firm (Landry, et al., 2006), (b) increased R&D expenditures were positively associated with the number of UK spinoffs (Lockett & Wright, 2005) and (c)

[2] Friedman and Silberman (2003) also measured the effects of federal funds on spinoff creation but the federal research variable is not directly entered in the spinoff explaining equation.

increased annual university-wide R&D expenditures were conducive to higher spinoff rates. All in all, researchers have found that improved access to financial resources is advancing university spinoff creation as fund availability boosts university R&D intensity.

Studies having specific location(s) as the unit of analysis have also found that the presence of a university is advantageous for firm startups since new firms have better access to knowledge spillovers. Audretsch et al. (2005), Kirchhoff et al. (2007) and Bade and Nerlinger (2000) found that firms tend to locate close to universities. In particular Audretsch et al. (2005) studied high-technology startups in Germany and found that depending on knowledge type firms locate close to universities; Kirchhoff et al. (2007) found that locations with high university R&D intensity were characterized by high startup rates while Bade and Nerlinger (2000) focused on new technology based firms in Germany and found that the firms in question locate close to universities performing R&D.[3] The effect of federal funding on firm births was measured directly by Zucker et al. (1998) who found that the number of faculty with federal grants in a region were positively associated to the region's firm founding rate, by Sambidi (2007) who used total state level NIH data for three years and found a positive association between biotechnology startups and increased university NIH support at the state level and by Chen and Marchioni (2008) who studied biotechnology firm births in 2006 and found a positive association between NIH grants awarded between 2003 and 2005 and firm births in 2006. (Note that unlike the present study, the studies using NIH measures focus on one type of institution and do not explicitly account for NIH funds towards the other two

[3] Another university startup study was conducted by Ferrand et al. (2009) who studied the Cincinnati biotechnology cluster and reported that biotechnology firms were founded in the city due to the ties the firm founders had with city universities.

types of institutions considered here. Further, the studies in question use data only for a limited number of years – or even for one year.) Overall the studies having specific locations as the unit of analysis corroborated the results of the university spinoff studies in that they also found that university R&D intensity and hence federal funds spur firm births.

Given these considerations it is possible that more federal funds towards a region's universities can boost local biotechnology firm births:

H 1: The number of local biotechnology firms is expected to increase as the amount of federal funds awarded to local universities increases.

2.2 Newly Established Firms and Incumbent Firms' Research

Klepper (2009) in his recent synthesis of the spinoffs phenomenon outlines several studies supporting the proposition that the primary means for cluster's maintenance is the most successful firm spinoffs[4] where former employees of established firms start new firms in proximity to their previous employer. The studies reviewed in Klepper (2009) span to industries such as footwear, apparel, automobiles and biotechnology.

Especially in high tech industries, such as biotechnology, where skilled human capital is among the most crucial factors of production spinoffs are a common way of market entry (Christensen, 1993; Garvin, 1983). Klepper and Sleeper (2005) and Franco and Filson (2006) studied the laser industry and found that the more successful firms had higher spinoff rates. Agarwal et al. (2004) analyzed the disk drive industry and they found that firms with strong technological or market pioneering know-how spur the most spinoffs while Gompers et al. (2005) showed that incumbent public firms are an

[4] There are contribution in the literature questioning the notion that more innovative/successful firms are the most prolific in spurring spinoffs (e.g. Hyytinen and Maliranta (2008)).

important source of venture capital – backed startups. In the context of biotechnology, the more successful firms are expected to attract more funds from the federal government; hence there is a straightforward connection between innovative/successful firms and accumulation of federal grants.

Successful existing firms performing research in high tech industries can be conducive to new firm formation in several ways. First, employees of innovative firms have more chances to observe new technologies, to broaden their knowledge and to follow the latest developments of their industry. These employees can either become valuable assets for new firm founders looking for human capital or they can start their own firms armed with knowledge, ideas and know – how gained during their previous employment[5]. Note for example the survey reported in Bhide (1994) where, seventy one percent of firm founders stated that their business originating idea came either through replication or modification of an idea encountered through previous employment. Further, empirical research has supported the notion of existing firms as labor pool creators attracting new firms close to them: Stuart and Sorenson (2003) studied the biotechnology industry and found that proximity to established biotechnology firms was advantageous to startups and Karlsson and Nyström (2006) found that accessibility to private firm R&D has a stronger impact on new firm formation than accessibility to university R&D.

Additional forces spurring firm births from established firms include imitation processes where successful firms serve as blueprints for potential entrepreneurs and push factors leading to employee or firm voluntarily spinoffs. Increases of federal grants can

[5] Previous employers can guard against the use of knowledge acquired internally (Kim & Marschke, 2005) but nevertheless the benefits towards new firm creation remain.

augment research intensity and/or research scope of established firms hence leaving promising projects unexplored. These projects can then be pursued either by employee startups or by spinoffs having the existing firm as the parent company. Voluntarily spinoffs are not uncommon in biotechnology; Connetics Corporation for example spun off Intermune Pharmaceuticals in 1999, Eli Lilly spun off Guidant in 1994 and GlaxoSmithKline spun off the chemistry department of its Milan research center into a separate company in 2001 (Ledbetter & Zipkin, 2002).

Given these considerations it is possible that more federal funds towards a region's private firms can boost local biotechnology firm births:

H 2: The number of local biotechnology firms is expected to increase as the amount of federal funds awarded to local existing biotechnology firms increases.

2.3 Newly Established Firms and Research Institutes' Research

Besides universities and private firms, research institutes and hospitals are also performing research in biotechnology but only a limited number of studies have focused on the contribution of institutes and hospitals to commercial activities such as firm births (Boardman, 2008; Davenport, Carr, & Bibby, 2002).

Except Boardman (2008) who found that university scientists collaborating with biotech centers center around knowledge transfer and not on commercial activities the rest of the studies incorporating research institutes/hospitals in their analysis support the notion that research in research institutes/hospitals can lead to firm births. Davenport et al. (2002) presented case studies of research center spinoffs, Sambidi (2007) found that proximity to hospitals and research centers fostered biotechnology startups while Bade and Derlinger (2000) and Ferrand et al. (2009) also report positive firm creation effects of

institutes and hospitals. Finally, Chen and Marchioni (2008) analyzed the birth of biotechnology firms in 2006 and found that biotechnology firms were located close to research institute and hospitals.

Given these considerations it is possible that more federal funds towards a region's private firms can boost local biotechnology firm births:

H 3: The number of local biotechnology firms is expected to increase as the amount of federal funds awarded to local research institutes and hospitals increases.

In the next sections, we empirically test the three stated hypotheses using NIH data for funding expenses towards universities, research institutes and hospitals over the 1992 to 2007 period. We first describe the econometric model we use to model the potential relationship between federal funding and biotechnology firm births, and we then proceed to present the data and the empirical results.

3. Methods and Procedures

We employ two way fixed effects models in which we associate the amount of federal grants awarded to different types of institutions located in all U.S. MSAs and the biotechnology firm birth rate in the MSAs in question. MSAs are used as the unit of analysis since they are small enough to incorporate regional characteristics and are also comparable across U.S. states[6]. The fixed effect model is formulated as follows [7]:

[6] MSAs reflect U.S. population centers' heterogeneity across states: while spatial units included in an MSA (cities, towns, suburbs, villages, neighborhoods, boroughs and the like) differ geographically and economically across U.S. regions, MSAs reflect special characteristics for each region and are hence comparable across U.S. states.

[7] The usual fixed effects estimators relying on differencing the data are potentially biased and inconsistent for panel data models including lag variables (Wooldridge, 2002). As such we use the dummy variable regression estimator which is equivalent to the fixed effects estimator (Wooldridge, 2002) but not subject to the potential biased and inconsistency in question since no data differencing is required.

$$y_{it} = \beta X_{it} + \sum_{i=1}^{N} a_i A_i + \sum_{t=1}^{T} \gamma_t \Gamma_t + \varepsilon_{it} \quad (1)$$

where y_{it} is a $NT \times 1$ vector indicating the number of biotechnology firm births at MSA i at year t. X_{it} is the $NT \times 7$ design matrix including six variables measuring the total amount of federal grants awarded to MSA i's universities, private firms and research institutes/hospitals at previous years in linear and quadratic form and one variable measuring each MSA's birth rate at $t - 1$. The βs are the estimated coefficients used to test our theoretical expectations for each of the variables in the design matrix X_{it}. The second term of (1) is the sum of $N - 1$ dummy variables A_i with $NT \times 1$ dimensions that equal 1 for MSA i and 0 otherwise. The $\alpha_i s$ are estimated coefficients measuring the effects of the MSA dummy variables. The third term of (1) is the sum of $T - 1$ dummy variables Γ_t with $NT \times 1$ dimensions that equal 1 for year t and 0 otherwise. The $\gamma_t s$ are estimated coefficients measuring the effects of the year dummy variables. Finally, ε_{it} is the $NT \times 1$ error term.

The dependent variable of (1) has a special feature in that it is a non-negative integer value counting the number of biotechnology firm births. Since linear regressions can result in inefficient, inconsistent and biased estimates when applied to models examining count outcomes (Long, 1997) we use a Poisson count data model to estimate the effects of federal grants on local firm birth rate. Note that since the Poisson model is often too restraining when the restriction of the mean of the dependent variable being equal to the variance is imposed, we relax that restriction in the present study[8].

[8] For comparison purposes we also estimated a count data Negative Binomial model which is often used to model cases where the dependent variable exhibits over dispersion (Wooldridge, 2002). As discussed later in the Results section the dependent variable of the present work is not over dispersed. Nevertheless, the results of the Negative Binomial model were in line with the results reported in Table 3. The main

The MSA and year dummy variables are used to capture time-constant unexplained variance correlated with the explanatory variables. The unexplained variance includes "generic" factors affecting firm location choice and are applicable to a range of industries among them biotechnology. The year dummies for example can capture the effects of favorable climate towards firm births emanating from "hot IPO markets" (Lowry & Schwert, 2002) while the MSA dummies can approximate the effect of taxes (Bartik, 1985, 1989; Gius & Frese, 2002; Rathelot & Sillard, 2008), economic initiatives (Woolley & Rottner, 2008), business climate including regulation, venture capital availability and cost advantages (Aguilar, 2009; Bartik & Gray, 2002; Goetz & Morgan, 1995; Stuart & Sorenson, 2003), amenities (Gottlieb, 1995) and a region's prestige (Frenkel, 2001) as relevant factors in location firm decisions. Despite potential deviations from year to year all the above mentioned variables are arguably time constant while they are also correlated with the independent variables of the empirical model; an MSA's business climate for example is expected to be related to the firms' quality in the MSA hence correlated with the amount of NIH money these firms are able to attract.

The control variable measuring the firm birth rate at each MSA at $t-1$ is included in the analysis in order to incorporate potential dynamic relationships present in the model. Regions conducive to new firm creation are expected to show a historical pattern of firm births (Crozet, Mayer, & Mucchielli, 2004), hence we expect a positive sign for the variable in question. Also note that the estimated coefficient of the variable

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difference was that the marginal effects of the Negative Binomial model were moderately larger (see Appendix Table A.2), hence the Negative Binomial model was over-predicting relative to the observed data. In order to account for potential censoring bias resulting from a large number of observations in our dependent variable taking the value of 0 we also estimated the two-stage Heckman model as outlined in Woodridge (2002). The results of the Heckman model are largely similar to the results reported in Table 3 (see Appendix Table A.1).

under consideration can be used to distinguish between the short and long run effects of federal funds on local firm birth rate (Wooldridge, 2009).

Stated hypotheses H 1 through H 3 are represented by corresponding variables included in X_{it} of (1) measuring the average total amount of federal grants awarded at MSA i's universities, private firms and institutes/hospital from $t-1$ to $t-5$[9] in linear and quadratic form. The amount that each MSA receives within a five year window from NIH is fairly stable since monies received are commonly continuations or extensions of grants awarded at previous years. Because of the similarity across lagged variables strong correlations exist among year lags, hence we employ an average value versus including separate year lags in the empirical model. We use a five year lag average since we see the period up to five years before firm births as the most relevant in explaining firm births at present time [10]. The quadratic form of the variables in question is included in the analysis in order to account for potential nonlinearities in the relationship between federal monies and firm births at the MSA level. Under H 1 through H 3 we expect a positive contribution of NIH funds, after accounting for potential nonlinearities, towards local firm births.

Before we proceed to a detailed presentation of the data used for the empirical model, we introduce the modification of the traditional fixed effect model we used for the empirical part of the present paper. The fixed effect model presented in equation (1) was originally tested with 424 MSA[11] dummy variables each reflecting the 424 U.S. MSAs.

[9] In order to include early years in the empirical analysis, we use a 5 year average for available observations. For year 1995 for example we use the average value of years 1992 to 1994 which is a 3 year average. Hence the analysis omits only year 1992.
[10] Longer and shorter lags were empirically tested (not reported here) verifying our *a priori* expectation of minimal changes between these lag structures and the 5 year lag window used in the analysis.
[11] There are 371 MSAs in the U.S. and 53 non-metropolitan areas which are also included in the analysis.

The inclusion of this large number of dummies substantially reduced the model's degrees of freedom, which could inflate the variance of the estimated parameters, thus creating potential inference issues[12]. As a remedy to the problem and without loosing much MSA-specific information since the impact on the model fit was only minimal, we constructed the final model including only those MSA dummies that were statistically strong at the original model. The exclusion of the statistically weak MSA dummies from the specification but not from the analysis, left us with 25 MSAs which entered the final specification with corresponding dummy variables having as an omitted category the non-significant MSAs of the original model. The set of the 25 statistically significant MSAs was composed of MSAs containing cities often referred to as the seedbeds of biotechnology such as Boston, Seattle, Houston and Rockville. Those MSAs are generally considered to provide an environment conducive to firm births providing capital and labor pool availability, potential for knowledge spillovers and the like. As such, we expect positive signs for the MSA dummies under consideration.

4. Data Sources and Presentation

The data used to test H1 through H3 were obtained from NIH. We collected historical data from 1992[13] to 2007 depicting the amount awarded by NIH to every principal investigator (PI) as well as each funded project's title and each PI's affiliation at the time the project was funded. In order to identify biotechnology grants, a keyword search was

[12] The inclusion of the full set of MSA dummies also created multicollinearity problems arising from correlations of the dummies in question and the rest of the elements in the design matrix of (1).
[13] The effect of NIH money on local firm birth could have been more instrumental in the early years since, potentially, the industry had not gained legitimacy during these years. Accordingly, firm births prior to 1992 would also be of interest to the present study. Unfortunately 1992 was the first year for which NIH data were available. Further, the boom of the industry occurred some years later than 1992, hence 1992 is arguably still among the early years.

performed for all project titles[14]. After we sorted out the biotechnology grants, we adjusted the nominal award money to 2007 values using the CPI and classified each project's PI affiliation to universities, private firms and research institutes/ hospitals after visiting each institution's website. The final step in order to construct the variables testing H 1 through H 3 was to add the inflation adjusted award monies for each MSA's different types of institutions[15]. Figure 2 presents the historical NIH funding towards biotechnology partitioned according to awarded institution type. Biotechnology funds increase through the 1990's, flatten out between 2003 and 2004 and decline starting in 2005. The proportion of funds towards different types of institutions remain stable over time mainly since typically each year's grants are continuations or extensions of previous years' grants. The bulk of funds is directed towards universities followed by funds to research institutes and hospitals while private firms receive the least amount of grants from NIH[16]. Interestingly, as seen in Table 1, the correlation coefficients between monies towards different types of institutions on a per MSA year base are relatively weak. Yearly NIH funds towards an MSA's private firm(s) have weak correlations with NIH funds towards the same MSA's universities (0.38) and research centers/hospitals (0.36) while the corresponding correlation coefficients between university and research centers funds

[14] The biotechnology keywords list was constructed after consulting with University of Missouri researchers working on biotechnology projects. The list included the following terms: Enzyme, peptide, antigen, mutation, clone, immunoassay, coli, hormone, neuron, PCR, cytokines, gene, collagen, bioreactor, elisa, nucleotide, plasmid, biomass, bacillus, bioassay, embryo and genetic.

[15] Starting in 2007 NIH has implemented a new system measuring the amount of funds towards biotechnology. Our measure of biotechnology funds, which is comparable to the updated NIH system, is conservative when compared to the NIH estimate; the 2007 real total biotechnology amount estimate of NIH is about 5 billion dollars while our estimate for the same year is about 3 billion dollars.

[16] NIH is currently required to set aside 2.5 percent of its extramural R&D budget exclusively for SBIR grants (Wessner (ed.), 2009) which mainly go towards private firms. The percentage required has slightly fluctuated over time but some of private firm NIH funds are SBIR grants. Also note that the majority of funds for private firms does not come from the federal government but from other sources like venture capital funds. Hence, the overall estimated transforming capacity of private firms will be underestimated here since we are not including in the analysis the total amount received by private firms (besides NIH funds).

is stronger (0.51). These correlations indicate that MSAs receive NIH funds typically either through universities, research institutes/hospitals or from private firms and less often through all types of institutions, which then suggests that firm birth effects of monies given towards different types of institutions are attainable to measure when having the MSA as the unit of analysis.

Figure 2. Historical NIH Financial Outlays Towards Biotechnology

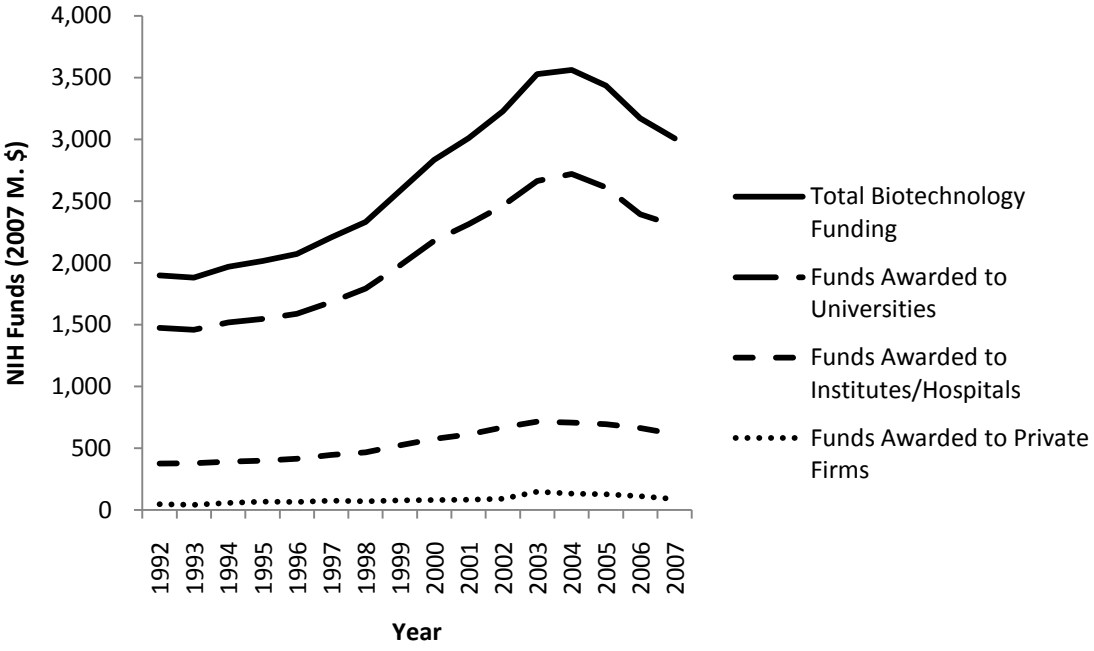


Table 1. Correlation Coefficients Between Award Amounts per MSA Year

	UN	IN	PR
UN	1.00	0.51	0.38
IN	0.51	1.00	0.36
PR	0.38	0.36	1.00

UN	Average NIH Funds from t-1 to t-5 towards universities per MSA Year
IN	Average NIH Funds from t-1 to t-5 towards institutes and hospitals per MSA Year
PR	Average NIH Funds from t-1 to t-5 towards private firms per MSA Year

Thomson's Financial SDC Platinum Database, Zoominfo web-based database and web-based Moneytree report were used to identify biotechnology firm births and use that information for the construction of the dependent variable. Each firm's location and founding date were available in all three data sources and whenever data were missing the website of each firm was visited in order to complete the information. Figure 3 presents the yearly firm births from the sample used in the empirical analysis while Figure 4 is a map associating firm births and NIH funding.

Figure 3. Biotechnology Firm Births from 1992 to 2007 (1015 Firm Births)

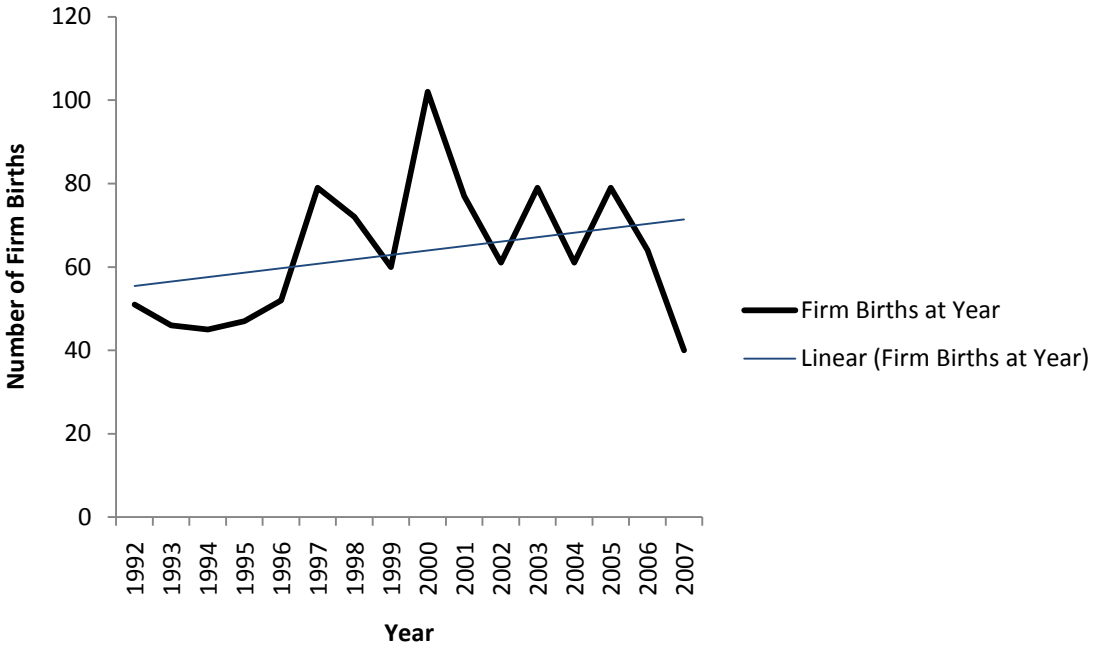
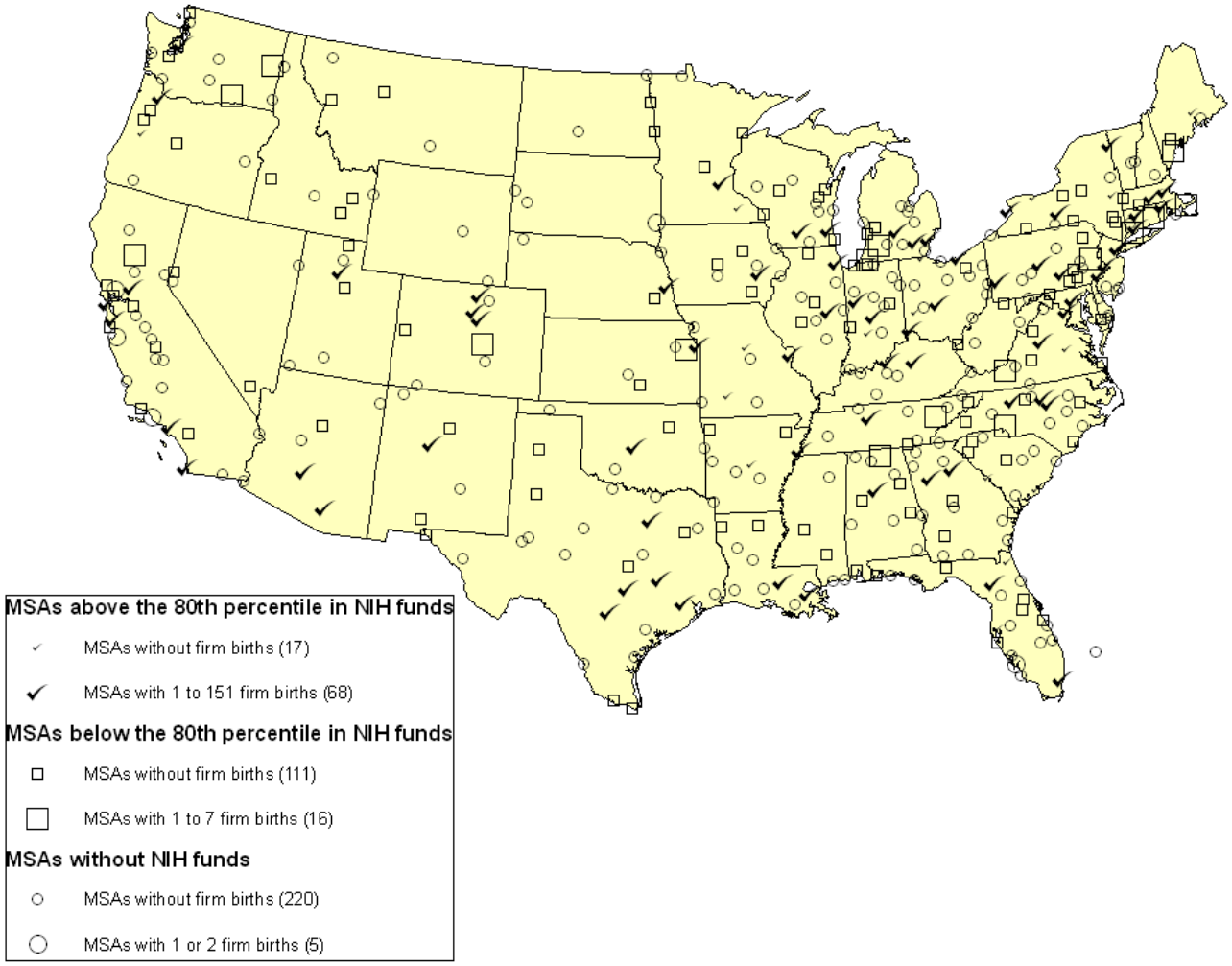


Figure 3 presents the yearly firm births of the sample showing that firm births are increasing over time even though year to year variations are substantial. Firm births peak at 2000 with 102 new biotechnology firms entering the market and decline drastically after 2005. While Figure 3 does not have a spatial component in it, Figure 4 accounts for the spatial component but it does not have a time dimension therefore only general patterns can be extracted from it. Figure 4 presents the cumulative amount of NIH grants collected from 1992 to 2007 for all the U.S. MSAs along with their cumulative firm births for the same time period. Each MSA is represented by its principal city as defined by the U.S. Census Bureau and for those MSAs with two principal cities, the more geographically central city in the MSA is depicted at the map. MSAs are classified according to their NIH funds accumulation with larger symbols indicating MSAs with more biotechnology firm births. The general trend from Figure 4 is that those MSAs

Figure 4. MSA NIH Funds (2007 $) and Firm Births from 1992 to 2007.



hosting institutions that have attracted large amounts from NIH have also experienced more firm births. Only twenty percent (17 of the 85) of the MSAs with the highest NIH funds accumulation did not have any firm births while the corresponding percentage for MSAs with some or nonexistent NIH funds accumulation was eighty seven (111 of the 127) and ninety eight (220 of the 225) percent respectively. Note for example Boston's MSA with 146 firm births and the largest funds accumulation of all MSAs with more than 4.2 billion NIH dollars from 1992 to 2007 or San Francisco's MSA which had 151 firm births while having the 6^{th} highest total NIH funds accumulation. While Figure 4 implies a positive association between firm births and total NIH funds, it does not draw a comprehensive picture of the relationship under consideration since it does not account for year and location effects while it also does not partition the total NIH value according to institutional recipients. The foregoing missing pieces of Figure 4 are accounted for in the empirical analysis and can explain why for example Los Angeles' MSA had only 23 firm births while having received the 3^{rd} total largest amount from NIH with more than 2.1 billion dollars from 1992 to 1997.

Table 2 presents descriptive statistics of the dependent variable and the yearly lags used to construct the variables associated with H1 through H3. The average number of firm births per MSA year is 0.15 with a standard deviation of 0.90 indicating the range of values of the dependent variable. Also, the dependent variable is left skewed since most of the MSA years did not have any firm births. Reflecting the gradual increase of federal funds (see Figure 2), the amounts awarded to institutions in $t-1$ exceed those awarded in previous years. Universities receive the majority of the funds with about 4.50 million dollars per MSA year, followed by institutes with close to 1.50 million dollars per

MSA year and private firms approaching 0.20 million dollars per MSA year. Note that regardless of type of institution, the standard deviation of NIH funds is greater than the variable's mean reflecting a dataset with a wide range of values. Similar to the vector of the dependent variable, the variables reflecting yearly lags are also left skewed with most observations having a value of 0.

Table 2. Descriptive Statistics of Variables Used in the Empirical Analysis

Statistic	Dependent Variable	Used to Construct Independent Variables														
	Firm Births	UN t-1	UN t-2	UN t-3	UN t-4	UN t-5	IN t-1	IN t-2	IN t-3	IN t-4	IN t-5	PR t-1	PR t-2	PR t-3	PR t-4	PR t-5
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	0.15	4.64	4.53	4.37	4.17	3.94	1.30	1.27	1.23	1.19	1.13	0.20	0.19	0.18	0.17	0.16
Mode	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard deviation (n)	0.90	17.38	17.11	16.60	15.89	15.09	10.64	10.47	10.24	9.92	9.48	1.42	1.41	1.39	1.33	1.11

Firm Births	Number of Biotechnology Firm Births for each MSA Year
UN t-1	Amount Awarded ($ 2007 M.) to MSA Universities in t-1
UN t-2	Amount Awarded ($ 2007 M.) to MSA Universities in t-2
UN t-3	Amount Awarded ($ 2007 M.) to MSA Universities in t-3
UN t-4	Amount Awarded ($ 2007 M.) to MSA Universities in t-4
UN t-5	Amount Awarded ($ 2007 M.) to MSA Universities in t-5
IN t-1	Amount Awarded ($ 2007 M.) to MSA Research Institutes and Hospitals in t-1
IN t-2	Amount Awarded ($ 2007 M.) to MSA Research Institutes and Hospitals in t-2
IN t-3	Amount Awarded ($ 2007 M.) to MSA Research Institutes and Hospitals in t-3
IN t-4	Amount Awarded ($ 2007 M.) to MSA Research Institutes and Hospitals in t-4
IN t-5	Amount Awarded ($ 2007 M.) to MSA Research Institutes and Hospitals in t-5
PR t-1	Amount Awarded ($ 2007 M.) to MSA Private Firms in t-1
PR t-2	Amount Awarded ($ 2007 M.) to MSA Private Firms in t-2
PR t-3	Amount Awarded ($ 2007 M.) to MSA Private Firms in t-3
PR t-4	Amount Awarded ($ 2007 M.) to MSA Private Firms in t-4
PR t-5	Amount Awarded ($ 2007 M.) to MSA Private Firms in t-5

5. Estimation Results

Each independent variable's marginal effect on the expected number of firm births is presented in Table 3. A variable's marginal effect in count data models depends on the value specified for the rest of the independent variables ($E_x\left[\frac{\partial E(y|x)}{\partial x_j}\right] = \beta_j E[\exp(x'\beta)]$) (Winkelmann, 2008). In order to have a representative measure of the effect of NIH money of local firm births, we estimate the marginal effects for the continuous variables as the average marginal effect of all observations in the dataset[17].

The log link function was specified for the Poisson model used to estimate the marginal effects reported on Table 3[18] [19]. The scale parameter of the Poisson model indicates under-dispersion of the dependent variable potentially emanating from the large number of observations with a 0 value. Due to the under-dispersion in question coupled with evidence of heteroskedasticity of unknown form the models were estimated using White's robust standard errors[20].

The joint significance tests suggest strong explanatory power for the MSA[21] and not for the year dummy variables[22] while the multicollinearity condition number (12.73)

[17] Footnote [a] in Table 3 provides details on the marginal effects of the dummy variables.
[18] The Poisson model with the variance equal to the mean is not reported in Table 3 since the variance assumption was not supported by the empirical data.
[19] We also considered a zero – inflated Poisson model which accounts for excess of dependent variable outcomes with 0 value. In unreported results, the findings of this model and the results presented in Table 3 are largely similar. For parsimony these results are not reported here.
[20] The Poisson model with White's standard errors was estimated with the Generalized Estimating Method (GEE) which is not a Maximum Likelihood (ML) method and so the only fit statistic provided by the software used was the Quasilikelihood under the Independence model Criterion (QIC), which is analogous to the AIC statistic of the ML estimators (Hardin & Hilbe, 2003).
[21] In unreported models we replaced the MSA fixed effects with variables capturing MSA effects such as an MSA's GDP, business climate index, venture capital availability etc. These models verify the importance of MSA effects but reduce the number of observations substantially since data for these variables were not available for all MSAs.

was at a level not raising concerns. Finally, note that the variables testing H 1 through H 3 are operationalized as the average amount of funds towards universities, private firms and research centers from $t-1$ to $t-5$.[23]

The empirical results provide support for H 1 indicating that universities have historically transformed federal money to local firm births. Our results suggest that besides their traditional contributions towards teaching research and service (Smilor, Dietrich, & Gibson, 1993) universities have also contributed to local firm births. The marginal effects reported in Table 3 indicate that universities located on a given MSA transformed 1 million of federal funds provided to them in previous years to 0.012 local firms per MSA year. The very small magnitude of the quadratic form of the variable in question suggests that the association between NIH monies towards universities and local firm births does not exhibit diminishing returns. The 0.012 figure may seem small at a first sight but note that it refers to an MSA-year. Hypothetically and as a crude measure, if an MSA's universities were receiving additional 80 million dollars from NIH per year at previous years a new biotechnology firm would have been created at the MSA at the present time. Regarding the short run and long run effects of federal money on local firm births, the short run effect is larger than the long-run effect[24]. The estimated short run multiplier of federal monies towards universities was 0.012 and the long run multiplier was 0.001.

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[22] Unreported models with only MSA fixed effects have largely similar results with those reported in Table 3.

[23] The use of average amount awarded was made in order to avoid multicollinearity problems occurring when separate amounts for each year were included in the analysis.

[24] The short run effect is the estimated marginal effect from the federal funds variables in linear and quadratic form
($university\ NIH\ marginal\ effect\ in\ linear\ form + 2 *$
$university\ NIH\ marginal\ effect\ in\ quadratic\ form$). The long run effect is estimated with $\beta\ /\ 1-\gamma$ where β is the short run effect and γ is the estimated coefficient of the lagged births variable (Wooldridge, 2009).

Table 3. Marginal Effects[a] of Poisson Model with Mean Equal Variance Assumption Relaxed Testing the Rate at Which Institutions Transform Federal Money to Firm Births at the MSA Level. The Dependent Variable is the Number of Firm Births at Time t in MSA i.

	Model	Poisson Model without Variance Restriction with Robust Standard Errors		
		β		S.E.
	Intercept	0.025	***	0.242
Variables Testing H 1 to H 3	Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5[b]	0.012	***	0.021
	Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5[b]	0.001		0.011
	Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5[b]	0.086	***	0.140
	(Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5)^2	-5.4E-05	**	1.0E-04
	(Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5)^2	7.2E-16		1.0E-04
	(Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5)^2	-3.7E-03	***	6.6E-03
Control Variable	Biotech Firm Births in MSA in t-1	0.012	**	0.030
Year Fixed Effects[c]	1994	-0.002		0.306
	1995	0.001		0.283
	1996	0.004		0.190
	1997	0.025	**	0.209
	1998	0.012		0.232
	1999	0.001		0.224
	2000	0.025	***	0.201
	2001	-0.003		0.243
	2002	-0.010		0.286
	2003	-0.006		0.298
	2004	-0.021	***	0.266
	2005	-0.015	*	0.318
	2006	-0.020	**	0.315
	2007	-0.026	***	0.311
MSA Fixed Effects	Albuquerque, NM Metropolitan Statistical Area	0.252	***	0.150
	Ann Arbor, MI Metropolitan Statistical Area	0.038		0.445
	Athens-Clarke County, GA Metropolitan Statistical Area	0.335	***	0.175
	Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area	0.085	***	0.238
	Austin-Round Rock, TX Metropolitan Statistical Area	0.502	***	0.156
	Baltimore-Towson, MD Metropolitan Statistical Area	0.063		0.512
	Birmingham-Hoover, AL Metropolitan Statistical Area	0.080	***	0.259
	Boston-Cambridge-Quincy, MA-NH Metropolitan Statistical Area	-0.017		1.072
	Boulder, CO Metropolitan Statistical Area	0.556	***	0.152
	Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	0.557	***	0.213
	Charlottesville, VA Metropolitan Statistical Area	0.095	***	0.243
	Chicago-Naperville-Joliet, IL-IN-WI Metropolitan Statistical Area	-0.009		0.427
	Denver-Aurora-Broomfield, CO Metropolitan Statistical Area	0.121	***	0.324
	Houston-Sugar Land-Baytown, TX Metropolitan Statistical Area	-0.007		0.431
	Kalamazoo-Portage, MI Metropolitan Statistical Area	0.672	***	0.204
	Madison, WI Metropolitan Statistical Area	0.091	***	0.295
	Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area	0.016		0.273
	New Haven-Milford, CT Metropolitan Statistical Area	0.032		0.411
	Pittsburgh, PA Metropolitan Statistical Area	0.032	**	0.267
	Raleigh-Cary, NC Metropolitan Statistical Area	0.819	***	0.179
	St. Louis, MO-IL Metropolitan Statistical Area	0.024		0.493
	Salt Lake City, UT Metropolitan Statistical Area	0.136	***	0.224
	Seattle-Tacoma-Bellevue, WA Metropolitan Statistical Area	0.045	*	0.445
	Trenton-Ewing, NJ Metropolitan Statistical Area	0.514	***	0.137
	Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area	0.101	**	0.513
Scale		0.515		
Fit Statistics	Wald Test of Joint Significance of Year Fixed Effects	0.94		
	Wald Test of Joint Significance of MSA Fixed Effects	98.00	***	
	GEE QICu	3979.70		
	Heteroskedasticity Test[d]	1010.36	***	
	Multicollinearity Condition Number	12.73		
	Number of Observations	6415		

[a] The marginal effects for continuous variables are the average marginal effect for all observations. For dichotomous variables: a. the continuous variables are evaluated at their mean, b.the year used is 1999 as the year with corresponding number of firm births closest to the mean and median number of firm births and c. the MSA fixed effect is held at 0. The change in the dependent variable resulting going from the 0 to the 1 category is approximated as the marginal effect for the dichotomous variables.

[b] In order to include years 1992 to 1996 in the analysis, the averages are calculated as the average of available observations. For year 1996 for example, the average used in the model is the average NIH$ from 1992 to 1995, which is a 4 and not 5 year average.

[c] The ommited years are 1992 and 1993

[d] An LM test employing results from an auxiliary regressions was used to test for heteroskedasticity.

*** .001 significance, ** .05 significance, * .10 significance

Note: The log link function was used for the Poisson model

Note: The standard errors correspond to the GEE estimates

H 2 was empirically supported suggesting that incumbent firms have also transformed federal monies to local firms. The marginal effects reported in Table 3 imply that incumbent firms located on a given MSA transformed 1 million of federal funds provided to them in previous years to 0.086 local firms per MSA year. Hypothetically and as a crude measure, if an MSA's incumbent private firms were receiving additional 12 million dollars from NIH per year at previous years a new biotechnology firm would have been created at the MSA at the present time. Note that the estimated capacity of private firms to transform federal funds to local firm births greatly outweighs the corresponding capacity for universities. Comparing the marginal effects reported on Table 3, private firms appear to be close to seven times more able to transform federal funds to local firm births than universities. This finding is rather expected: First, not all research that takes place in universities has commercial applications. Second, unlike private firms which focus mainly on R&D, universities employ some of their resources towards teaching and service (Smilor, et al., 1993). Similarly to the monies given towards universities, the estimated short run multiplier of NIH monies towards private firms was greater than the long run multiplier (0.079 and 0.067 respectively).

Contrary to H 1 and H 2 the empirical results do not provide support for H 3. Federal money towards research centers and hospitals appear to have an insignificant impact on local firm creation. A possible explanation for that finding stems from Boardman's (2008) rational who proposed, that biotechnology centers center around knowledge creation and not necessarily on commercial activities such as firm formation. Scientific discovery, based on curiosity without an end use in mind can be easier pursued

in nonprofit settings (Lawlor, 2002). Private firms are seeking profit while the entrepreneurial university is also expected to exhibit some degree of financial/commercial performance. On the other side, research centers and hospitals may face less incentives or obligations that could lead to firm births hence focusing more on science for the sake of science/curiosity.

Consistent with prior expectations, prior local firm births were conducive to firm births. One additional firm birth in a given MSA in $t-1$ was associated with 0.012 local firm births at time t. Dynamic relationships on firm births in biotechnology appear to significantly affect an MSA's firm birth rate. MSAs with previous firm births seem to create an environment contributive to current firm births.

The year fixed effects were mostly statistically weak indicating that year to year variations did not have much explanatory power in terms of local biotechnology firm births. On the other side, the MSA dummy variables were largely significant suggesting that MSA characteristics encompassing business climate, capital availability and the like were important in affecting firm births. Note though, that the empirical analysis presented in Tables 3 includes only the MSAs with statistically strong coefficients from the regression with dummies for all 424 U.S. MSAs. That said, certain MSAs such as those of Seattle or Boston still appear to have an advantage in boosting local firm births.

6. Concluding Comments

The phenomenal growth of the biotechnology industry in terms of revenues and number of firms entering the industry has prompted scholarly work to explain why certain regions are more able to boost firm births than others. Often starting from a resource-based view,

researchers have found that R&D intensity, attraction of prominent scientists, knowledge spillovers and other mechanisms affected by the resource base of a region are conducive to firm births. In this paper we reaffirm and deepen the abovementioned findings. Using a unique dataset we reaffirm because we also find that new firms start at regions with more financial resources; we deepen not only because we measure directly (vs. indirectly using measures such as R&D intensity) the effect of federal financial resources on firm births but also and perhaps more importantly because we separate firm birth effects of the financial resources acquired from different types of institutions after controlling for the firm birth effects of other types of institutions.

The empirical results suggest that while federal monies translate to new local firms there are significant differences in the transforming capacity across different types of institutions. The capacity of private firms to transform federal research funds to new local biotechnology firms outweighs the corresponding capacity of universities, while federal funds towards research institutes and hospitals do not appear to translate to local firm births. It is possible that private firms are more effective in transforming federal funds to local firm births because unlike universities they focus on research with commercial implications and do not have teaching and service duties. Regarding research institutes and hospitals their potentially limited focus on project with commercial value may hamper their ability to boost local firm births.

The present paper can initiate further research in a number of routes. The exact mechanisms allowing private firms to transform federal funds to new firms more effectively than other types of institutions is an area for further investigation. Also, given the purposes of our analysis all institutions in the university, private firm and research

institute/hospital categories are implicitly treated as the same with their main difference lying in their ability to attract NIH funds. Taking into account that differences in the spinoff rates across universities exist (Di Gregorio & Shane, 2003) it is possible for further research to examine whether even at the MSA level institutions of the same type differ in their capacity to transform NIH funds to new firms.

More generally, our analysis does not say much about the welfare implications of federal research funding. New firm formation is universally regarded as an economic good, but firms are heterogeneous, and it is possible that those firms emanating from federally funded research could differ from other firms. Follow-up research could look at the performance characteristics of these different types of firms, looking at measures of innovation, profitability, and the like.

7. References

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8. Appendix A

Appendix A exhibits the marginal effects of the two-stage Heckman model and the marginal effects of the count data Negative Binomial model.

Appendix Table A.1. Marginal Effects of Two Stage Heckman Model Testing the Rate at Which Institutions Transform Federal Money to Firm Births at the MSA Level. The Dependent Variable is the Number of Firm Births at Time t in MSA i.

	Model	2 stage Heckman Model with Robust Standard Errors		
		β		S.E.
	Intercept	3.934	*	0.983
Variables Testing H 1 to H 3	Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5[a]	0.003	***	0.019
	Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5[a]	0.000		0.012
	Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5[a]	0.090	***	0.115
	(Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5)^2	-4.2E-08	***	6.8E-05
	(Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5)^2	-1.9E-08		8.8E-05
	(Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5)^2	-2.8E-04	***	6.8E-03
Control Variable	Biotech Firm Births in MSA in t-1	0.082	***	0.073
Year Fixed Effects[b]	1994	0.004		0.041
	1995	0.000		0.025
	1996	0.022	*	0.069
	1997	0.036	***	0.075
	1998	0.000		0.042
	1999	0.001		0.027
	2000	0.062	***	0.093
	2001	0.013		0.059
	2002	0.045	*	0.090
	2003	0.012	*	0.057
	2004	0.051	***	0.088
	2005	0.001		0.032
	2006	0.174	*	0.178
	2007	0.304	***	0.222
MSA Fixed Effects	Albuquerque, NM Metropolitan Statistical Area	1.172	*	0.459
	Ann Arbor, MI Metropolitan Statistical Area	-0.030		0.259
	Athens-Clarke County, GA Metropolitan Statistical Area	1.159	*	0.487
	Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area	0.026		0.273
	Austin-Round Rock, TX Metropolitan Statistical Area	1.309	***	0.494
	Baltimore-Towson, MD Metropolitan Statistical Area	0.698		0.552
	Birmingham-Hoover, AL Metropolitan Statistical Area	0.023		0.232
	Boston-Cambridge-Quincy, MA-NH Metropolitan Statistical Area	13.361		1.908
	Boulder, CO Metropolitan Statistical Area	2.479	***	0.634
	Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	1.765	*	0.564
	Charlottesville, VA Metropolitan Statistical Area	0.178		0.267
	Chicago-Naperville-Joliet, IL-IN-WI Metropolitan Statistical Area	1.211	***	0.417
	Denver-Aurora-Broomfield, CO Metropolitan Statistical Area	0.153		0.333
	Houston-Sugar Land-Baytown, TX Metropolitan Statistical Area	0.721		0.545
	Kalamazoo-Portage, MI Metropolitan Statistical Area	2.920	***	0.653
	Madison, WI Metropolitan Statistical Area	0.018		0.398
	Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area	-0.031	***	0.184
	New Haven-Milford, CT Metropolitan Statistical Area	-0.016		0.241
	Pittsburgh, PA Metropolitan Statistical Area	-0.113		0.293
	Raleigh-Cary, NC Metropolitan Statistical Area	3.187	***	0.693
	St. Louis, MO-IL Metropolitan Statistical Area	0.109		0.276
	Salt Lake City, UT Metropolitan Statistical Area	0.105		0.343
	Seattle-Tacoma-Bellevue, WA Metropolitan Statistical Area	-0.012		0.555
	Trenton-Ewing, NJ Metropolitan Statistical Area	1.571	*	0.563
	Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area	6.356		1.217
Inverse Mill's Ratio		0.639	*	0.372
Fit Statistics	Wald Test of Joint Significance of Year Fixed Effects	18.57		
	Wald Test of Joint Significance of MSA Fixed Effects	8.95	***	
	Adjusted R^2	0.66		
	White's Test[d]	5661	***	
	Multicollinearity Condition Number	12.73		
	Number of Observations	6415		

[a] In order to include years 1992 to 1996 in the analysis, the averages are calculated as the average of available observations. For year 1996 for example, the average used in the model is the average NIH$ from 1992 to 1995, which is a 4 and not 5 year average.

[b] The ommited years are 1992 and 1993

*** .001 significance, ** .05 significance, * .10 significance

Appendix Table A.2. Marginal Effects[a] of Negative Binomial Model Testing the Rate at Which Institutions Transform Federal Money to Firm Births at the MSA Level. The Dependent Variable is the Number of Firm Births at Time t in MSA i.

	Model	Negative Binomial Model with Robust Standard Errors		
		β		S.E.
	Intercept	0.018	***	0.233
Variables Testing H 1 to H 3	Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5[b]	0.018	***	0.012
	Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5[b]	0.004		0.012
	Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5[b]	0.103	***	0.107
	(Average Amount Awarded ($2007 M.) to MSA Universities from t-1 to t-5)^2	-7.2E-05	***	1.0E-04
	(Average Amount Awarded ($2007 M.) to MSA Inst./Hospitals from t-1 to t-5)^2	-2.4E-05	*	1.0E-04
	(Average Amount Awarded ($2007 M.) to MSA Private Firms from t-1 to t-5)^2	-4.6E-03	***	5.4E-03
Control Variable	Biotech Firm Births in MSA in t-1	0.021	***	0.031
Year Fixed Effects[c]	1994	0.007		0.284
	1995	0.004		0.251
	1996	0.006		0.233
	1997	0.013	**	0.226
	1998	0.004		0.276
	1999	0.000		0.263
	2000	0.012	**	0.230
	2001	0.001		0.258
	2002	-0.006		0.280
	2003	-0.003		0.232
	2004	-0.010	**	0.297
	2005	-0.004		0.329
	2006	-0.010	**	0.345
	2007	-0.013	***	0.331
MSA Fixed Effects	Albuquerque, NM Metropolitan Statistical Area	0.175	***	0.125
	Ann Arbor, MI Metropolitan Statistical Area	0.016	*	0.334
	Athens-Clarke County, GA Metropolitan Statistical Area	0.221	***	0.133
	Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area	0.049	***	0.185
	Austin-Round Rock, TX Metropolitan Statistical Area	0.358	***	0.127
	Baltimore-Towson, MD Metropolitan Statistical Area	0.032		0.424
	Birmingham-Hoover, AL Metropolitan Statistical Area	0.046	***	0.193
	Boston-Cambridge-Quincy, MA-NH Metropolitan Statistical Area	-0.014		0.925
	Boulder, CO Metropolitan Statistical Area	0.378	***	0.127
	Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	0.388	***	0.148
	Charlottesville, VA Metropolitan Statistical Area	0.055	***	0.187
	Chicago-Naperville-Joliet, IL-IN-WI Metropolitan Statistical Area	-0.008		0.341
	Denver-Aurora-Broomfield, CO Metropolitan Statistical Area	0.059	***	0.226
	Houston-Sugar Land-Baytown, TX Metropolitan Statistical Area	-0.007		0.401
	Kalamazoo-Portage, MI Metropolitan Statistical Area	0.498	***	0.144
	Madison, WI Metropolitan Statistical Area	0.051	***	0.230
	Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area	0.010	**	0.212
	New Haven-Milford, CT Metropolitan Statistical Area	0.013	*	0.317
	Pittsburgh, PA Metropolitan Statistical Area	0.019	***	0.222
	Raleigh-Cary, NC Metropolitan Statistical Area	0.549	***	0.137
	St. Louis, MO-IL Metropolitan Statistical Area	0.010		0.353
	Salt Lake City, UT Metropolitan Statistical Area	0.083	***	0.181
	Seattle-Tacoma-Bellevue, WA Metropolitan Statistical Area	0.021	**	0.317
	Trenton-Ewing, NJ Metropolitan Statistical Area	0.324	***	0.124
	Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area	0.085	***	0.391
Dispersion		0.628		
Fit Statistics	Wald Test of Joint Significance of Year Fixed Effects	0.27		
	Wald Test of Joint Significance of MSA Fixed Effects	64.30	***	
	GEE QICu	1271.34		
	Heteroskedasticity Test[d]	49		
	Multicollinearity Condition Number	12.73		
	Number of Observations	6415		

[a] The marginal effects for continuous variables are the average marginal effect for all observations. For dichotomous variables: a. the continuous variables are evaluated at their mean, b.the year used is 1999 as the year with corresponding number of firm births closest to the mean and median number of firm births and c. the MSA fixed effect is held at 0. The change in the dependent variable resulting going from the 0 to the 1 category is approximated as the marginal effect for the dichotomous variables.

[b] In order to include years 1992 to 1996 in the analysis, the averages are calculated as the average of available observations. For year 1996 for example, the average used in the model is the average NIH$ from 1992 to 1995, which is a 4 and not 5 year average.

[c] The ommited years are 1992 and 1993

[d] An LM test employing results from an auxiliary regressions was used to test for heteroskedasticity.

*** .001 significance, ** .05 significance, * .10 significance

Note: The log link function was used for the Negative Binomial Model

Note: The standard errors correspond to the GEE estimates

ESSAY 3: Academic Entrepreneur's Firm Location Choice; Evidence from the US Biotechnology Industry.

1. Introduction

Faced with an increasingly competitive economic environment that shifts towards knowledge-intensive production, universities in the U.S. have expanded their traditional "Mertonian" (Merton, 1968) role of teaching, research and service (Smilor, Dietrich, & Gibson, 1993) to include the entrepreneurial role (Etzkowitz, 1998) which, among other functions, contributes to universities becoming important growth engines for local economies. U.S. universities today enhance aggregate regional economic activity (Goldstein, 2009) through different channels including job creation, productivity gains and increases in innovative activity. Local firm creation, as the most entrepreneurial form of technology transfer (Gartner, 1988), is one of the means for the entrepreneurial university to enhance regional development as firms are generally considered to expand local economic activity (Brett, Gibson, & Smilor, 1991). Accordingly, universities have invested in mechanisms such as research parks, incubators and technology transfer offices in order to boost local firm births (Djokovic & Souitaris, 2008).

In many cases academic entrepreneurs lead the effort in developing new firms but in order for such effort to contribute to the entrepreneurial role of the university firm births need to be local. Academic entrepreneurs are individuals with high human capital and starting their firm close to their affiliated institution is only one of their firm location options since knowledge is transferable and their entrepreneurial intentions can be realized in regions different than their institution's location.

It follows that an understanding of the factors determining when academic entrepreneurs start their firms locally is crucial for local economic development and for assisting universities in achieving their goal as local growth engines. In this paper we analyze factors affecting academic entrepreneurs to start their firm locally.

Although researchers have studied institutional, personal and environmental attributes affecting academic entrepreneurs' decision to start a firm (Landry, Amara, & Rherrad, 2006; Renault, 2006; Stuart & Ding, 2006) relatively little is known about academic entrepreneurs' firm location choice. In one of the few studies on the matter Audretsch and Stephan (Audretsch & Stephan, 1996) indicate that some academic entrepreneurs start their firms locally while others prefer distant locations. In the sample used for their study, which covered the period between 1990 and 1992, 16 of the 38 university-based firm founders started their biotechnology firm(s) outside their location.

Why some academic entrepreneurs choose to start their firm in distance to their institution while others prefer to stay local is not very clear. On the one hand, academic entrepreneurs face forces to start their firm locally: they need to fulfill their academic duties, they have a better knowledge of the local business environment, they can have better access to university know-how (Markman, Gianiodis, Phan, & Balkin, 2004) and the like. On the other hand, they could be motivated to start their firm outside their location; they often belong in epistemic communities and have an extended professional nexus enabling them to identify financial opportunities and research potential outside of their location. Further, they are typically experts in their field so they could be invited (and accordingly rewarded) to start a firm outside their location by venture capitalists or other scientists. Taken together, the abovementioned forces imply that academic

entrepreneur's firm location choice is a complex decision since it depends on a number of often conflicting factors.

In order to empirically analyze the factors behind academic entrepreneur's firm location choice we employ a unique sample of 266 U.S.-based academic entrepreneurs who founded 187 biotechnology firms between 1983 and 2008. Biotechnology is a fruitful area for commercialization of university research particularly due to the immediate applications of basic biotechnology research (Shane, 2004), which then makes the field we study prolific for our research. Also, by focusing our attention to a specific group of people who most likely face similar opportunities and opportunity costs we attempt to reduce the unobserved heterogeneity of the sample (Andersson & Hellerstedt, 2009) which accordingly implies that our results could be more easily generalized to larger populations.

The paper is organized as follows: in the next section, we present the theoretical framework and develop research hypotheses of the factors affecting firm location choice for academic entrepreneurs. In section 3 we specify the econometric model used to test our research hypotheses and in section 4 we describe our dataset. We then discuss the estimation results in section 5 and in section 6 we offer concluding comments.

2. Theoretical Framework

Firm location choice is a decision that can crucially determine a firm's long term success; hence entrepreneurs are expected to locate at regions they see as contributive to firm's performance. In the case of knowledge based industries such as biotechnology a firm's location should contribute to a firm's performance by offering opportunities for

knowledge growth, providing the firm with scientific labor supply and increasing the firm's chances for funding. Besides the location characteristics important for a firm's success, academic entrepreneurs face another unique consideration when choosing their firm's location: they are already employed at academic institutions where they have academic duties to perform. Academic entrepreneurs are in the core of the entrepreneurial university but besides their entrepreneurial functions they often also contribute to research, teaching and extension services. Firm location choice should accordingly accommodate their academic duties.

Considering firm's success potential and academic duties we assume that academic entrepreneurs maximize utility u when making their firm location choice. Further, we assume that utility is derived from the location characteristics affecting success potential for the newly founded firm (Carlton, 1983) and from the entrepreneur's characteristics determining the amount of time necessary for her physical presence in the chosen location. We assume that the entrepreneur faces three location choices we are considering here: (1) locating her firm on or within walking distance to her academic institution's campus, (2) locating her firm outside campus but within or around her institution's city and (3) locating her firm outside her institution's city at a distant location. We assume that the farther the firm from the entrepreneur's academic institution, the more effort the entrepreneur needs to expend to fulfill her academic duties. As such, the three location choices are ordered according to the distance from the entrepreneur's academic institution and one can conceptualize the distance as an increase in the disutility. Further, the difference among the three ordered location options is not necessarily consistent across choices, hence an ordered multinomial probabilistic model

is appropriate for modeling purposes[1]. While utility u is not directly observable, we follow Bartik (1985) in modeling location choice by considering a latent variable u^* which determines the observed location choice and can be linearly approximated with a set of K explanatory variables capturing location and the academic entrepreneur's characteristics:

$$u^* = \sum_{k=1}^{K} \beta_k x_k + \varepsilon_i \, , \varepsilon_i \backsim N(0,1) \; (1)$$

The observed category of u is based on the latent variable u^* and takes three values

$$u = 1 \; (on \; campus \; location) \quad if \quad u^* \leq \mu_1 \; (2)$$

$$u = 2 \; (within \; city \; location) \quad if \quad \mu_1 \leq u^* < \mu_2 \; (3)$$

$$u = 3 \; (outside \; city \; location) \quad if \quad u^* \geq \mu_3 (4)$$

where the μ_s are unknown threshold parameters separating the utility levels for the three adjacent location choices. Intuitively the μ_s represent the level of utility which the entrepreneur needs to reach or surpass in order to choose one of her available location choices. Setting the normalization restriction as $\mu_3 = 0$, the probability that u falls in a particular choice can then be estimated as:

[1] It is possible that in certain cases the location choices considered here do not have an ordered meaning (for example for scientists that do not live in their institution's city). However, we believe that these cases represent the exception rather the rule. In order to test the robustness of our results on the assumption that the location choices are ordered we run generalized logit model, whose results are not presented here, and found only minimal changes across these results and the results presented in Table 3.

$$Prob(u = 1) = Prob\ (\ u^* \leq \mu_1) = Prob\left(\sum_{k=1}^{K} \beta_k x_k + \varepsilon_i \leq \mu_1\right)$$

$$= Prob\left(\varepsilon_i \leq \mu_1 - \sum_{k=1}^{K} \beta_k x_k\right) = F\left(\mu_1 - \sum_{k=1}^{K} \beta_k x_k\right) \quad (5)$$

$$Prob(u = 2) = Prob\ (\mu_1 \leq u^* < \mu_2) = Prob\left(\mu_1 \leq \sum_{k=1}^{K} \beta_k x_k + \varepsilon_i < \mu_2\right)$$

$$= Prob\left(\varepsilon_i < \mu_2 - \sum_{k=1}^{K} \beta_k x_k\right) - Prob\left(\varepsilon_i \leq \mu_1 - \sum_{k=1}^{K} \beta_k x_k\right)$$

$$= F\left(\mu_2 - \sum_{k=1}^{K} \beta_k x_k\right) - F\left(\mu_1 - \sum_{k=1}^{K} \beta_k x_k\right) \quad (6)$$

$$Prob(u = 3) = Prob\ (u^* \geq \mu_3) = Prob\left(\sum_{k=1}^{K} \beta_k x_k + \varepsilon_i \geq \mu_3\right)$$

$$= Prob\left(\varepsilon_i \geq \mu_3 - \sum_{k=1}^{K} \beta_k x_k\right) = F\left(\sum_{k=1}^{K} \beta_k x_k - \mu_3\right) \quad (7)$$

where F is a general cumulative distribution. In the case of the probit model F becomes the normal cumulative distribution $\Phi(.)$ and in the case of the logit model it becomes the logistic cumulative function L(.).

In line with our foregoing discussion on the factors affecting entrepreneur's utility u we include in vector K of (1) variables capturing location and entrepreneur's characteristics expected to affect success potential and accommodate the academic entrepreneur's need for physical presence at the location respectively. We look for guidance on what specific factors might be included in the vector K in the literature. In

the next section we present and discuss the expected effects of the elements of the vector K.

2.1 Location Characteristics and Firm Location Choice

Using Barney's (Barney, 1991) Resource Based View (RBV) we can develop concrete arguments on the factors that may enter an entrepreneur's choice of location since one of the main tenets of RBV is seeking necessary resources for a firm's long term success. Accordingly, many of the arguments that follow stem from RBV.

Biotechnology is a knowledge intensive industry and potential firm founders are expected to seek locations that can boost a firm's knowledge scale and focus. An asset related to a firm's knowledge is human capital. Dedicated Biotechnology Firms (DBFs) increase their chances of success if they have access to skilled and specialized scientists and lab technicians (Powers & McDougall, 2005). Many of these scientists are typically holders of a PhD degree in biosciences. Starting a firm close to a large pool of such scientists is important not only because recruiting the most qualified scientists becomes easier but also because academic entrepreneurs can be in an advantageous position in case of short employee turnover. That is, if some of the employed scientists leave the firm the academic entrepreneur can replace them easier if located close to a large pool of potential employees. In this context we hypothesize:

H 1: The probability that academic entrepreneurs start their biotechnology firms in their institution's location increases with the number of PhD holders in the biosciences in the local labor market.

A second source of knowledge enhancement for DBFs is knowledge spillovers[2]. Knowledge spillovers are present in biotechnology (Audretsch, Lehmann, & Warning, 2005; Moodysson & Jonsson, 2007) especially due to the tacit character of biotechnology knowledge. DBFs can realize knowledge spillovers through collocation with other DBFs since spatial proximity facilitates knowledge diffusion through knowledge dissemination (Sorenson & Stuart, 2001), relationship formation (Liebeskind, Oliver, Zucker, & Brewer, 1996), direct observation, participation or shared experience. Firms founded by academic entrepreneurs can potentially benefit more than other firms from knowledge spillovers. It is possible that academic entrepreneurs transfer an academic atmosphere in their firm(s) so that knowledge sharing and exchange of ideas is prominent not only internally but also from external sources such as proximate DBFs. Accordingly, we hypothesize:

H 2: The probability that academic entrepreneurs start their biotechnology firms in their institution's location increases with the number of existing biotechnology firms in proximity to the institution.

A third source of knowledge enhancement for DBFs founded by academic entrepreneurs is their affiliated institution engagement in biotechnology research. Biotechnology R&D intensive academic institutions are conducive to DBF births (Zucker, Darby, & Brewer, 1998). When a large number of researchers/projects are devoted to biotechnology R&D, research scale increases expanding the knowledge that can flow to local firms (Acs & Armington, 2006) and creating epistemic communities

[2] We subscribe to Griliches (1992) definition of knowledge spillovers: Spillovers occur whenever a firm shares knowledge with other bodies (firms, universities and government institutions) performing research and development, without having to pay for such knowledge in market transaction.

embodied with knowledge that can be valuable for a DBF (Varga, 1998). At the same time, when academic institutions focus most of their research on biotechnology, knowledge focus can be gained which in turn can also help local DBFs by creating specialized knowledge. Accordingly, we hypothesize:

H 3: The probability that academic entrepreneurs start their biotechnology firms in their institution's location increases with the institution's biotechnology research focus and scale.

Beyond research scale and focus, an entrepreneur's academic institution can influence firm location with the rate it produces startups. In the process of transitioning from the Mertonian to the entrepreneurial university U.S. universities have drastically increased their number of startups especially after pro-commercialization federal legislation such as the Bayh-Dole and Stevenson-Wydler Acts in 1980 (Shane, 2004) as well as the Supreme court decision in the Diamond vs. Chakrabarty case[3]. Universities active in startup formation provide incentives and technical assistance to academic entrepreneurs, who typically have limited prior business experience, to start their firms locally. A large number of startups by any particular university would typically indicate that the university has the expertise, experience and culture to facilitate firm formation. Accordingly, we hypothesize:

H 4: The probability that academic entrepreneurs start their biotechnology firms in their institution's location increases with the institution's startup rate.

[3] Lehrer and Asakawa (2004) argue that federal legislation had only a small effect on universities pro-commercialization efforts. They posit that commercialization efforts in the U.S. were mostly an unplanned "bottom-up" phenomenon.

Besides being a knowledge intensive industry, biotechnology is a capital intensive industry and so academic entrepreneurs are expected to start their firms close to sources providing necessary capital. Shortage of capital pools in close proximity can be a major obstacle for academic entrepreneurs since they typically do not have an extended nexus of relationships in the business world, which then limits their options for alternative capital sources. Even in the presence of an adequate business network, the time devoted towards academic duties can potentially increase the academic entrepreneurs' capital search opportunity costs. One of the main sources of capital for DBFs is venture capital firms. Venture capital firms operate mostly locally (Sahlman, 1990) and provide risk capital and operating assistance to new firms (Florida & Kenney, 1988). By locating close to venture capital firms, DBFs can acquire resources easier, can have access to a larger network and can increase the amount of venture capital funds they receive (see Essay 1). Accordingly, we hypothesize:

H 5: The probability that academic entrepreneurs start their biotechnology firms in their institution's location increases with venture capital availability at the institution's region.

2.2 Academic Entrepreneur's Characteristics and Firm Location Choice

We generally expect that academic entrepreneurs (a) have the initial human capital and incentives required to start a DBF; (b) desire to maintain their academic role while being involved with the firm they start; and (c) become more valuable assets to the entrepreneurial university after their business founding experience. The ease that academic entrepreneurs employ their human capital in order to succeed in their firm and maintain their academic role while serving the entrepreneurial university can affect firm

location choice. We argue that certain personal characteristics of academic entrepreneurs affect the ease in question and hence influence firm location choice. As discussed in the later paragraphs on this section, personal characteristics unrelated with maintaining an academic role are also expected to play a role in firm location choice.

Younger faculty early in their career invest in knowledge creation so that they create a reputation (Audretsch & Stephan, 1996). Firm location close to campus can enhance knowledge growth for younger faculty since such location choice is conducive to frequent interactions between colleagues that can exchange ideas (Rothaermel, Agung, & Jiang, 2007) provide stimuli and role models (Brett, et al., 1991). Younger faculty are also typically assigned heavy teaching loads which then implies that their firm's location needs to accommodate their teaching duties. Locating on campus can make part time employment in the firm and in the academic institution easier enabling thus young faculty to fulfill their teaching duties while being involved with their firm (Brett, et al., 1991). Further, founder's reputation absent, firms started by younger faculty usually need to signal their potential by having eminent scientific consultants or/and by "borrowing" legitimacy by locating on campus. On campus location can increase a firm's legitimacy and reputation by "borrowing" prestige from the academic institution and by recruiting top scientists as consultants. Particularly after the growth of the entrepreneurial university, campuses in the U.S. and elsewhere often host research centers performing high quality research and employing renowned scientists offering thus to the university a reputation that can be useful for new firms founded by younger faculty. Accordingly, we hypothesize:

H 6: The probability that academic entrepreneurs start their biotechnology firms in their institution's location decreases with the academic entrepreneurs' age.

Contrary to faculty that have not established a reputation, eminent faculty can signal their firm's legitimacy and potential through their status. They have reached an academic status where their academic position is safeguarded and potentially limited physical presence on campus does not jeopardize their academic identity[4]. Also, eminent faculty are in an advantageous position in recruiting consultants regardless of the consultants' location while they are in much smaller need for role models. Further, the more eminent faculty are expected to have an extensive network emanating from their experience which can make them more mobile than the less established faculty. Accordingly, we hypothesize:

H 7: The probability that academic entrepreneurs start their biotechnology firms in their institution's location decreases with the academic entrepreneurs' eminence.

Besides academic entrepreneur's age and eminence additional personal characteristics are expected to affect firm location choice. While in general we expect these characteristics to influence firm location choice, and as such they need to be included in the analysis, whether they enhance local or distant firm creation is not clear *a priori* hence no specific hypotheses are formed for them.

Employment at a previous academic institution can influence firm location choice with two potentially conflicting effects. On the one hand, academic entrepreneurs with previous work experience at other academic institutions may have a large nexus of

[4] Jain (2009) describes ways academic entrepreneurs use to maintain their academic identity.

contacts allowing them to recognize opportunities regardless of location. On the other hand, academic entrepreneurs who decided to move from one academic institution to another did so probably because they wanted to and not because they were forced; hence one would expect them to start firms locally after they moved to an institution with more resources available to start a firm or because they may exhibit a "settle down" attitude.

Further, the commercial potential of an entrepreneur's research can have an effect on firm location choice. It is possible that academic entrepreneurs with more applied research have developed business opportunity skills due to the nature of their research which can involve interactions with industry professionals, presentations at industry meetings and the like. These business opportunity skills may enable entrepreneurs to start their firm wherever they find the most favorable conditions regardless of proximity to their academic institution. But, it is possible that especially if entrepreneurs have a strong preference for local firm creation potentially due to emotional reasons (Dahl & Sorenson, 2009), that they employ their business recognition skills only at the local level. Similarly to academic entrepreneurs whose research has commercial potential, scientists with previous business founding experience can also develop improved business recognition skills (Shane, 2000). As previously explained, the direction of the effect that these skills have on firm location choice is difficult to untangle beforehand[5].

[5] Note that including both variables enhancing an academic entrepreneur's business opportunity skills in one empirical specification may lead to double-counting the effects of business opportunity skills which could potentially artificially make either or both variables appear insignificant. First, when the source of acquiring business skills is different (applied research versus having prior business experience), it is possible that these skills differ in some unobserved factors. Second, in order to ensure that we are avoiding such double-counting we measured the correlation coefficient among the two variables and found that is about .03 which then suggests that the danger of double-counting is relatively low.

In the next sections we empirically test the seven hypotheses stated previously controlling for the entrepreneur's characteristics for which the direction of the effect is not expected *a priori*. We first describe the econometric model we use and we then proceed to present the data and empirical results.

3. Methods and Procedures

We operationalize empirically the above-mentioned hypotheses by specifying an ordered logit[6] model measuring how the probability of each location choice presented in equations 5, 6 and 7 is affected by the elements of vector K which is populated with variables testing each of the stated hypotheses. Each probability is estimated with maximum likelihood and is the product of probabilities described in equations 5, 6 and 7 for each sample observation. In the empirical model the estimated probability that the academic entrepreneur chooses one of her firm location options versus the others is given by:

$$Prob\,(y \leq j) = Prob\left(y^* \leq \mu_j\right) = \frac{e^{\mu_j - \sum_{k=1}^{K} \beta_k x_k}}{1 + e^{\mu_j - \sum_{k=1}^{K} \beta_k x_k}} \qquad (8)$$

Hypotheses H 1 through H 7 are tested through the parameters on the K explanatory variables in (1). First, the relationship between potential employee pool and academic entrepreneur's firm location as stated in H 1 is represented with a variable measuring the number of doctoral scientists employed in bioscience occupations in the

[6] The normal distribution was also tested (probit model) and provided analogous results to the logistic distribution (logit model). For parsimony we only report the logit estimates here.

academic entrepreneur's state[7] before firm birth *(PhDLabor $_{t-1\ to\ t-5}$)*. We expect the larger the number of doctoral scientists in the founder's state the more likely the academic entrepreneur to start her firm locally.

We test H 2 by including a variable that measures the number of DBFs existing before firm birth within 10 miles radius from the entrepreneur's academic institution *(DBFs10)*[8]. Under H 2 we expect the probability of academic entrepreneurs locating their firm close to their institution to increase as more DBFs exist close to it.

Next, three variables are used to represent the effects of academic entrepreneur's institution as stated in H 3 and H 4. H 4 is tested with a variable reflecting the number of university startups from the founder's institution before firm birth *(Startups $_{t-1\ to\ t-5}$)* and we expect the probability of local firm creation to increase with institutions more conducive to startup creation. Under H 3 we expect academic entrepreneurs employed in institutions focusing on biosciences and performing large scale bioscience research to be more likely to locate their firms close to their institution. The scale of bioscience research is captured through a variable measuring the number of PhD graduates in biosciences at entrepreneur's institution before firm birth *(BioScale $_{t-1\ to\ t-5}$)*. Academic entrepreneur's institution bioscience focus is represented with a variable measuring the

[7] Although the state level of aggregation for this variable might be too coarse to represent local labor availability, we were unable to identify other proxy variables that may capture local factor at a finer level such as the county.

[8] DBFs are located in both rural and urban areas, hence the relevant geographic spread that knowledge spillovers from existing DBFs can flow to newly founded firms can vary across regions. In order to ensure that our empirical estimations do not pertain only to the 10 miles radius we also constructed models including variables measuring the number of existing DBFs at 5, 15 and 20 miles radius from the founder's institution. The results of these models are largely similar to those of Table 3 and are not reported here for parsimony.

percentage of bioscience PhD graduates over the total number of PhD graduates from the founder's institution before firm birth *(BioFocus $_{t-1 \text{ to } t-5}$)* [9].

Venture capital availability is approximated with two variables; the first measures the number of venture capital firms existing at 10 miles radius from the entrepreneur's academic institution *(Vc10)* and the second variable reflects the total amount invested by those venture capital firms in all DBFs *(VcSize10)* [10] . Under H 5 we expect the probability of local firm creation to increase with local venture capital availability.

The relationship between academic entrepreneur's personal characteristics and firm location choice as stated in H 6 and H 7 is represented with separate variables included in (1). Consistent with H 6 we expect younger entrepreneurs to be more likely to locate their firms on their institution campus. Accordingly, we include a variable measuring the entrepreneur's age at firm founding *(Age)*.

In line with H 7 we expect the more eminent academic entrepreneurs to be more likely to locate their firms far from their affiliated institution. We approximate eminence with a dummy variable taking the value of 1 if the founder was a member of the Academy of Sciences and/or had an endowed chair professorship and/or had won a Nobel Prize and/or had a distinguished professor title at firm birth, and taking the value of 0 otherwise *(Eminence)*.

[9] For an alternative approximation of institutions' bioscience focus and scope we also collected data on bioscience R&D expenditures for each institution in the dataset. When using the variables in question the parallel slope assumption of the ordered logit model was not satisfied while the sample size was reduced considerably, hence the variables were not used for the model presented here.

[10] The choice of the 10 miles radius for the variables measuring the effects of venture capital availability was based on our finding in the 1st essay. These finding suggest that the most influential venture capital firms for a DBF's venture capital growth are located on a 10 miles radius from each DBF. Albeit, we also constructed models with the variables testing H 5 operationalized at 5, 15 and 20 miles radius from the founder's institution. The results of those models were in line with the results of Table 3 and are not reported here for parsimony.

In order to approximate the effects of previous academic employment on firm location choice we add a dummy variable coded as 1 when the entrepreneur had worked at another academic institution before the one he was affiliated with at firm birth and 0 otherwise *(Previouswork)*. In order to operationalize how applied the academic entrepreneur's research is we add a variable measuring the total amount the founder had received as a principal investigator before firm birth from National Institutes of Health (NIH) grants *($NIH_{t-1\ to\ t-5}$)*. Finally, the effects of previous business experience on firm location choice is approximated with a dummy variable coded as 1 when the academic entrepreneur had founded at least one firm before firm birth and 0 otherwise *(Serial Entrepreneur)*.

Before we proceed to a detailed presentation of the data employed for the empirical model, we introduce the empirical specification we used. The model, expressed as the deterministic part of (1) is:

$$
\begin{aligned}
&p(location\ choice\ at\ time\ t) \\
&= a + \beta_{PhdLabor_{\ t-1\ to\ t-5}}(PhdLabor_{t-1\ to\ t-5}) + \beta_{DBFs10}(DBFs10) \\
&+ \beta_{BioFocus_{\ t-1\ to\ t-5}}(BioFocus_{t-1\ to\ t-5}) + \beta_{BioScale_{\ t-1\ to\ t-5}}(BioScale_{t-1\ to\ t-5}) \\
&+ \beta_{Startups_{\ t-1\ to\ t-5}}(Startups_{t-1\ to\ t-5}) + \beta_{Vc10}(Vc10) + \beta_{VcSize\ 10}(VcSize10) \\
&+ \beta_{AGE}(Age) + \beta_{Eminence}\ (Eminence) + \beta_{PreviousworkK}\ (Previouswork) \\
&+ \beta_{NIH_{t-1\ to\ t-5}}(NIH_{t-1\ to\ t-5}) \\
&+ \beta_{Serial\ \ Entrepreneur}\ (Serial\ Entrepreneur) \qquad (9)
\end{aligned}
$$

For variables reflecting academic entrepreneur's institution effects, NIH awards and labor availability we use a five year lag average since we see the period up to five years before firm birth as the most relevant in explaining firm location. Lagged values from $t-1$ to $t-5$ are largely similar for the variables in question because the amount that each scientist receives within five years from NIH is fairly stable since monies received are commonly continuations or extensions of grants awarded at previous years. Further, the number of startups originating from academic institutions, as well as the institutions' bioscience PhD graduates are also measures with small variation across a five year window. Because of the similarity across lagged variables strong correlations exist among year lags, hence we use an average value versus including separate lags in the empirical model.

4. Data Sources and Presentation

Thomson's Financial SDC Platinum Database (SDC), Zoominfo web-based database and Moneytree web-based report were used to identify biotechnology firm births and employ that information for the construction of the sample and the variable associated with H 2 *(DBFs10)*. Each firm's location, founding date and founder(s) were available in all three data sources and whenever data were missing the website of each firm was visited in order to complete the information. The dependent variable indicated whether founders had started their firms on or around campus, in their institution's city or outside the city. Cities were defined at the metropolitan statistical area level. In order to classify firm birth in one of the three categories of the dependent variable we visually assessed each

founder's institution and firm location using Google Earth®. Firms located within three blocks from the last building on campus were also included in the on campus category.

For the purposes of this paper institutions are defined by campus so all relevant variables *(Startups* $_{t\text{-}1 \text{ to } t\text{-}5}$*, BioFocus* $_{t\text{-}1 \text{ to } t\text{-}5}$*, BioScale* $_{t\text{-}1 \text{ to } t\text{-}5}$*)* reflect values from each campus while academic entrepreneurs are matched with institutions whenever their name appeared at the institutions' departmental listings. In the few cases where an entrepreneur was affiliated with a university and the university's associated hospital, then she was listed as affiliated with the university in question as long as she held an office/lab space at the university.

Data used to reflect some of academic entrepreneur's characteristics (age, prior founding experience, eminence) were collected from (a) listings in Marquis who's who, (b) listings in Women and Men of Science and (c) academic entrepreneurs' biographies as included in their personal websites. To form the explanatory variables associated with H 2 *(DBFs10)* and H 5 *(Vc10),* we calculated the number of DBFs and venture capital firms in 10 miles radius from academic entrepreneurs' institutions using addresses provided by SDC. We converted these addresses to coordinates with tools available at http://www.batchgeocode.com. SDC also provided the data for the variables associated with H 5 *(VcSize10)* approximating the size of venture capital firms proximate to academic entrepreneur's institution. To form the explanatory variables used to account for labor availability *(PhDLabor* $_{t\text{-}1 \text{ to } t\text{-}5}$*)* and academic institutions bioscience PhD graduates measures *(BioFocus* $_{t\text{-}1 \text{ to } t\text{-}5}$ *,BioScale* $_{t\text{-}1 \text{ to } t\text{-}5}$*)* we collected data available from the National Science Foundation. The data of academic entrepreneur's institution startups *(Startups* $_{t\text{-}1 \text{ to } t\text{-}5}$*)* used to test H 4 came from the Licensing Survey of the

Association of University Technology Managers (AUTM). The variable measuring each academic entrepreneur's NIH funds was constructed from NIH records and was adjusted for inflation to reflect 2007 values using the CPI[11]. The final dataset, after collection from all sources was completed, was composed of 301 observations reflecting 187 DBFs founded by 266 academic entrepreneurs from 1983 to 2008.

Table 1 shows the institutions included in the dataset while the map presented in Figure 1 classifies them according to the number of academic entrepreneurs employed in them. Institutions with increasing number of academic entrepreneurs who have either founded or co-founded a firm in proximity to their institution (on campus or within institution's city limits) are presented with larger symbols in the map. Note that our sample covers institutions located in both rural and urban areas which then implies that our results are potentially not specific to one type of region. Further, most of the academic entrepreneurs in our dataset are employed at universities while some are employed at research institutes.

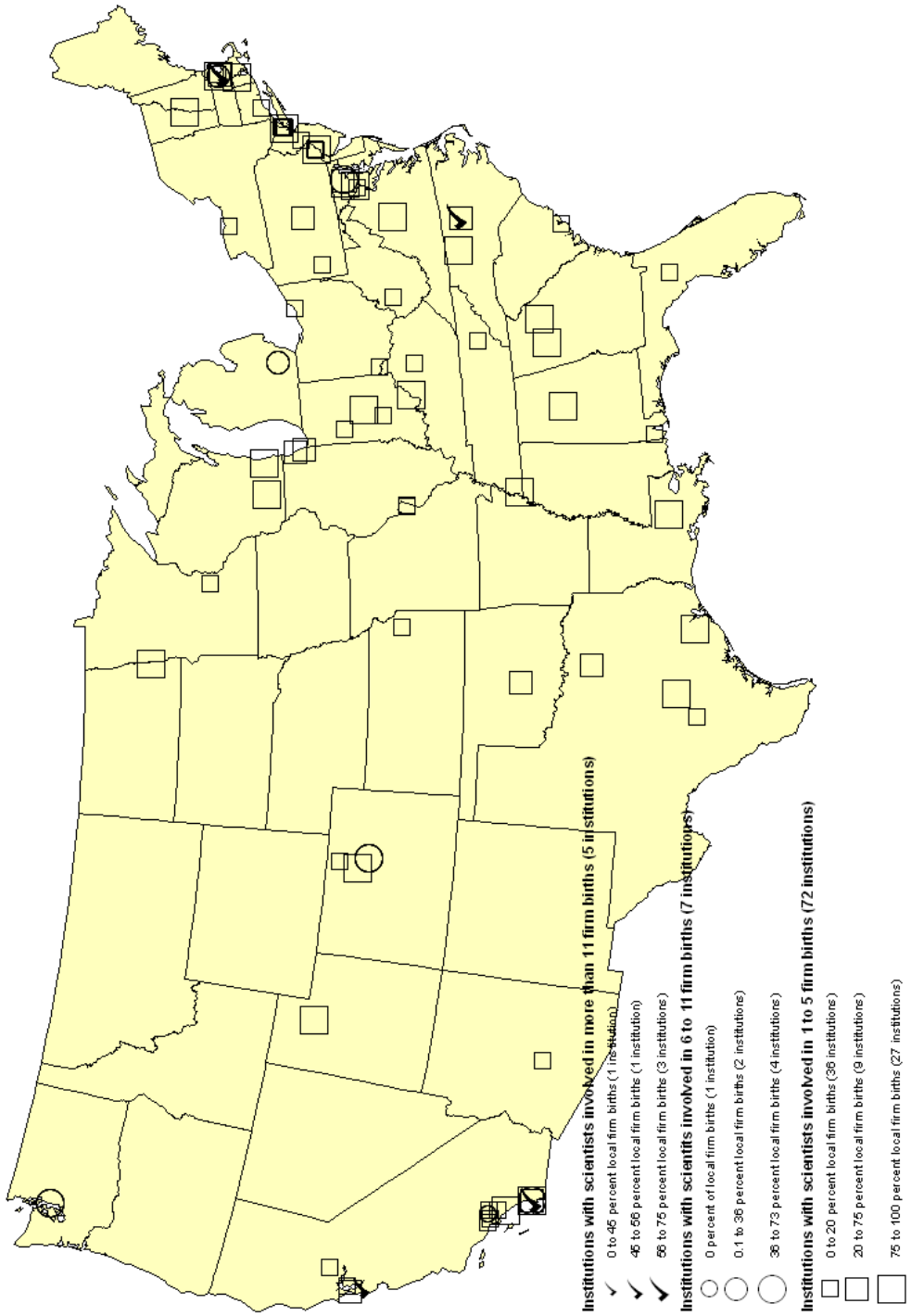
Close to eighty six percent (seventy two of the eighty four) of the institutions in the dataset had scientists involved in only one to five firm births in the period from 1983 to 2008. Most of the firms started by the academic entrepreneurs employed at the institutions in question were located in distance to the institution. Columbia university for example had five scientists who founded five firms from 1983 to 2008, with only one of the firms in question located in the greater New York city area and four of them

[11] The NIH records depict the amount awarded by NIH to every principal investigator (PI) and each PI's affiliation at the time the project was funded, which then enabled us to measure the amount of NIH funds awarded to each founder while being associated with his institution at firm birth.

Table 1. Institutions Included in the Dataset

Institution Name (Listed Alphabetically)	Number of Firms Births Associated with Institutions' Scientists	Institution Name (Listed Alphabetically)	Number of Firms Births Associated with Institutions' Scientists
Arizona State University	1	University Of Alabama Birmingham	1
Beckman Research Institute of City of Hope	1	University Of California Berkeley	3
Boston University	3	University Of California Davis	3
Broad Institute Of MIT And Harvard	1	University Of California Irvine	2
Brown University	2	University Of California Los Angeles	2
California Institute Of Technology	9	University Of California San Diego	13
California State University	1	University Of California San Francisco	4
Case Western Reserve University	1	University Of Chicago	4
City University Of New York	2	University Of Cincinnati	1
Colorado State University	2	University Of Colorado At Boulder	3
Columbia University	5	University Of Colorado Denver/Hsc Aurora	11
Cornell University Medical School	2	University Of Florida	4
Dartmouth College	1	University Of Georgia	1
Duke University	16	University Of Kansas	1
Emory University	2	University Of Kentucky	4
Georgetown University	1	University Of Louisville	1
Harvard University	6	University Of Maryland Baltimore	6
Harvard University Medical School	24	University Of Maryland Baltimore County	1
Indiana University	1	University Of Maryland College Park	1
Indiana University Purdue University Indianapolis	2	University Of Michigan At Ann Arbor	11
Institute Of Genomic Research	1	University Of Minnesota	1
Johns Hopkins University	3	University Of North Carolina Chapel Hill	4
Louisiana State University	1	University Of Oklahoma	4
Massachusetts Institute Of Technology	22	University Of Pennsylvania	2
Medical College Of Wisconsin	1	University Of Pittsburgh At Pittsburgh	3
Medical University Of South Carolina	1	University Of Rochester	1
New York University	4	University Of South Alabama	1
North Dakota State University	1	University Of Southern California	1
Northwestern University - Evanston	4	University Of Tennessee Knoxville	1
Pennsylvania State University-University Park	3	University Of Tennessee Memphis	1
Princeton University	1	University Of Texas Austin	5
Purdue University West Lafayette	1	University Of Texas Dallas	3
Rockefeller University	1	University Of Texas HSC at Houston	1
Saint Louis University	1	University Of Texas HSC at San Antonio	1
Salk Institute For Biological Studies	5	University Of Utah	2
Scripps Research Institute	9	University Of Virginia Charlottesville	2
Southern Research Institute - Birmingham	1	University Of Washington	11
Stanford University	16	University Of Wisconsin Madison	5
Temple University	1	Wake Forest University	1
Thomas Jefferson University	2	Washington University	1
Torrey Pines Inst For Molecular Studies	1	Yale University	5
Tufts University	4	Yeshiva University	1

Figure 1. Firm Births in Proximity and Distance to the Founder's Institution.



located outside New York. On the other side, institutions with academic entrepreneurs involved in more than five firm births, had a higher percentage of firms founded close to the institution[12]. Duke university for instance had sixteen scientists who founded sixteen firms from 1983 to 2008 with eleven of those firms founded on Duke's campus. Taken together, the abovementioned statistics suggest that there is an institution effect in firm location. Without controlling for location characteristics, academic entrepreneurs affiliated with institutions more conducive to firm births, appear more inclined to start their firms locally.

Table 2 presents descriptive statistics of the variables used in the empirical model. Slightly over fifty two percent of the firms in the dataset were founded within the city limits of the founder's institution (about forty one percent of them on campus) while close to forty eight percent of the firms were founded at regions distant to the founder's institution. The almost even distribution of "local" versus "distant" firm births suggests that a number of location decision forces are at play.

The variable with the least variability in the dataset was the academic entrepreneur's age at firm founding, with the average age of the founders being forty seven years old at firm birth. The majority of the 266 entrepreneurs in the dataset had not received NIH funds, ninety eight founders were classified as eminent with forty eight of them having started their firm(s) within their institution city limits, fifty three had worked at a previous university with eighteen of them having started their firm within their institution city limits and seventy six had started a firm before firm birth in question.

[12] For example 3 out of 5 institutions with more than 11 firm births, had 56 to 75 percent of those firms located closely.

Table 2. Descriptive Statistics of the Variables Used in the Empirical Models

	Variable	No. of observations	Mean	Median	Mode	Standard Deviation
Continuous Variables	PhdLabor $_{t-1 \text{ to } t-5}$	281	5.87	5.19	6.34	3.88
	DBFs10	301	25.85	5.00	0.00	34.87
	BioFocus $_{t-1 \text{ to } t-5}$	222	0.22	0.16	0.00	0.19
	BioScale $_{t-1 \text{ to } t-5}$	222	53.68	52.40	0.00	28.65
	Startups $_{t-1 \text{ to } t-5}$	223	5.57	3.33	2.00	5.70
	Vc10	301	38.99	12.00	0.00	47.84
	VcSize10	301	443.30	255.40	0.00	513.69
	Age	292	47.74	47.00	47.00	10.42
	NIH $_{t-1 \text{ to } t-5}$	289	0.77	0.20	0.00	2.49

		Category 1: Firms Started on Founder's Campus	Category 2 : Firms Started Outside Founder's Campus but within Founder's City	Category 3 : Firms Started Outside Founder's City
Dependent Variable	301	65	92	144

		Total Number of Founders	Total Number of Founders with the Dummy Variable value at 1	Number of Founders in Categories 1 and 2 of the Dependent Variable
Dummy Variables	Eminence	266	98	48
	Previouswork	266	53	18
	Serial Entrepreneur	266	76	35

PhDLabor $_{t-1 \text{ to } t-5}$	Average number of doctoral scientists employed in bioscience occupations in founder's affiliated institution state 1 to 5 years before firm birth (thousand)
DBFs10	Number of biotechnology firms in 10 miles radius from founder's affiliated institution before firm birth
BioFocus $_{t-1 \text{ to } t-5}$	Average percentage of bioscience PhDs over total number of PhDs from founder's affiliated institution 1 to 5 years before firm birth
BioScale $_{t-1 \text{ to } t-5}$	Average number of bioscience PhDs awarded at founder's affiliated institution 1 to 5 years before firm birth
Startups $_{t-1 \text{ to } t-5}$	Average number of spinoffs from founder's affiliated institution 1 to 5 years before firm birth
Vc10	Number of venture capital firms existing before firm birth in a 10 miles radius from founder's affiliated institution
VcSize10	Total amount invested in biotechnology firms for venture capital firms located in a 10 miles radius from founder's affiliated institution (Million $)
Age	Founder's age at firm birth
NIH $_{t-1 \text{ to } t-5}$	Average amount awarded to founder from NIH in the last 5 years before firm birth (2007 Million $)
Eminence	Dummy variable taking the value of 1 if founder was classified as eminent before firm birth and 0 otherwise
Previouswork	Dummy variable taking the value of 1 if founder had worked at another academic institution before firm birth and 0 otherwise
Serial Entrepreneur	Dummy variable taking the value of 1 if founder had started at least on firm before firm birth and 0 otherwise

The variable measuring the number of PhD graduates from founders' institutions included institutions with a wide range in bioscience focus and scale. The variable under discussion followed an approximately normal distribution covering institutions with varying degrees in the number of PhD graduates in biosciences.

The variables measuring the number of university startups and the agglomeration of DBFs and venture capital firms close to entrepreneurs' institutions were left skewed but still had observations for a wide range of values. About thirty nine venture capital firms were located on a ten miles radius from the entrepreneur's institution. The corresponding number for DBFs was close to twenty six. Finally, the venture capital firms close to founder's institution had invested on average about 440 million dollars over time in biotechnology firms. Note that the 440 million figure reflects a monetary sum over a lengthy period and as such it should be adjusted for inflation. Unfortunately in many cases we had complete information only on the total amount invested by each venture capital firm but not on the amounts invested on a per year basis, hence we could not adjust for inflation.

5. Estimation Results

Each independent variable's marginal effect[13] on the academic entrepreneur's probability of choosing one of the three locations options considered is presented in Table 3[14]. The

[13] Marginal effects for interior cases are calculated as follows:
$\frac{\partial Prob\,(y=j)}{\partial x_k} = \left[\phi\left(\mu_{j-1} - \sum_{k=1}^{K}\beta_k x_k\right) - \phi\left(\mu_j - \sum_{k=1}^{K}\beta_k x_k\right)\right]\beta_k, 0 < j < J$ (Greene, 2003). For the endpoints the marginal effects are calculated as follows:
$\frac{\partial Prob\,(y=0)}{\partial x_k} = -\beta_k\phi(\mu_0 - \sum_{k=1}^{K}\beta_k x_k), \frac{\partial Prob\,(y=J)}{\partial x_k} = \beta_k\phi\left(\mu_J - \sum_{k=1}^{K}\beta_k x_k\right)$ (Wooldridge, 2009) where ϕ is the logistic probability distribution function and β_k are the estimated ordered logit coefficients. For dummy variables the marginal effect is approximated as the change in probability resulting after the dummy variable's value changes from 0 to 1.

Likelihood ratio test is statistically strong indicating that the model presented in Table 3 has explanatory power. McFadden's pseudo-R^2 [15] is about 0.11 while the multicollinearity condition number is within acceptable levels (21.32) indicating that potential inference issues associated with inflated standard error emanating from multicollinearity are not an issue. Finally, the χ^2 test for the parallel slopes assumption fails to reject the null hypothesis that the independent variables shift the cumulative distribution to the right or to the left but they do not alter the slope of the distribution, hence the ordered logit model is supported (Greene, 2003).

The results provide support for H 1 implying that scientific labor availability is a predictor of academic entrepreneur's firm location choice. Given that the $PhdLabor_{t-1\ to\ t-5}$ variable is measured at the state level the increase in the probability of locating outside the institution's city associated with the variable in question indicates that the more bioscience PhDs employed in the state the more likely the founder to start her firm in the state. One would expect most of the state scientist not to be located in one city (in this case the founder's institution city), hence, as H 1 predicts, academic entrepreneurs locate their firms closer to scientific labor pool. These results corroborate the importance of skilled and specialized labor in knowledge intensive industries such as biotechnology.

H 2 is also empirically supported indicating that agglomeration of local DBFs associated with potential knowledge spillovers attracts academic entrepreneurs in a given location. The corresponding coefficient is statistically significant at the 1 percent

[14] μ_1 and $\mu_2$of Table 4 are the estimated threshold parameters presented in Equations 6 and 7.
[15] McFadden's R^2 is analogous to the OLS R^2 where the Log Likelihood for the null model replaces the total sum of squares and the Log Likelihood for the model with the regressors replaces the residual sum of squares, hence increases of the statistic indicate better model fit (Long, 1997).

Table 3. Marginal Effects[1] of Variables Affecting Location Choice. Results from Ordered Logit Model

Variable	Change in Probability of on Campus Firm Location		Change in Probability of in City Firm Location		Change in Probability of outside City Firm Location	
PhdLabor $_{t-1 \text{ to } t-5}$	-1.5027	**	-1.0797	**	2.5824	**
DBFs10	0.3667	***	0.2635	***	-0.6302	***
BioFocus $_{t-1 \text{ to } t-5}$	24.5026	*	17.6055	*	-42.1081	*
BioScale $_{t-1 \text{ to } t-5}$	-0.0403		-0.0289		0.0692	
Startups $_{t-1 \text{ to } t-5}$	0.8761	*	0.6295	*	-1.5056	*
Vc10	-0.2997	***	-0.2153	***	0.5150	***
VcSize10	0.0110	**	0.0079	**	-0.0189	**
Age	-0.4379	**	-0.3146	**	0.7525	**
Eminence	1.2280		0.8672		-2.0952	
Previouswork	-12.7223	***	-13.3821	***	26.1044	***
NIH $_{t-1 \text{ to } t-5}$	0.2164		0.1555		-0.3720	
Serial Entrepreneur	6.8102		3.9231		-10.7333	
μ_1			-0.2186			
μ_2			1.5606			
Observations			204			
McFadden's Pseudo R^2			0.1082			
Likelihood Ratio of all Variables = 0			46.7087			***
Multicollinearity Condition Number			21.3239			
Proportionality Assumption χ^2			13.2865			

*** .01 significance, ** .05 significance, * .10 significance

Note: μ_3 is normalized at 0

[1] For continuous variables the marginal effects are approximated with the variable magnitudes held at their mean value. For dichotomous variables the marginal effects are approximated as the change in the probability resulting after the variables' value changes from 0 to 1.

level and suggests that one additional DBF in proximity to the founder's institution decreases the probability of the founder starting her firm outside the institution's city by approximately 0.63 percent. At the same time, one additional DBF increases the probability of on campus location by approximately 0.36 percent and the probability of in city location by approximately 0.26 percent.

H 3 is only partially supported by the empirical results. While an increase in the focus of the founder's institution towards bioscience research is associated with higher probability of local firm location, an increase in the scale of bioscience research has no effect on academic entrepreneur's location choice. These results are potentially related with our finding that labor pool availability is important for firm location choice. Since DBFs typically employ labor with specialized knowledge, their preference towards specialization may also be reflected on the founder's attraction towards universities with strong biotechnology focus.

In line with H 4 the empirical results imply that academic entrepreneur's institution startup rate is a predictor of her firm location choice[16]. These findings agree with stylized facts about university startups in the U.S. where many startups locate close to the university. In 2003 for example out of the 409 university startups reported in the Licensing Survey of the Association of University Technology Managers (AUTM), 330 of them were founded in the institution's home state. Regarding the estimated marginal effects reported on Table 3, they suggest that one additional startup from the academic entrepreneur's institution in previous years increases the probability of the founder starting his firm on campus by approximately 0.81 percent and reduces the probability of outside institution's city location by approximately 1.41 percent.

The results associated with H 5 are mixed. While local agglomeration of venture capital firms discourages academic entrepreneurs from starting their firm locally, the size

[16] In unreported results the startups variable is marginally insignificant when a dummy variable indicating whether the founder's institution had a research park is included in the analysis. A possible explanation for the change in significance for the startups variable is that some of the startups are located in research parks. The research park variable was not included in the analysis presented here because the data available to us did not capture qualitative differences across research parks.

of the venture capital firms in proximity increases the probability of local firm creation. Despite appealing theoretical arguments and mainly anecdotal evidence, Shane (2004) notes that only limited empirical evidence supports the positive effects of venture capital availability on firm creation. Our results corroborate Shane's note only partially. We find that academic entrepreneurs are not attracted to regions hosting a large number of venture capital firms but rather to regions with large venture capital firms. It is possible that our findings stem from anchoring effects where large venture capital firms invite and provide support to entrepreneurs only if they start their firms close to the venture capital firms.

The results of Table 3 also suggest that the beneficial effects of locating close to campus are more attractive for younger entrepreneurs. As H 6 predicts older founders appear more likely to start their firm outside their city compared to younger entrepreneurs[17]. One additional year of age decreases the probability of on campus firm location by approximately 0.45 percent and increases the probability of locating outside the city limits by approximately 0.77 percent.

Contrary to H 7 the empirical results suggest that academic entrepreneur's eminence does not have explanatory power with regard to firm location choice. It is possible that, controlling for age, the more eminent academic entrepreneurs use the same criteria with the less established academic founders when making their location choice, hence their eminence has little explanatory power in the matter.

[17] In unreported results a variable indicating the founder's age in quadratic form was included in the analysis in order to check for potential nonlinearities in the relationship between age and firm location choice. The variable was statistically insignificant suggesting that the effect of founder's age on location choice is not nonlinear. Given its statistical insignificance the variable was not included in the analysis presented here for parsimony.

Regarding the variables for which their *a priori* influence of firm location choice was not clear, they suggest that academic entrepreneurs with previous work experience at another academic institution are approximately 26 percent more likely than the rest of the founders to start their firm outside their institution's city. This finding potentially asserts that the effects of an extended professional network outweigh other effects conducive to local firm creation. Finally, the results suggest that the academic entrepreneur's business opportunity skills do not have explanatory power her firm location choice; both variables used to approximate serial entrepreneurs and academic entrepreneurs with more applied research do not appear with statistically strong coefficients.

6. Concluding Comments

Today U.S. universities have added a fourth mission to their purpose besides teaching, research and service; that of enhancing local economic development through, among others, boosting local firm births. This fourth mission has often been at the core of a gradual transformation from the Mertonian (Merton, 1968) to the entrepreneurial (Etzkowitz, 1998) university . In order for the entrepreneurial university to succeed in its goal and for local communities to reap the economic benefits of the entrepreneurial university, a better understanding of the factors needed to enhance local firm births is in place.

In this paper we analyze the conditions prompting academic entrepreneurs to start their firms locally. The relative scarcity of research on the topic seems surprising especially in the face of the entrepreneurial university, its focus on regional development and the role of scientists in the entrepreneurial university.

We find that scientific labor availability, agglomeration of biotechnology firms, age, and founder's academic institution effects are important determinants of academic entrepreneur's firm location choice. Contrary to expectations we find that academic entrepreneur's eminence does not have explanatory power on firm location choice. Our results with regard to venture capital availability are mixed since we find that while local agglomeration of venture capital firms decreases the probability of local firm creation, the presence of large venture capital firms increases that probability. While many explanations are possible we attribute the finding in question to venture capital anchoring effects where large venture capital firms attract newly founded firms close to them.

Further research can be initiated from the present work in a number of routes. In the empirical models it was implicitly assumed that all academic entrepreneurs needed to devote the same time towards their newly founded firm. New research can examine whether potential differences across founders in the necessary time needed to devote to the firm can affect firm location choice. Also, research can incorporate in the analysis the weight that social ties carry on academic entrepreneur's firm location choice.

More generally, a fruitful area of inquiry would be to analyze whether and to what extent firm location choice can influence academic entrepreneur's performance and devotion to other venues of academic entrepreneurship such as patent activity and licensing. Further analysis could also examine how (if) considerations regarding *ex post* performance in patent activity or/and licensing affect firm location choice at the first place.

7. References

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