GEOGRAPHIC SCOPE OF PROXIMITY EFFECTS AMONG SMALL LIFE SCIENCES FIRMS[1]

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Geographic Scope of Proximity Effects among Small Life Sciences Firms

1. Introduction

Early stage seed funding for small innovative firms is critical and scarce. In the US, a common source of capital for these innovative firms is the Small Business Innovation Research (SBIR) program under which 11 federal agencies allocate 2.5 percent of their annual budget to firms with promising research ideas using a two phase process.[1] Phase 1 grants are used to explore the scientific and commercial feasibility of an idea/technology and, typically, do not exceed $100,000. Phase 2 grants are considerably larger and are given to the most meriting Phase 1 winners to expand their initial results. Angel and venture funds are alternative sources of capital for such early stage projects but, as a whole, they lag the SBIR grant pool. In 2007, for instance, the SBIR program awarded $2.3 billion for research and seed funding in the US while the corresponding figure for private venture markets was $1.2 billion (pg. 5, Wessner 2009b).

A key goal of the SBIR program is to stimulate technological innovation (Wessner 2009a)[2]. As a result, the bulk of SBIR funds are awarded to small firms operating in cutting edge research areas such as the life sciences, electronics, materials and energy conversion. An important research finding about such firms that has largely gone unnoticed in the literature is that when these firms are located in close proximity to one another they tend to have a higher chance of winning SBIR grants (Wallsten 2001) – a spatial externality of sorts that has been attributed to knowledge spillovers, network effects and other benefits associated with knowledge transfers among neighboring firms. These proximity effects have been found to be stronger

[1] There is also a Phase 3 but federal agencies do not provide funds during that phase.
[2] Evidence suggests that the SBIR program has, generally, been successful in promoting innovation (Audretsch 2003; Audretsch et al. 2002a; Audretsch et al. 2002b)

within one tenth of a mile and to be effectively exhausted within half mile from their origins. This finding is generally unique in the literature as few other studies have determined proximity effects to be geographically so limited in scope (Aharonson et al. 2007; Rosenthal and Strange 2003)[3]. Indeed, most studies of proximity effects in innovative industries do not generally measure their precise geographic reach and those that do, find them to be significantly broader in scope (e.g. Acs et al. 2002; Anselin et al. 1997; Baldwin et al. 2008; Baldwin et al. 2010; Orlando 2004)[4].

In this study we return to the question of whether proximity effects exist among neighboring firms funded through SBIR grants and we measure how far they extend when they do exist. Our point of departure is Wallsten (2001)[5] who examined the effects of spatial proximity on the binary outcome of winning/not winning an SBIR grant among small innovative firms over a four year period (i.e. 1993-1996). To evaluate the robustness of Wallsten's (2001) findings we introduce a number of changes. First, we use a sharper measure of proximity effects. Specifically, we quantify the relationship between the amount of SBIR grants raised by a given firm and the number of SBIR winners at various distances and this measure should prove more sensitive than the binary winning/not winning an SBIR measure used by Wallsten (2001). Second, we extend the period of analysis to almost 25 years (i.e. 1983- 2006), which should ensure that any presence of proximity effects is structural and not a chance event. Finally, we focus on the presence of proximity effects among small firms in the life sciences industry

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[3]Aharonson et al. (2007) study the firm location choice of biotechnology firms conditional on the existence of knowledge spillovers, which are approximated as the level of R&D spending; Rosenthal and Strange, (2003) also study firm location choice and operationalize knowledge spillovers as the level of employment in a given industry. Hence, empirical evidence from these studies does not specifically pertain to SBIR firms.

[4] The benefits from the agglomeration of firms and industries discussed in the literature are, generally, of two kinds: The first involves efficiency gains from reductions in firm production costs through access to local labor pools and services as well as reductions in transaction costs through improved access to local suppliers and buyers. The second involves gains in firm knowledge and innovation that typically result from knowledge spillovers, network effects, increased collaboration among proximate firms and other forms of knowledge transfer. Because these later effects rely heavily on human capital (e.g. labor mobility, face to face interactions), the associated benefits are generally assumed to be more geographically limited (termed proximity effects here).

[5] Black (2005) also studied the probability for a given firm to win Phase 2 SBIR awards but his analysis did not include proximity effects across similar firms.

receiving SBIR grants. We focus on the life sciences industry because it is said to be well-suited for knowledge spillovers, network externalities and other modes of knowledge transfers which can lead to proximity effects (Shane 2004).[6] Hence, if spatial proximity does benefit firms pursuing SBIR grants, proximity effects should be measurable among small innovative firms specializing in the life sciences[7].

Our interest to the question at hand is, primarily, motivated by the apparent divergence of empirical evidence on the geographic scope of proximity effects which is found to be quite narrow in a small number of studies (Aharonson et al. 2007; Rosenthal and Strange 2003) and much broader in a larger number of studies (e.g. Acs et al. 2002; Anselin et al. 1997; Audretsch and Feldman 1996; Bottazzi and Peri 2003; Delaney 1993; Funke and Niebuhr 2005; Jaffe 1989; Jaffe et al. 1993; Keller 2002; Orlando 2004; Varga 2000). Resolving this seeming divergence in the empirical evidence presented in the literature goes beyond academic curiosity. There are ongoing efforts for the development of clusters in knowledge-intensive sectors, such as the life sciences, in many parts of the world (Doeringer and Terkla 1995; OECD 1999, 2007; Schmitz and Nadvi 1999) and such investments could prove ineffective if the geographic scope of proximity effects and their underlying causes are not well understood. Similarly, given the increasing popularity of SBIR like programs around the world (i.e. UK's SIRI program, Australia's IIF program and programs in Sweden, Russia, Canada, UK etc.) (Cumming et al. 2007; Wessner 2009b) understanding and promoting possible proximity effects could secure greater returns on the public funds invested through these programs.

[6] Proximity effects have been found in a number of studies that have analyzed the life sciences industry (e.g. DeCarolis and Deeds 1999; Kolympiris et al. 2011; Owen-Smith and Powell 2004; Ponds et al. 2010; Zucker et al. 1998a).

[7] The life sciences industry is also characterized by a large number of university and other life science firm spinoffs created in close proximity to the original sources of knowledge. This is a firm creation mechanism described in the knowledge spillover theory of entrepreneurship and refers to the process where firms are founded in order to exploit knowledge that is not fully developed at the institution that first produced it (Audretsch and Keilbach 2007). Accordingly, our analysis could also provide insights on the proximity effects and the geographic scope of knowledge spillover entrepreneurship.

We proceed with the rest of the paper then as follows: In sections 2 and 3 we review the relevant literature on the sources of proximity effects and what is known about their geographic scope. In section 4 we introduce the empirical hypotheses of our study and we describe our estimation procedures. In section 5 we review the data used in our empirical analysis and examine in some detail the spatial characteristics of various regions that could influence the geographic scope of proximity effects that could emerge among neighboring life science firms receiving SBIR funds. In section 6, we present the estimation results and in section 7 we summarize and conclude.

2. The literature on the sources of proximity effects

Why should firms of a particular industry located in close proximity have higher chances of winning SBIR grants than non-proximate firms? Knowledge spillovers, network effects, increased collaboration among nearby firms and other forms of knowledge transfer could cause such effects and the general consensus in the literature is that geographic proximity matters for two main reasons: First, because it facilitates the transmission of tacit knowledge and, in turn, innovation (Asheim and Gertler 2005). Second, because it allows access to a local knowledge pool enabling economic actors to interact with more ease and with more actors (Asheim and Gertler 2005). This ease of interaction and knowledge transfer is essential as firms, confronted with a dynamic business environment as well as technical challenges and financial constraints, constantly look for knowledge resources outside their own to improve their performance (Cohen and Levinthal 1990; Conner and Prahalad 1996; Grant 1996).

Along these lines, a well-developed body of literature has documented the contribution of knowledge transfers on firm performance and innovation (e.g. Acs et al. 2002; Anselin et al. 1997; Audretsch and Feldman 1996; Bottazzi and Peri 2003; Delaney 1993; Funke and Niebuhr

2005; Jaffe 1989; Jaffe et al. 1993; Keller 2002; Orlando 2004; Rosenthal and Strange 2003; Varga 2000; Wallsten 2001) [8]. Knowledge transfer mechanisms such as face-to-face interactions, local professional networks and labor mobility are the primary means through which spatial knowledge transfers are realized.

Saxenian (1990) explained in some detail how face-to-face interaction among individuals is a significant knowledge transfer mechanism. Routine personal encounters among employees of proximate firms can enhance the knowledge base of a given firm through deliberate or chance reciprocal exchange of ideas, information sharing, and technical advice. Knowledge tends to diffuse locally when economic actors working in similar problems locate in proximity (Liebeskind et al. 1996; Saxenian 1994; Sorenson and Stuart 2001). For instance, so called, "local buzz" (Bathelt et al. 2004; Storper 1997) allows valuable knowledge transfers, such as accounts of failures in scientific experiments (Asheim and Gertler 2005), to diffuse locally mainly due to network relationships sustained by geographic proximity.

More broadly, a large number of studies have supported the importance of interpersonal relationships as a knowledge transfer mechanism. For instance, Dahl and Pedersen (2004) found that for employees of proximate wireless communication firms in Denmark interpersonal interactions were a major source of knowledge transfers. Sorenson and Stuart (2001), Gupta and Sapienza (1992), Lobo and Strumsky (2008), and Athanassiou and Nigh (2000) are some of the many authors that have similarly emphasized the role of interpersonal interactions as a primary knowledge transfer mechanism. Sweeney (1987) discussed how important interpersonal encounters are for small firms and Von Hippel (1994) explained the significance of interpersonal communication among small firm employees in knowledge intensive industries, which can be effective due to the "stickiness" of tacit, non-codified information that is difficult to transmit through more formal channels. By their very nature, frequent face-to-face interactions and

[8] Among others, contributions from Breschi and Lissoni (2001) and Håkanson (2005) take a critical stand towards tacit knowledge and positive spatial externalities.

interpersonal relationships often have a spatial scope that extends to a firm's immediate proximity as social connections that involve recurring interactions develop, mainly, at short distances (Porter 1998; Rosenkopf and Almeida 2003; Rosenthal and Strange 2003; Walker et al. 1997).

Firms can also source knowledge from other firms through local professional networks and there is growing evidence that suggests such networks are significant conduits of knowledge transfers (Huggins and Johnston 2010; Powell et al. 1996). In high technology industries collaborations among firms that are sustained by local professional networks are common (Hagedoorn 2002; Von Hippel 1988) partly due to scientific complexities and high costs which can be shared among firms. Along these lines, Saxenian (1990, 1991) described how semiconductor firms in the San Francisco Bay area – even competitors - collaborate to solve common problems. Similarly, Huggins and Johnston (2010) reported that high-technology firms in Northern England use localized networks to exchange knowledge and Autant-Bernard et al. (2007) discussed how European high technology firms are more likely to cooperate if located in the same area. In principle, the geographic reach of collaborative efforts is not spatially bounded because firms can develop ties with distant ones (Boschma 2005; Gilding 2008). Nevertheless, because professional networks are mostly local (Sorenson and Stuart 2001; Stuart and Sorenson 2003) the geographic scope of knowledge transfer from inter-firm collaborations is often also local.

Labor mobility is another mechanism regarded as a core conduit of knowledge transfer, particularly in industries that rely heavily on human capital (Audretsch and Feldman 1996). Highly trained workers with developed skills and expertise can act as "knowledge spillover agents" (Schiller and Diez 2010) as they move from one organization to another (Almeida and Kogut 1999; Dahl and Pedersen 2004; Franco and Filson 2006; Kim and Marschke 2005; Maier et al. 2007; Malecki and Poehling 1999).

A number of empirical studies have supported the notion of labor mobility as a knowledge transfer mechanism. Almeida and Kogut (1999) used patent citations to approximate knowledge flows and found that the level of labor mobility in a region is a significant predictor of such knowledge flows. Rosenkopf and Almeida (2003) also used patent data and reached similar conclusions. Boeker (1997) found that managerial expertise gained at prior organizations affected new product introduction at the new firm and Maliranta et al. (2009) used data from Finland to conclude that firms which hired workers with R&D experience increased their productivity and profitability. Because the expertise and skills that make workers attractive for a given employer are typically tailored to a specific research area, labor mobility occurs, chiefly, across firms in the same industry. At the same time, employees in high demand tend to exhibit spatial inertia (Almeida and Kogut 1999; Angel 1989) partly because they seek to maintain social and professional ties. Taken together, these tendencies suggest that the spatial scope of knowledge transfers from labor mobility is also expected to be limited.

All knowledge transfer mechanisms discussed above, involve human interactions and human capital. Industries that are heavily dependent on human capital are therefore more likely to experience knowledge transfers which are, most likely, limited in geographic scope. The life sciences is an industry built on human capital and capacity to innovate (Stuart and Sorenson 2003; Zucker et al. 1998b). Therefore, the chance of discovering spatially limited proximity effects in the life sciences industries is expected to be high.

3. The literature on the geographical scope of proximity effects

In line with the arguments presented in the previous section, the standard view in the related empirical literature is that proximity effects from knowledge spillovers, network effects, increased collaboration among nearby firms and other forms of knowledge transfer must have a geographic upper bound largely because the marginal costs of knowledge transmission increase with distance (Acs and Audretsch 2010; Audretsch 1998).

A number of studies have empirically tested this proposition using both direct and indirect measures of proximity effects and geographic reach. Some studies have analyzed the relationship between knowledge inputs (e.g. R&D expenditures) and knowledge outputs (e.g. number of patents) (Anselin et al. 2000; Audretsch and Feldman 1996; Black 2005; Jaffe 1989; Jaffe et al. 1993). The unit of analysis in these studies is typically the state or the Metropolitan Statistical Area (MSA) and the empirical results support the notion that the transmission of knowledge is indeed confined within these regional units. Using similar methods, studies have examined the geographic scope of proximity effects specifically in the life sciences industry and have reached similar conclusions (e.g. DeCarolis and Deeds 1999; Owen-Smith and Powell 2004; Ponds et al. 2010; Zucker et al. 1998a).

Other researchers have not specified *a priori* the geographic boundaries where proximity effects could occur and have instead compared their strength across increasingly distant spatial units from a central actor. Orlando (2004) reported that spatial externalities from industrial R&D can carry up to 200 miles; Anselin et al. (1997) and Acs et al. (2002) showed that university research has an effect on high technology innovations that is strong up to 75 miles; and Keller (2002) found that the productivity of R&D research across countries declines with distance while spatial externalities occur up to 745 miles. Bottazzi and Peri (2003) used European regions as their unit of analysis and found that R&D spending in a given region had a small but significant and positive effect on the patenting rate of regions located up to 186 miles away while Funke and Niebuhr (2005) showed that in selected German regions knowledge spatial externalities extended 14 miles or more. Finally, Baldwin et al. (2010) found that labor productivity in individual Canadian firms was positively related to the agglomeration of similar firms within a 3 mile radius and in a similar exercise Baldwin et al. (2008) estimated the cutoff point of spatial externalities to be roughly 6 miles[9]. Both Baldwin et al. (2010) and Baldwin et al. (2008) attributed their findings to agglomeration economies including buyer-supplier networks, larger labor pools and knowledge spillovers.

The geographic scope of proximity effects in the life sciences industry has not been measured as frequently or directly. Delaney (1993) found that the majority of the biotechnology firms in his sample had sourced information from a 50 miles radius while Kolympiris et al. (2011) measured positive spatial externalities in the venture capital funding of biotechnology firms for up to 10 miles distance and attributed that, in part, to knowledge spillovers and network externalities.

A common feature of all the empirical studies reviewed above is that the spatial units of analyses extend well beyond the immediate proximity of firms or firm clusters and often represent long geographic distances. This methodological choice can primarily be attributed to the research setting of each study where narrow geographic proximity was not of primary interest. Still, the mere variance in the geographic scope of proximity effects measured in existing empirical studies leaves the reader wondering just how strong are such effects in the immediate vicinity of firms and how far they might extend?

In this context, we find the empirical results of the few studies that have examined the presence of positive externalities in the immediate proximity of focal firms intriguing as they suggest that, at least in some instances, proximity effects may be significantly narrower than generally assumed. Rosenthal and Strange (2003) examined firm births in a number of industries conditional on proximity effects which were measured at different geographical distances. Proximity effects were found to have the strongest impact on firm births within a 1 mile radius of all units considered and such impact was exhausted at a 15 miles radius. Aharonson et al. (2007) estimated that the location choice of Canadian biotechnology firms in the 1990s was heavily

[9] Relatedly, Funderburg and Boarnet (2008) report that the majority of the labor force of a given cluster is located within 5 to 7.5 miles from the cluster.

influenced by the R&D activity of existing firms in a one third of a mile radius. Finally, Wallsten (2001) employed even smaller units when he estimated the probability of winning an SBIR grant among high-technology firms controlling for the presence of previous SBIR winners situated at increasingly distant geographical units. Again, the firms located in the narrowest of these units defined as a one tenth of a mile radius had the most pronounced effect on the probability of the origin firm to win an SBIR grant while spatial effects remained economically relevant only up to half a mile radius.

The findings of Wallsten (2001) are of particular interest to this study. Wallsten (2001) investigates SBIR firms which operate, mostly, in knowledge intensive industries and hence are heavily dependent on human capital. Furthermore, the firms he considers are small and, given their inherent resource constraints, they are more likely to seek knowledge resources outside their boundaries. This is just the kind of environment that proximity effects from knowledge spillovers, network effects, increased collaboration among nearby firms and other forms of knowledge transfer would tend to exist. Wallsten (2001) then looks for the presence of proximity effects at the narrowest possible geographic units, which have rarely been considered in previous studies. In this context, Wallsten (2001) finds proximity effects to be very narrow in geographic scope indeed. If Wallsten's results could be replicated and generalized, they could influence both the conceptual foundation of proximity effects, the underlying knowledge transfers and the government policies that pursue them in practice. In this sense, these results must be also explained. Just what factors could keep proximity effects so geographically limited?

We return to the question of whether proximity effects among small firms in knowledge-intensive industries are as narrow in geographic scope as reported by Wallsten (2001). Specifically, we measure whether positive spatial externalities in the level of funding of proximate SBIR firms in the life sciences industry do in fact exist and if so, how far they extend, and seek to replicate his results. Furthermore, we seek to understand the sources of these proximity effects, if they exist, and what kind of knowledge transfers might explain them.

To confirm Wallsten's results in a robust way we use a more general measure of spatial externalities and a much longer period of analysis. Specifically, we employ a unique dataset that includes all Phase 1 SBIR grants awarded to life sciences firms since SBIR's first award in 1983 up to 2006 and evaluate the potential presence of proximity effects through a continuous response variable instead of the binary win/not win a grant used in Wallsten. We also measure potential proximity effects among life science firms (LSFs) that have received SBIR grants, as well as between such firms and other neighboring LSFs that have not participated in the SBIR program, venture capital firms which have funded LSFs. We do so, in order to evaluate whether proximity effects may be attributable to different types of knowledge transfers. If knowledge in the life sciences, in general, is a key factor of success in securing SBIR grants, then all LSF firms and venture capital firms active in the industry could contribute knowledge that improves the performance of LSFs participating in the SBIR program[10]. We also control for regional and firm characteristics that can also influence the capacity of LSFs to secure SBIR grants. We discuss the methods and procedures we use in our empirical analysis in the next section.

4. Empirical Hypotheses and Procedures

Consistent with the previous discussion the empirical part of the present work needs to account for proximity effects that extend to different narrow spatial units and are expected to be potent at those unit(s) that are closer to the origin firm. Given these considerations, we follow a standard practice in the literature to use neighbors at increasing distances from a central actor in order to

[10] It is possible that knowledge specific to the SBIR program itself but not related to the life sciences could also result in an increase in the level of SBIR funding of LSFs. In such a case, proximity to SBIR winners from other industries could also contribute to the funding performance of LSFs receiving SBIR grants. We consider this possibility in our empirical analysis and report relevant results in Appendix Table 1.

approximate the geographic reach of spatial externalities (see for example Aharonson et al. 2007; Bottazzi and Peri 2003; Kolympiris et al. 2011; Rosenthal and Strange 2003; Wallsten 2001). The general form of the model is

$$y_{it} = X_{it}\beta + \varepsilon \qquad (1)$$

where y_{it}, is an $nt \times 1$ vector of the dependent variable and X_{it} is a matrix of variables used to assess the strength and spatial scope of proximity effects. In our application, the dependent variable is the natural logarithm of the inflation-adjusted sum of the total Phase 1 SBIR amount raised by a given LSF i at year t (*Phase1*) where year t is a year where the LSF has won at least one SBIR grant. We use this dependent variable because it increases with two features of the SBIR program that can be influenced by proximity effects; namely the number of grants awarded to an LSF and the amount of each grant.

The independent variables used to test whether potential proximity effects among SBIR firms exist, measure the number of LSFs that have won at least one SBIR grant between $t-1$ and $t-5$[11] and are located at increasingly distant spatial units from the origin firm. To compare our results with the findings of Wallsten (2001), the first set of neighbors in the empirical model consists of LSFs with at least one LSF SBIR award winner located within 0.1 miles from the origin firm (*SBIR_0.1*) and the corresponding parameter $\beta_{0.1}$ measures the semi-elasticity between the SBIR funds raised by the origin LSF and the number of other LSF SBIR winners in that spatial ring. Similarly, LSFs with SBIR awards located between 0.1 and 0.5 miles from the origin firm compose the second set of neighbors (*SBIR_0.5*) whose effect is measured with the corresponding parameter $\beta_{0.5}$. For consistency and to allow for a comparison between the spatial units considered, we build analogous variables that measure the density of SBIR winners located

[11] We use a 5 year lag because we expect the effects of the knowledge transfer mechanisms to be stronger during that period. However, given the relative lack of theoretical guidance from the extant literature (albeit this lack Acs et al. 2009; and Baum et al. 2000 have, among others , also used 5 year windows) we performed a robustness check and tried shorter and longer lag periods. The results of this robustness check revealed that our estimates are not sensitive to the choice of the lag structure and are not reported here for parsimony.

in radii of 0.5 miles that are increasingly distant from the origin firm. To test whether proximity effects are potent at immediate vicinity we compare the statistical significance and the estimated magnitude of *SBIR_0.1* with the corresponding values for the remaining density variables. We estimate the spatial unit at which proximity effects cease to exist as the density variable after which the proceeding variables are statistically insignificant and of small economic magnitude. For instance if the *SBIR_0.5* variable was significant and the variables that reflect SBIR winners located between 0.5 and 1 miles and 1 and 1.5 miles from the origin firm were statistically insignificant, we would conclude that proximity effects are effectively exhausted at the 0.5 miles radius. We also expect the magnitude of the β's to decrease as we move farther away from the origin LSF which would indicate that the strength of proximity effects decays with distance until it eventually dies off. [12]

It is possible that SBIR LSFs can benefit through knowledge transfers from proximate venture capital firms as well as from other LSFs that are not participating in the SBIR program. To test for the presence of such proximity effects we evaluate the potential presence of spatial externalities among SBIR LSFs and Venture Capital Firms (VCFs) active in the life sciences industry. SBIR LSFs can use nearby VCFs as sources of knowledge since local networks of VCFs tend to generate non publicly-available knowledge (Shane and Cable 2002) and empirical evidence (Kolympiris et al. 2011) suggests that the presence of VCFs in proximity is beneficial for the performance of LSFs. As before, we expect any benefits of collocation with VCFs to wane with distance and, accordingly, we specify six non-overlapping variables (*VCFs_0.1,*

[12] It should be noted that in addition to measuring the association of the sum of SBIR funds raised by a given LSF with the density of SBIR winners located in different spatial rings we also considered its association with the sum of funds raised by the proximate SBIR winners. Initial empirical results from the two alternative approaches were qualitatively similar and we opted for using the density of SBIR firms for two reasons: First, it allows for a direct comparison with Wallsten (2001) who also considered firm density in his study. Second, Phase 1 grants are typically of similar magnitude across firms and as a result the amount of funds from SBIR grants accumulated from LSFs in a given radius was found to be highly correlated with the corresponding measure of SBIR firm density in the relevant spatial rings.

VCFs_0.5, VCFs_1, VCFs_1.5, VCFs_2, VCFs_2.5)[13] that include the number of VCFs located in the same radii considered for the SBIR winners. We expect positive signs for these variables and the magnitude to decrease as we move from *VCFs_0.1* to *VCFs_2.5*.

In order to account for possible proximity effects between the origin firm and LSFs that have not received SBIR grants we also include in X_{it} of equation (1) variables that measure the number of non-SBIR LSFs in the same rings used for the SBIR winners (*NON_SBIR_0.1, NON_SBIR_0.5, NON_SBIR_1, NON_SBIR_1.5, NON_SBIR_2, NON_SBIR_2.5*). The performance of the origin firm may improve due to knowledge transfers from the proximity with the non-SBIR LSFs which could eventually lead to an increase of SBIR funds for the origin firm, generating positive coefficients [14].

To effectively measure the strength and geographic scope of knowledge spillovers we must also account for regional characteristics that could affect the level of SBIR funding received by LSFs at different locations. For instance, LSFs that are close to universities may benefit from potential knowledge transfers (Acosta et al. 2009; Ponds et al. 2007) and previous research has shown that knowledge transfers from universities can extend up to the MSA level (Anselin et al. 1997; Anselin et al. 2000; Black 2005; Varga 2000). Accordingly, we include a variable (*Universities*) that measures the number of universities active in life sciences research that are in each firm's MSA and we expect a positive sign for the coefficient of this variable.

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[13] As with SBIR LSFs we initially specified variables that measured potential spatial externalities with VCFs at larger distances from the origin firm but we pared down the specification of our variables to those presented above as we could not find statistically significant impacts in larger distances. We also examined proximity effects with VCFs and SBIR LSFs through an alternative specification. Because many locations do not host a large number of VCFs and because the potential impact of VCFs may go beyond immediate proximity, following previous literature (i.e. Samila and Sorenson 2011) we also measured the density of VCFs at the MSA level. We discuss the empirical results of these alternative specifications in the next section.

[14] As we explain in the next section, the empirical assessment of such potential proximity effects is hampered by the fact that while we can locate the non-SBIR LSFs in space we cannot assess whether they never applied for an SBIR grant or they were unsuccessful in sourcing SBIR grants. This is important as underperforming firms may have a negative proximity effect on the origin SBIR LSF. Beaudry and Breschi (2003) document the potential of negative effects arising from collocation with underperforming firms. As a result, we include the particular variables in the analysis to account for the potential knowledge transfer but, as we explain below, we interpret the results with caution.

A number of states provide support services to LSFs applying for SBIRs through their Small Business Administration offices but also through private consulting organizations.[15] Highly effective consulting services could greatly enhance the capacity of LSFs to secure larger sums through the SBIR program and we account for the potential impact of such consulting services available at different states in the empirical analysis.

LSFs can become more efficient and secure more SBIR grant funds if they benefit from urbanization economies, defined as gains from collocation with firms in different industries (Rosenthal and Strange 2003). We account for this effect on SBIR funds by including the average number of non-LSF establishments in the LSF's zip code from 1992 to 2006 (*Establishments*) as an indicator of such urbanization economies. We expect the sign of the coefficient for this proxy variable to be positive.

We also include a set of variables that are specific to a given LSF and are expected to influence the magnitude of SBIR funds raised in a given year. A firm's prior experience with the SBIR program may be important and we evaluate the potential effects of such past experience with two variables. The first measures the average of the real SBIR funds awarded to the origin LSF from $t-1$ up to $t-5$ (*PreviousSBIR)* while the second variable measures the number of years since the last SBIR grant awarded to the origin LSF (*Last*). Since organizations benefit from experience and prior knowledge (March 1988) we expect a positive sign for the first variable and a negative sign for the second variable[16].

A core criterion for SBIR awards is the degree of innovation in the proposed project(s) (Wessner 2009a). Accordingly, more innovative firms are expected to attract more SBIR funds. To account for such a potential effect, we follow previous literature (e.g. Autant-Bernard 2001;

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[15] Examples of private organizations that offer consulting services on securing SBIR grants include Foresight S&T in Rhode Island and the Larta Institute in California and the District of Columbia.

[16] Note that in addition to experience, the *PreviousSBIR* variable may capture unobserved qualities and characteristics of the LSF that make it successful in acquiring SBIR funds and as such the relevant empirical results should be interpreted carefully.

Boix and Galletto 2009) that used patents as a proxy for innovation and add a variable that measures the total number of patents awarded to each LSF by 2006 (*Patents*). We expect this variable to have a positive sign[17].

LSFs can receive grants from a number of funding agencies under the SBIR program including the United States Department of Agriculture, the Environmental Protection Agency and the Department of Electricity Development. However, LSFs in the biopharmaceutical industry receive most of their funds from the National Institutes of Health (NIH). Up to 2006, NIH was the only agency in the SBIR program whose Phase 1 grants exceeded the $ 100,000 cap (pg. 39, Wessner 2009a) imposed by other agencies. Furthermore, biopharmaceutical LSFs tend to have access to grants from a broader set of agencies as compared to other LSFs (say those focused on agriculture or energy). As such, we expect that biopharmaceutical LSFs might have, on average, higher levels of funding and we include a dummy variable that equals 1 for biopharmaceutical LSFs (and 0 otherwise) and expect a positive sign (*BioPharma*).

We also analyze the potential effects of time on an LSF's development process with a variable that measures the age of the LSF at the SBIR award(s) year (*Age*). Older LSFs may become less aggressive in pursuing government funds, plausibly, due to increased reliance on alternative sources of capital. Therefore, we expect a negative sign for the *Age* variable. In order to incorporate potential nonlinearities in the relationship between age and SBIR funds acquisition, we also include the age variable in its quadratic form (*AgeSquare*).

Along the same lines, we examine the potential impact of the size (number of employees) of the origin LSF firm at time t (*Size*)[18] on its capacity to secure SBIR grants. Firm size may

[17] It should be noted, that there is potential for simultaneity of the patent variable with the dependent variable because we report the total number of patents over a range of years and some of the patents may have resulted from SBIR grants. Unfortunately, differential and often unobserved lags in the dates of discovery, patent submission and patent issuance make proper allocation of the patents by year exceedingly difficult and as a result we opt for including a total patent count as an indicator of the innovative character of each firm. For this reason, the relevant empirical results should be treated with caution.
[18] We, however, followed the codification scheme described in Table 2 because the number of employees is typically reported by firms in discrete categories.

have two opposing effects on SBIR funds grant acquisition, and as such the sign of the variable is not clear beforehand. On the one hand, larger firms may generate a larger portfolio of projects for which they may pursue and acquire larger sums of SBIR grants. On the other hand, larger firms may have more in-house resources to fund early stage projects and, as a result, they may be less interested in SBIR grants.

Finally, we control for a policy change in 1994 that increased the total number of SBIR grant awards (Wallsten 2001) and we expect LSFs to increase their total SBIR funds as a result of this policy shift. In particular, following the 1992 congressional reauthorization of the program, the set aside of each agency that participated in the SBIR program increased gradually from 1.5% in 1993 to 2.5% in 1997. Moreover, differential rates across agencies for the SBIR set-aside were also eliminated. These changes resulted in substantial increases in the total amount of Phase 1 SBIR awards. Accordingly, we include a dummy variable (*After_94*) that equals 1 if the dependent variable corresponds to a year after 1994 (0 otherwise) and expect a positive sign.

5. Data, Variable Definition and Descriptive Statistics

InKnowVation, Inc. provided a dataset on the Phase 1 SBIR grants awarded to LSFs from the first SBIR award in 1983 up to 2006. The dataset included specific information about the dollar amount and nature of each grant as well as about the LSF that won each individual grant. This information was used to construct the dependent variable and the *Age*, *AgeSquare*, *Size*, *Patents*, *Last*, *After_94*, and *PreviousSBIR* variables. For the *PreviousSBIR* variable we converted the nominal amounts of each grant to real amounts (2006 $) using the CPI. The data from InKnowVation, Inc. included the address of each SBIR winner which we converted to geographic coordinates to develop the *SBIR_0.1, SBIR_0.5, SBIR_1, SBIR_1.5, SBIR_2,* *SBIR_2.5* variables. In order to identify biopharmaceutical firms and construct the *BioPharma* variable, a keyword search was performed for all LSF descriptions[19] included in the InKnowVation dataset. The total number of establishments at each LSF's zip code (*Establishments*) was collected from the U.S. Bureau of the Census. The number of universities with life sciences research activity located at each LSF's MSA (*Universities*) was compiled from information provided by the Association of University Technology Managers and the publicly available list of research grant recipients from the National Institutes of Health. Finally, we used the Thomson's Financial SDC Platinum database, the Zoominfo web-based database, and the web-based Moneytree report to identify LSFs that have not won SBIR grants as well as VCFs active in the life sciences located in the areas of interest. The address of each relevant LSF and VCF were transformed to geographic coordinates[20] which were, in turn, used to construct the *VCF_0.1, VCF_0.5, VCF_1, VCF_1.5, VCF_2, VCF_2.5, NON_SBIR_0.1, NON_SBIR_0.5, NON_SBIR_1, NON_SBIR_1.5, NON_SBIR_2,* and *NON_SBIR_2.5* variables. The final dataset consisted of 4832 observations from 1673 LSFs that won 7731 Phase 1 grants from 1983 up to 2006.

[19] The biopharmaceutical keywords list was constructed after consulting with biotechnology researchers employed at the authors' institution. The list included the following terms: Allergen, Antibodies, Antigen, Ascites, Biomedicine, Cancer, Cardiovascular, Cartilage, Central Nervous System, Chinese Hamster Ovary, Cho cells, Collagen, Dermal, Endocrine, Gene therapy, Genetic disorders, Growth hormone, Immune suppression, Immunodeficiency, Infectious disease, Insulin, Ligament, Lymphoma, Magnetic resonance imaging (MRI), Monoclonal antibodies, Myocardial infarction, Oncogene, Pharmacokinetics, Polyclonal antibodies, Polyvalent vaccine, Renal, Respiratory.

[20] One issue that has plagued previous research is how to correctly identify the location of relevant organizations. For example, often only the address of the corporate headquarters or main university campus may be recorded in datasets while the locations of other facilities are not reported. We cope with such potential issues in our dataset in the following ways: For SBIR LSFs and non-SBIR LSFs, proper identification of location is relatively straightforward because these firms are typically small and they only have one location. For the small number of firms with a relatively large number of employees, we visited the website and for a handful of firms with multiple locations we recorded all such locations. For the venture capital firms active in the life sciences sector, we visited their websites in all occasions and we used their multiple locations in the very few cases that multiple locations existed. In the case of the universities used in our analysis, we received data from AUTM on campus locations with active research life sciences programs which we complemented with data available from NIH on all university locations that received NIH funding over the period of analysis. We further used Google Earth ® and visited the website of each institution to ensure that we could identify the proper locations of the universities and associated medical schools in our sample. While it is still possible that some locations of relevant organizations might have been overlooked, our focus on the life sciences has allowed us to minimize such potential shortcoming.

[Table 1 about here]

[Figure 1 about here]

Table 1 presents the zip codes, cities and states with the most SBIR winners in our sample. The top 5 states host a bit over 50 percent of all SBIR winners (the top 3 states alone host 42 percent of the winners) while the corresponding shares for the top 5 cities and zip codes are almost 15 and 11 percent respectively. In some states SBIR winners are more heavily concentrated at the city or the zip code level than others. For instance, in California SBIR winners are geographically concentrated as 3 zip codes are home to more than 31 percent of all LSF firms in the state receiving SBIR grants. In fact, 94 of the 412 SBIR winners in the state are located in the 92121 zip code in San Diego[21]. Even more interesting is the spatial distribution of firms in the 92121 zip code which is illustrated in Figure 1. With the exception of two LSFs, which do not appear in the map, the rest of the LSFs in the zip code are located within walking distance from at least one other LSF as they often locate in the same office park or the same business incubator; hence they reside within yards from other LSFs. Office parks and incubators are in the center of a life science research and development cluster that includes a major research university, renowned research institutes, a number of large LSFs and four venture capital firms active in the industry. Further, almost all office parks and business incubators in the area are located within 2 miles distance from each other as they are connected through a major highway.

The location patterns of zip code 92121 are replicated in a number of other states. For instance, the 20850 zip code in Rockville, MD along with the city of Gaithersburg, MD hosts 51 of the 112 SBIR winners in the state. Most of these LSFs are located very close to each other and often in the same building, office park or incubator. Similarly, 5 of the 10 SBIR winners in Arkansas are located at the same zip code and within walking distance to each other and 12 of

[21] Walcott (2002) provides a detailed case study of the growth of the San Diego bioscience cluster with insightful references on geographical patterns.

the 19 SBIR winners in Arizona reside in the same city in proximate locations. These spatial characteristics and the implied collocation of LSFs acquiring SBIR grants and other relevant firms could, at least in part, rationalize the potential presence of proximity effects with limited geographic scope.

There are also states that LSF SBIR winners exhibit less geographic concentration, however. LSFs that have received SBIR funds located in Massachusetts are more spread out geographically with only 31 of the 178 winners in the state residing in 1 of the top 5 zip codes. Similarly diffused patterns are observed in other states as well. 23 zip codes in 15 cities host the 33 SBIR winners in Florida while 11 zip codes in 8 cities host the 16 SBIR winners in Indiana.

[Figures 2a to 2d about here]

The maps presented in Figures 2a to 2d show the location of the SBIR LSFs in our sample. LSFs are classified according to their total SBIR funds from 1983 up to 2006, and larger symbols in the Figures indicate LSFs surrounded by a greater number of SBIR winners from $t-1$ to $t-5$ in the same zip code.[22] Many LSFs in our sample are located in East Coast and West Coast cities such as San Diego, San Francisco, Boston and New York. However, a number of LSFs winning SBIRS are located in urban and rural interior cities such as Gainesville, Florida; Scottsdale, Arizona; Atlanta, Georgia; and Chicago, Illinois.

The general pattern observed from Figures 2a to 2d implies that, on average, LSFs receiving the most SBIR funds are surrounded by an above average number of SBIR winners in their zip code and the opposite. LSFs with low success and levels of SBIR funding are surrounded by a lower than average number of SBIR winners in their zip code. While Figures 2a to 2d imply a positive association between the number of neighboring SBIR firms and origin

[22] We used the zip code – instead of the units used in the empirical analysis - as the unit of presentation in the map because it is the smallest spatial unit for which symbols do not overlap to the degree of making the map prohibitively difficult to assess visually.

LSF's SBIR funding over a 23 years period, they do not account for the influence of other proximate LSFs and VCFs or for relevant regional and firm characteristics. We use the estimated empirical model to provide a more complete account of all such relationships in the next section.

[Table 2 about here]

Table 2 presents descriptive statistics for the dependent and explanatory variables. On average, the LSFs in our sample sourced $162,442 per year with most of them receiving close to $ 97,000. LSFs located in close proximity to other LSFs (typically in the same office park or business incubator) accumulated, on average, substantially more SBIR funds over time than more isolated LSFs. Across the whole sample, each LSF had, on average, 0.37 SBIR winners in a 0.1 miles radius, another 0.68 winners in a 0.5 miles radius and about 1 more winner in each of the remaining spatial units considered in the empirical analysis. Note that regardless of the spatial unit considered, the standard deviation of the number of winning LSFs in that unit is larger than the average value, which indicates the wide range of values in the observed spatial density among winners. Also, the modal value of most spatial units considered was 0, which indicates that most of the observations in the dataset come from spatially disconnected regions.

On average, each LSF: was located in MSAs with more than 8 universities that conducted some life sciences research; had 0.03 and 0.22 VCFs in a 0.1 and 0.5 miles radius respectively; had 0.2 and 0.7 LSFs with no SBIR funding in a 0.1 and 0.5 radius respectively; and had more than 1,000 non-LSF business establishments in the same zip code. With regard to firm-specific features, the average LSF receiving SBIR funds had more than 14 patents, it was about 7 years old when it received the SBIR grant(s) and had 15 to 19 employees.

Not reported in Table 2, is the geographic location of the non-SBIR LSFs which resembles the geographic distribution of SBIR winners, though there is a higher relative concentration of non-SBIR LSFs in California and Massachusetts. This pattern may be explained by the higher concentration of venture capital firms in the East and West Coast

(Powell et al. 2002) which may have provided alternative funding sources for non-SBIR LSFs. SBIR LSFs and non-SBIR LSFs have similar number of patents (non-SBIR LSFs had, on average, close to 13 patents) and had a similar average age and age distribution. Finally, the distribution of LSFs according to their research specialization was somewhat different across the two sets. While approximately 32 percent of the SBIR winners were biopharmaceutical LSFs, the corresponding share for the non-SBIR LSFs was close to 45 percent.

6. Estimation Results

White's test suggests strong presence of heteroskedasticty and for that reason we estimated the model with OLS using White's heteroskedastic-robust variance estimator. The parameter estimates from this model are reported in the first column of Table 3. LSFs that have won SBIR grants in multiple years enter the dataset more than once.[23] These LSFs may possess unobserved characteristics that allow them to be more successful in sourcing grants from the federal government on a yearly basis and, hence, the errors associated with different annual observations of individual LSFs may be correlated.

The errors associated with observations of different LSFs located in the same state may also be correlated because the amount of funds raised by such LSFs may be influenced by systematic differences in the portfolio and quality of support services provided by Small Business Administration offices and private consulting organizations to firms interested in SBIR grants across different states. Ideally, we would like to directly account and measure any potential qualitative differences in the support services received by LSFs across states, but any such effects, if they exist, are difficult to observe and measure. Hence, in addition to firm effects,

[23] Approximately one third of the LSFs in the sample are repeated winners and are mostly larger firms.

there might also be unobserved state effects which could lead to the errors associated with different annual observations of individual LSFs in the same states to be correlated.

The potential firm- and state-specific unobserved factors above may lead to violations in the assumption of independence across observations (Nichols and Schaffer 2007; Stimson 1985). In order to evaluate whether such potential violations are present and correct for them, the last two columns of Table 3 report parameters and standard errors that are estimated using generalized estimating equations (GEE),[24] which account for the potential clustering of residuals at the firm and the state level respectively. Overall, the estimated parameters remain the same but their statistical significance does change with the type of estimator used. Based on the statistical significance of all the estimated parameter estimates, we find that the model accounting for the potential clustering of errors at the state level is superior and we use it as the basis for the discussion of our empirical results below (see third column of Table 3).

[Table 3 about here]

Because the dependent variable is in logarithmic form and the variables that measure the number of SBIR winners in different spatial units are in level form, the corresponding coefficients can be interpreted as semi-elasticities. An additional SBIR winner located within a 0.1 miles radius from the origin LSF is associated with a 4.5 percent increase in the SBIR funds acquired by the origin firm. Evaluated at the mean of the dependent variable ($162,442), the 4.5 percent increase translates into an additional $7,378 per year for each one additional SBIR winner located in the immediate proximity. To put this figure in context, one might think of the 10 SBIR winners that are, on average, found to collocate in close proximity (0.1 miles radius) in San Diego. Collocation in such close proximity is then associated with $73,782 more funding

[24] GEE is a method to estimate the standard errors which first estimates the variability within the defined cluster and then sums across all clusters (Zorn 2006).

for each origin LSF, or almost half of the $162,442 average SBIR funding received by LSFs in the sample. Just as Wallsten (2001) did, we therefore also find strong evidence that LSFs receiving SBIR grants located in very close proximity with other SBIR winners enjoy a significant advantage in securing such funds – a proximity effect with a very narrow geographic scope.[25]

With regard to the threshold level where the proximity effects are exhausted, we find that the benefits from collocation cease at a 1.5 miles radius from the origin firm. We also find a sort of discontinuity in the impact of collocation with other SBIR winners. While the variables that measure the impact of SBIR LSF density at a 0.1 to 1 mile radius from the origin firm are statistically insignificant, the corresponding variables for a 1 to 1.5 miles radius are statistically strong and of meaningful size. Specifically, an additional SBIR winner located between 1 and 1.5 miles radius from the origin LSF is associated with a 2.38 percent increase in the SBIR funds acquired by the origin firm. Therefore, as in previous studies, we find that the effects of proximity decline with distance.

The discontinuity in the above proximity effects, however, is of interest. Close inspection of the geographic location of firms in our dataset reveals that in many regions there is significant and dense clustering of LSFs that receive SBIR grants through collocation in the same office parks or business incubators. These types of facilities typically cover areas between 0.5 and 0.7

[25] The size and reach of research collaborations and networks has increased over time as communication costs have declined. These types of effects have also been mentioned in the literature (Johnson and Lybecker 2012) and such changes could have changed the geographic scope of the proximity effects. As a robustness check to the sensitivity of our results against such considerations we constructed two alternative empirical specifications: (a) one where a time trend was added to our base model (to represent ongoing reductions in communication costs) and where the trend was interacted with the independent variables that measure the density of SBIR winners in close proximity to the origin firm (to test for changes in the geographic scope of proximity effects); (b) another where our base model was modified to allow the above-mentioned density coefficients to differ over two selected sub-period spanning the 1983-2006 period of analysis. The results were generally similar but because of the limited number of observations in the early years of the sample and the increase in the size of the SBIR program in 1994, the inclusion of a time trend in our model conflicted with the 1994 dummy variable and generally caused significant multicollinearity that raised the condition index well above the generally accepted threshold of 30 and rendered inference from such results problematic. The empirical results from the second specification were generally invariant to the choice of sub-periods. We have reported the empirical results for one of such models in the Appendix Table 2. All the empirical models we estimated, including the one reported here, did not support any shift over time in the geographic scope of the proximity effects in our sample.

mile radius. Hence, the strong spatial externalities effects that we measure among LSFs in very close proximity seem to be driven by cohabitation of many of these small firms in the very same facilities. Weaker but still meaningful proximity effects are also found within distances of 1.5 miles from the origin firms and these appear to be related to the presence of other nearby firms but which do not occupy the same quarters.[26]

Increased density of non-SBIR LSFs in very close proximity (within 0.1 mile radius) is found to have a positive and statistically significant impact on the SBIR funding of the origin LSF. More specifically, an additional LSF that has not received SBIR funding located within a 0.1 miles radius from the origin LSF is associated with a 2.71 percent increase in the SBIR funds secured by the origin firm. However, the impacts of non-SBIR LSFs located in more distant spatial units are statistically insignificant. These empirical results therefore support the presence of proximity effects only among very closely located SBIR and NON_SBIR LSFs[27].

The presence and density of VCFs active in the life sciences and located at immediate proximity to the origin LSF does not have a significant impact on the level of SBIR funds received as none of the estimates for *VCF_0.1, VCF_0.5, VCF_1, VCF_1.5, VCF_2, VCF_2.5* is found to be statistically significant. Hence, we do not find empirical support for the presence of

[26] Note, for instance, that clustering of two firm cohorts in side by side office parks or business incubators of typical size would tend to imply that firms within the cohabitating cohorts would, typically, be less than 0.2 miles apart from each other while firms between cohorts would be located 1-1.5 miles apart. These types of patterns will tend to influence all empirical measures of proximity effects and must be explicitly taken into account.

[27] It is possible that there may be additional proximity effects between the origin LSF and firms from industries other than the life sciences which have received SBIR grants. The performance of the origin LSF may improve from proximity with non-LSF SBIR winners if knowledge specific to acquiring SBIR grants is useful, yielding positive coefficients. To capture any such potential proximity effect, we include in X_{it} of equation (1) a variable that measures the number of non-LSF SBIR winners (NON_LSF_SBIR) that are located in the same zip code as the origin LSF. We examine proximity effects with non-LSF SBIR winners at the zip code rather than through a sequential ring specification due to the very large number of non-LSF SBIR winners which makes the ring specification practically intractable. For instance, in our empirical analysis, construction of a variable that would measure the density of non-LSF SBIRs in a single ring over a 23 years period would require 556,021,550 calculations (14,450 non LSF-SBIR firms * 1673 LSFs * 23 years). We present the empirical results of this specification in Appendix Table 1 and we find that while the remaining of the parameter estimates are largely unchanged, the estimated coefficient of NON_LSF_SBIR is negative. As a result, we do not find empirical support that proximity of LSFs to firms from industries other than the life sciences which have won SBIR grants could improve their funding performance.

proximity effects from the collocation of VCFs and LSFs receiving SBIR grants[28]. Our empirical results indicate that the presence of universities with some research in the life sciences located within the same MSA with LSFs acquiring SBIR funds have a positive, but relatively modest, effect on their funding and each additional proximate university contributes a 0.18% increase. We also find that LSFs located in regions with high concentration of businesses, an indicator of urbanization economies, benefit from such environment and associated agglomeration effects and have higher average levels of SBIR funding.

Our empirical results suggest that the individual characteristics of the LSFs in the sample also affect their levels of SBIR funding. Our estimates suggest that biopharmaceutical LSFs accumulate, on average, 7% more SBIR funds than all other LSFs in the sample. Experience and prior success in acquiring SBIR grants also matter. *PreviousSBIR* is statistically significant and an additional $1000 raised within the previous five years by the origin LSF is expected to generate a 0.28 percent increase in SBIR funds at present time. The age and size of LSFs, however, do not have a distinguishable impact on the amount of SBIR funds secured by these firms.

We also find that LSF's patenting activity does not explain the amount of SBIR funds secured by LSFs in the sample. While our measure of patenting activity is aggregate in nature and somewhat crude, it still suggests that a strong overall patent portfolio is not associated with success in SBIR grant activity among LSFs in our sample. Finally, we find that the policy changes which resulted in a significant shift in the overall amount of SBIR funds distributed by the various agencies, is closely reflected in the average amount secured by LSFs in our sample.

[28] As we explain in footnote 13 we also built models where the density of VCFs is measured at the MSA level. Because the density of VCFs at the MSA level and the count of research universities at the same level were highly correlated (correlation coefficient 0.78) we could only use one of the two variables at a time as the multicollinearity index of the model where both variables were included raised significant inference concerns. When the density of VCFs in the MSA replaces the density of research universities in the MSA, the empirical estimates suggest that the presence of variable of interest is statistically significant and positive but it has a very small effect on the amount of SBIR funds raised by a given LSF. The rest of the empirical results remain robust as discussed in the base model in Table 3.

7. Discussion and Concluding Comments

Prompted, in large part, by the apparent clustering of firms in knowledge industries, a large number of studies have examined the effects of spatial proximity on firm knowledge and innovation. Numerous theoretical and empirical contributions have demonstrated that the innovative performance of firms can benefit from spatial proximity with other like firms but fewer studies have attempted to measure the exact geographic scope of such proximity effects. Those studies that do measure them have typically focused on the outer limits of the proximity effects and, most often, have concluded that such spatial externalities extend over long geographic distances. Little attention, however, has been given to the strength and scope of proximity effects among firms located in close vicinity to one another and this is curious since most theoretical constructs would predict that proximity effects should be most evident among nearby firms.

In this study we examine the size and geographic scope of proximity effects among life sciences firms that receive SBIR grants. We investigate the potential presence of proximity effects among all LSFs in the US that have received SBIR grants over a 23 year period while controlling for relevant regional and firm characteristics. From our empirical analysis we conclude that proximity effects among nearby firms are strong and are exhausted within a radius of 1.5 miles. Indeed, we find that the benefits from collocation are significantly stronger among firms located within one tenth of a mile from each other, a tiny distance by all measures. Our empirical results are consistent with those of Wallsten (2001), Aharonson et al. (2007) and Rosenthal and Strange (2003), the few studies that have measured spatial externalities in the immediate proximity of firms.

By focusing on the life sciences alone, we are able to distinguish the potential sources of proximity effects by the type of knowledge they might possess (e.g. SBIR LSFs, non-SBIR

LSFs, VCFs, non-LSFs receiving SBIR funds) and such distinction is important for understanding the modes of knowledge transfer that might contribute more significantly to proximity effect. Furthermore, by focusing on a single industry we examine proximity effects in a theoretically consistent way since knowledge spillovers, network externalities and other forms of knowledge transfers are generally presumed to occur mainly across firms of the same industry.

Importantly, our focus on a single industry allows a detailed look in the underlying data and relevant insights. By examining the exact geographic location of each firm in our sample we can rationalize how proximity effects can materialize in very short distances. A large number of firms in our sample are found to cohabitate in the same office complexes or business incubators, in some cases being located a few yards from each other and frequently at a walking distance. These phenomena are, in part, specific to the types of firms we study– smaller firms that generally need less space and more technical assistance during their early stages of development. Accordingly, proximity effects among larger firms with more human resources and more extensive networks could prove of greater geographic scope. Still, we contend, that from our study we can draw some useful conclusions that are broadly applicable.

First, we find that to fully understand the true nature of proximity effects and the mechanisms that make them possible we must first measure them with some degree of accuracy. This implies the need to evaluate their strength and geographic scope in various settings. Second, since knowledge spillovers, network externalities and other forms of knowledge transfers are, generally, not directly observable and difficult to measure, starting with distances and industries where proximity effects most likely exist would seem to make sense. Third, by linking the size of proximity effects to sources of particular types of knowledge, specific physical assets and patterns of industrial organization, useful policy recommendations maybe possible. For instance, in our study we find that spatial externalities are particularly strong in very close proximity and such vicinity most often materializes through collocation of small life sciences firms in office parks, business incubators and like facilities. If this result could be generalized, it would strongly suggest that there is significant scope for public investments in such facilities and associated services. In fact, such a result would not only suggest that in the absence of public investment a market failure would likely result (less than socially optimal capital investment) but it would also imply that the burden of such investment should be shared by governments in locales where direct, indirect, induced and employment effects could materialize.

Understanding the exact nature, geographic scope, mechanisms and assets that nurture proximity effects is of interest to public granting agencies promoting innovation, directors of national and regional industrial development policies, directors of technology transfer at different universities, venture capital investors, designers of facilities and developers of clusters, and all kinds of policy makers. The interest is understandable as knowledge spillovers, network externalities and other forms of knowledge transfers that yield improvements in industrial innovation are about as close to a "free lunch" as one gets in economics. Measuring the size and scope of proximity effects is an important first step to fully understanding and we find here that "starting small" can provide important insight.

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Figure 1

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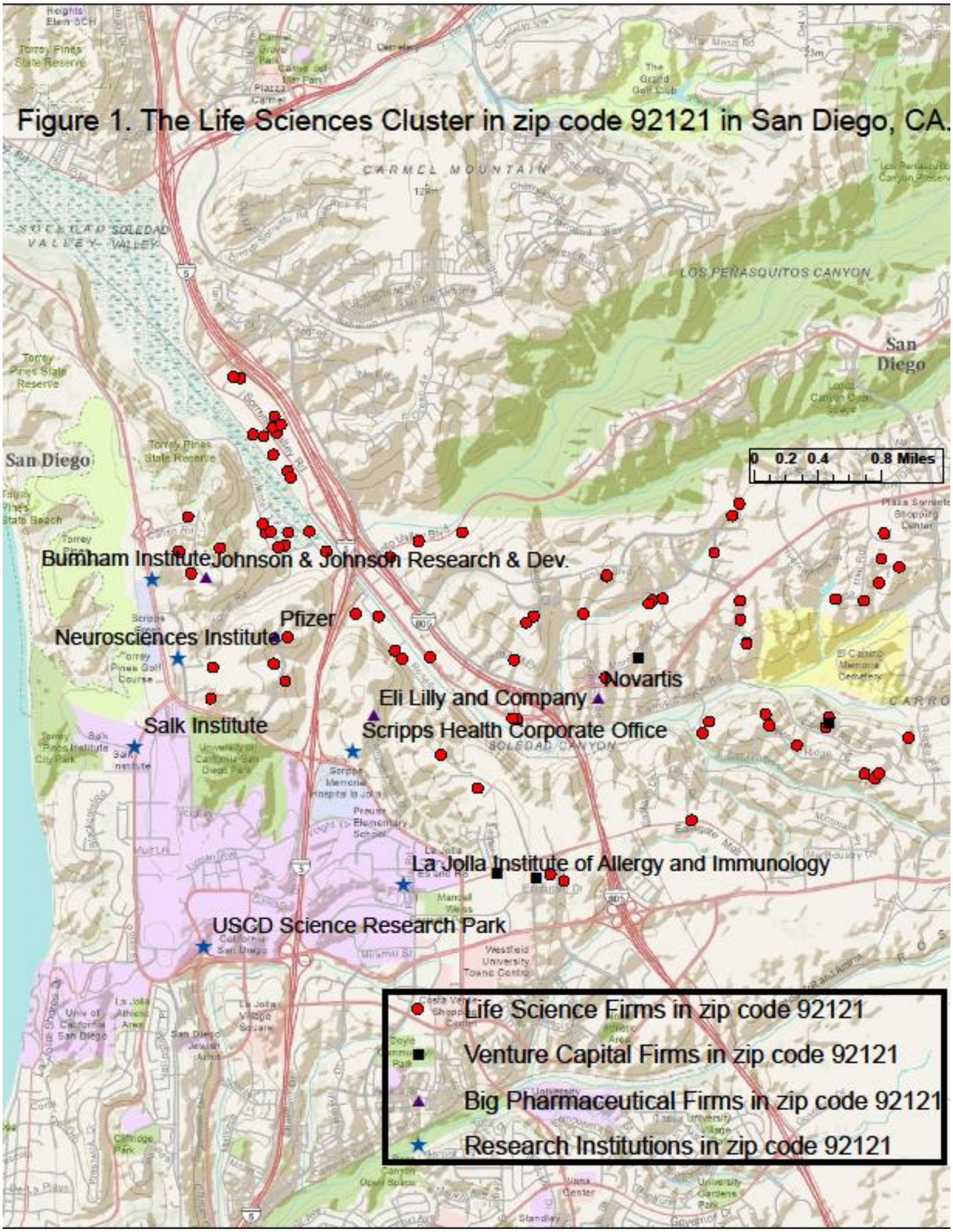

Figure 2a
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Figure 2a. Life Sciences Firms with the Highest Sum of SBIR Funds from 1983 to 2006.

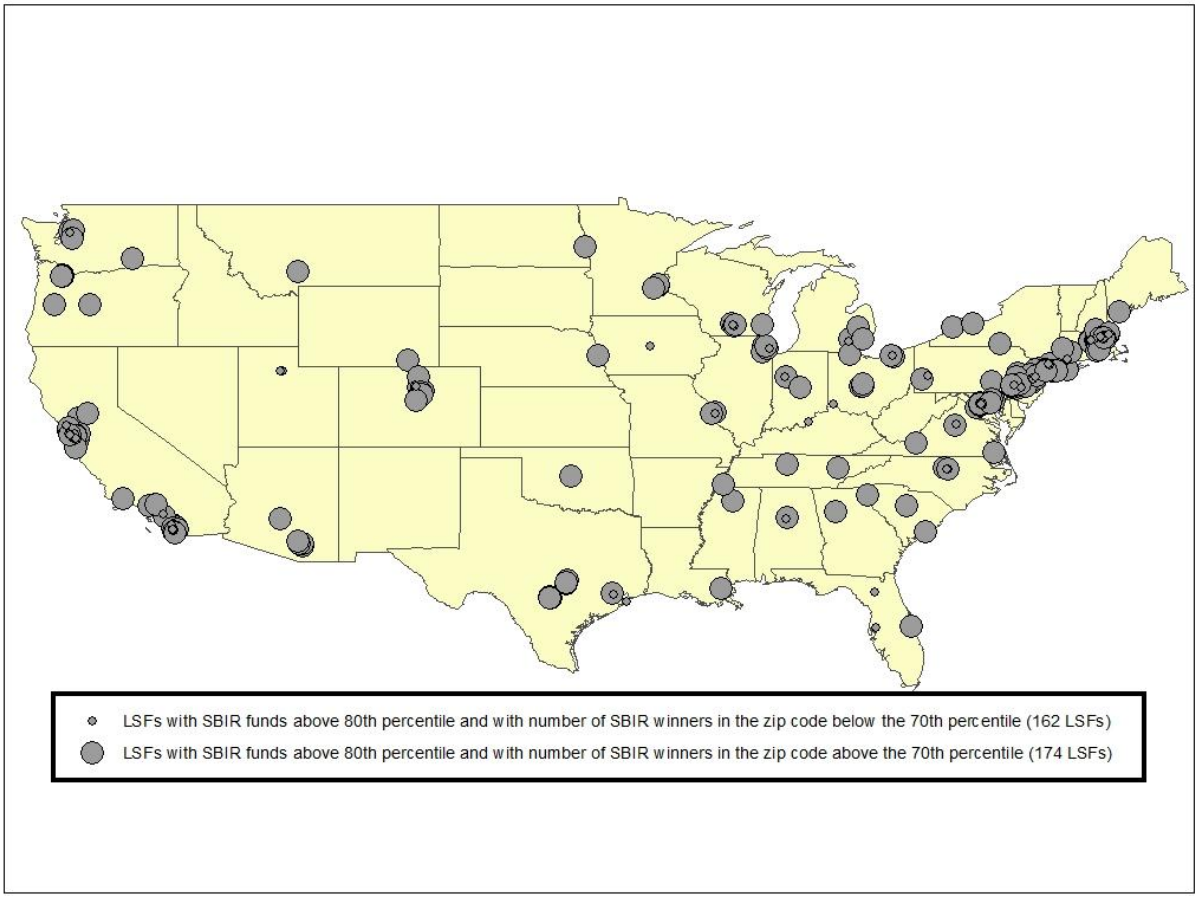

Figure 2b. Life Sciences Firms with Above Average Sum of SBIR Funds from 1983 to 2006.

Figure 2c
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Figure 2c. Life Sciences Firms with Below Average Sum of SBIR Funds from 1983 to 2006.

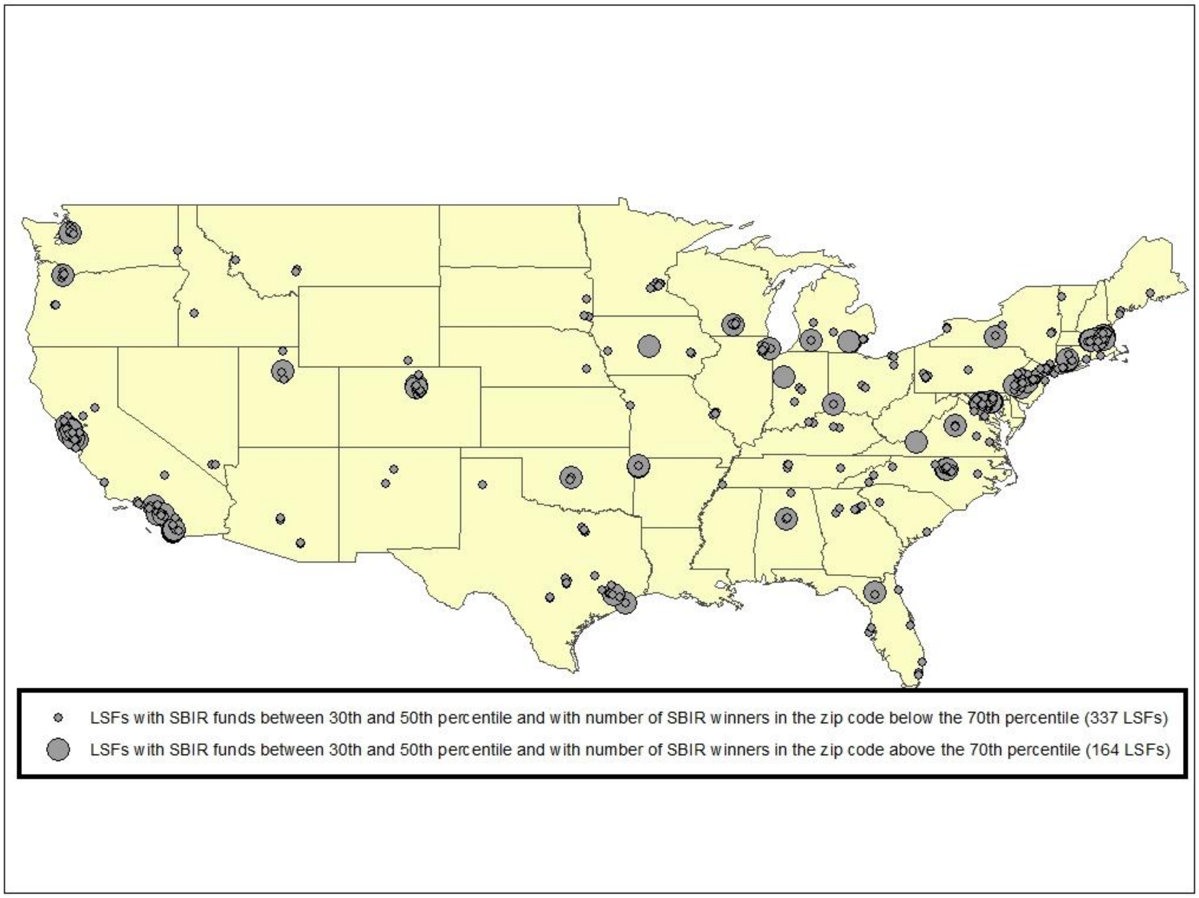

Figure 2d
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Figure 2d. Life Sciences Firms With the Lowest Sum of SBIR Funds from 1983 to 2006.

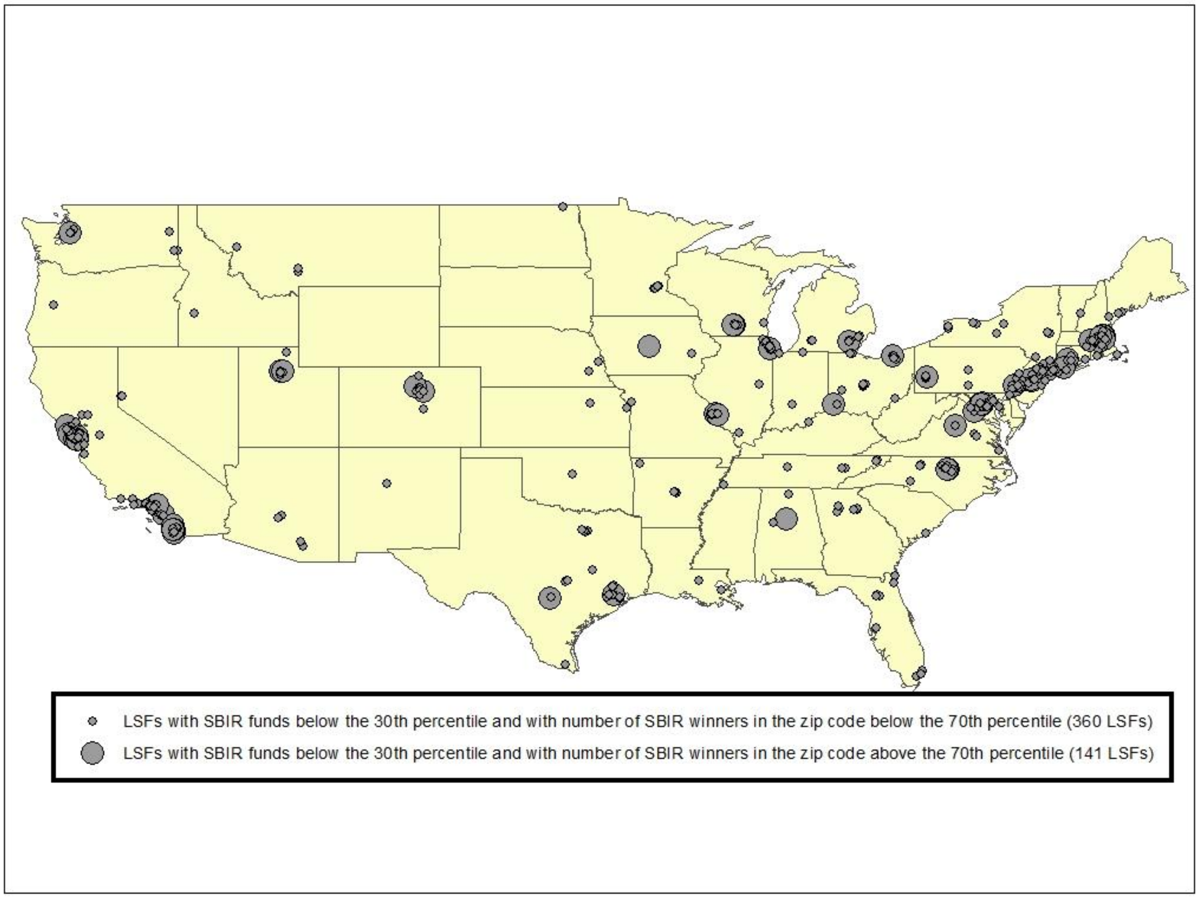

Table 1 Top 5 Zip codes, Cities and States in terms of SBIR LSFs (1671 SBIR LSFs in the sample)

	Zip Code	City	State	# of SBIR LSFs	Percentage of Total SBIR LSFs in the Sample
Top 5 Zip codes	92121	San Diego	CA	94	5.63%
	02139	Cambridge	MA	31	1.86%
	20850	Rockville	MD	22	1.32%
	94080	South San Francisco	CA	19	1.14%
	94043	Mountain View	CA	17	1.02%
Top 5 Cities		San Diego	CA	115	6.88%
		Cambridge	MA	47	2.81%
		Seattle	WA	30	1.80%
		Gaithersburg	MD	29	1.74%
		Madison	WI	28	1.68%
Top 5 States			CA	412	24.66%
			MA	178	10.65%
			MD	112	6.70%
			NY	77	4.61%
			PA	72	4.31%

Table 2
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Table 2 Descriptive Statistics of Variables Used in the Empirical Model (4832 observations in the dataset from 1673 LSFs SBIR winners)

Variables / Statistic	Number of Observations with a Value of 1	Mean	Median	Mode	Standard Deviation
Total Phase 1 SBIR amount raised by a Life Sciences Firm (LSF) at a given year (2006 $)		162,442.000	96,865.797	80,853.175	168,184.377
SBIR winners located 0.1 miles from the origin firm		0.369	0.000	0.000	1.034
SBIR winners located 0.5 miles from origin firm (net of winners in other radii)		0.687	0.000	0.000	1.728
SBIR winners located 1 mile from the origin firm (net of winners in other radii)		1.216	0.000	0.000	3.335
SBIR winners located 1.5 miles from the origin firm (net of winners in other radii)		1.140	0.000	0.000	3.124
SBIR winners located 2 miles from the origin firm (net of winners in other radii)		0.998	0.000	0.000	2.903
SBIR winners located 2.5 miles from the origin firm (net of winners in other radii)		0.992	0.000	0.000	2.642
non - SBIR winners located 0.1 miles from the origin firm		0.197	0.000	0.000	0.584
non - SBIR winners located 0.5 miles from origin firm (net of non - SBIR winners in other radii)		0.732	0.000	0.000	1.877
non - SBIR winners located 1 mile from the origin firm (net of non - SBIR winners in other radii)		1.219	0.000	0.000	3.202
non - SBIR winners located 1.5 miles from the origin firm (net of non - SBIR winners in other radii)		1.091	0.000	0.000	2.749
non - SBIR winners located 2 miles from the origin firm (net of non - SBIR winners in other radii)		0.867	0.000	0.000	2.461
non - SBIR winners located 2.5 miles from the origin firm (net of non - SBIR winners in other radii)		0.883	0.000	0.000	2.417
Venture Capital Firms located 0.1 miles from the origin firm		0.032	0.000	0.000	0.301
Venture Capital Firms located 0.5 miles from the origin firm (net of venture capital firms in other radii)		0.219	0.000	0.000	1.927
Venture Capital Firms located 1 mile from the origin firm (net of venture capital firms in other radii)		0.361	0.000	0.000	1.961
Venture Capital Firms located 1.5 miles from the origin firm (net of venture capital firms in other radii)		0.662	0.000	0.000	2.998
Venture Capital Firms located 2 miles from the origin firm (net of venture capital firms in other radii)		0.658	0.000	0.000	2.513
Venture Capital Firms located 2.5 miles from the origin firm (net of venture capital firms in other radii)		0.709	0.000	0.000	2.569
Venture Capital Firms located in the same Metropolitan Statistical area with the origin firm (net of venture capital firms in other radii)		20.947	7.000	0.000	29.609
Number of research universities located in the same Metropolitan Statistical Area with the origin firm		8.435	4.000	1.000	9.107
Number of non-LSF establishments in the same zip code with the origin firm (thousand)		1.162	0.987	2.826	0.768
Average SBIR funds awarded to the origin firm in the five years preceeding award year (2006 thousand $)		0.047	0.017	0.000	0.096
Number of years since the last SBIR grant awarded to the origin firm since award year		1.241	1.000	1.000	1.638
Total number of patents awarded to the origin firm by 2006		14.063	2.000	0.000	49.877
Dummy variable that equals 1 for biopharmaceutical firms	1530				
Age of origin firm at SBIR award(s) year		7.026	5.000	2.000	6.556
Variable that is increasing with the number of the employees at the origin firm [1]		4.331	3.000	2.000	3.139
Dummy variable that equals 1 if the dependent variable corresponds to a year later than 1994	4084				
Total amount (2006 $) from SBIR grants from 1983 to 2006 for LSFs located in the same address with at least one more LSF		560,413.672	280,523.059	91,269.841	849,585.785
Total amount (2006 $) from SBIR grants from 1983 to 2006 for LSFs not located in the same address with at least one more LSF		447,330.807	241,614.221	93,700.397	731,300.841

[1]The values of the variable follow the following codification: 1 for LSFs with 1 to 4 employees, 2 for LSFs with 5 to 9 employees, 3 for LSFs with 10 to 14 employees, 4 for LSFs with 15 to 19 employees, 5 for LSFs with 20 to 24 employees, 6 for LSFs with 25 to 49 employees, 7 for LSFs with 50 to 74 employees, 8 for LSFs with 75 to 99 employees, 9 for LSFs with 100 to 149 employees, 10 for LSFs with 150 to 249 employees, 11 for LSFs with 250 to 500 employees)

Table 3

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Table 3 Estimates for models with dependent variable the log of the sum of Phase 1 SBIR funds awarded to a given Life Sciences Firm in year t. (standard errors in parentheses)

Variable Code	Variable Description	OLS Estimates with White's standard errors	GEE Estimates with standard errors clustered at the firm level	GEE Estimates with standard errors clustered at the state level
Intercept	Intercept	-3.0086 ***	-3.0086 ***	-3.0086 ***
		(0.0335)	(0.0449)	(0.0313)
SBIR_0.1	SBIR winners located 0.1 miles from the origin firm	0.0454 ***	0.0454 ***	0.0454 ***
		(0.0093)	(0.0102)	(0.0065)
SBIR_0.5	SBIR winners located 0.5 miles from origin firm (net of winners in other radii)	0.0016	0.0016	0.0016
		(0.0086)	(0.0094)	(0.0083)
SBIR_1	SBIR winners located 1 mile from the origin firm (net of winners in other radii)	0.0122	0.0122	0.0122
		(0.0063)	(0.0067)	(0.0064)
SBIR_1.5	SBIR winners located 1.5 miles from the origin firm (net of winners in other radii)	0.0238 ***	0.0238 ***	0.0238 ***
		(0.0069)	(0.0081)	(0.0066)
SBIR_2	SBIR winners located 2 miles from the origin firm (net of winners in other radii)	-0.0003	-0.0003	-0.0003
		(0.0077)	(0.0077)	(0.0087)
SBIR_2.5	SBIR winners located 2.5 miles from the origin firm (net of winners in other radii)	0.0094	0.0094	0.0094
		(0.0073)	(0.0084)	(0.0067)
NON_SBIR_0.1	non - SBIR winners located 0.1 miles from the origin firm	0.0271	0.0271	0.0271 ***
		(0.0198)	(0.0217)	(0.0099)
NON_SBIR_0.5	non - SBIR winners located 0.5 miles from origin firm (net of non - SBIR winners in other radii)	-0.0026	-0.0026	-0.0026
		(0.0082)	(0.0091)	(0.0134)
NON_SBIR_1	non - SBIR winners located 1 mile from the origin firm (net of non - SBIR winners in other radii)	-0.0061	-0.0061	-0.0061
		(0.0076)	(0.0087)	(0.0049)
NON_SBIR_1.5	non - SBIR winners located 1.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0061	-0.0061	-0.0061
		(0.0083)	(0.0105)	(0.0067)
NON_SBIR_2	non - SBIR winners located 2 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0152	-0.0152	-0.0152
		(0.0085)	(0.0095)	(0.0111)
NON_SBIR_2.5	non - SBIR winners located 2.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0062	-0.0062	-0.0062
		(0.0065)	(0.0073)	(0.0035)
VCFs_0.1	Venture Capital Firms located 0.1 miles from the origin firm	0.0026	0.0026	0.0026
		(0.0443)	(0.0483)	(0.0486)
VCFs_0.5	Venture Capital Firms located 0.5 miles from the origin firm (net of venture capital firms in other radii)	0.0108	0.0108	0.0108
		(0.0068)	(0.0076)	(0.0085)
VCFs_1	Venture Capital Firms located 1 mile from the origin firm (net of venture capital firms in other radii)	-0.0046	-0.0046	-0.0046
		(0.0071)	(0.0076)	(0.0053)
VCFs_1.5	Venture Capital Firms located 1.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0014	-0.0014	-0.0014
		(0.0047)	(0.0066)	(0.0034)
VCFs_2	Venture Capital Firms located 2 miles from the origin firm (net of venture capital firms in other radii)	-0.0001	-0.0001	-0.0001
		(0.0058)	(0.0066)	(0.0063)
VCFs_2.5	Venture Capital Firms located 2.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0030	-0.0030	-0.0030
		(0.0051)	(0.0067)	(0.0050)
Universities	Number of research universities located in the same Metropolitan Statistical Area with the origin firm	0.0018	0.0018	0.0018 **
		(0.0010)	(0.0011)	(0.0009)
Establishments	Number of non-LSF establishments in the same zip code with the origin firm (thousand)	0.0239	0.0239	0.0239 **
		(0.0131)	(0.0151)	(0.0103)
PreviousSBIR	Average SBIR funds awarded to the origin firm in the five years preceeding award year (2006 thousand $)	0.0028 ***	0.0028 ***	0.0028 ***
		(0.0002)	(0.0002)	(0.0003)
Last	Number of years since the last SBIR grant awarded to the origin firm since award year	-0.0037	-0.0037	-0.0037
		(0.0058)	(0.0058)	(0.0058)
Patents	Total number of patents awarded to the origin firm by 2006	0.0000	0.0000	0.0000
		(0.0002)	(0.0001)	(0.0001)
BioPharma	Dummy variable that equals 1 for biopharmaceutical firms	0.0734 ***	0.0734 ***	0.0734 ***
		(0.0204)	(0.0237)	(0.0278)
Age	Age of origin firm at SBIR award(s) year	-0.0063 **	-0.0063	-0.0063
		(0.0032)	(0.0038)	(0.0039)
AgeSquare	(Age of origin firm at SBIR award(s) year)^2	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Size	Variable that is increasing with the number of the employees at the origin firm	0.0000	0.0000	0.0000
		(0.0035)	(0.0041)	(0.0033)
After_94	Dummy variable that equals 1 if the dependent variable corresponds to a year later than 1994	0.8276 ***	0.8276 ***	0.8276 ***
		(0.0268)	(0.0417)	(0.0326)
Observations			4236	
R-Square			0.3747	
Adjusted R-Square			0.3705	
White's Test			843.3 ***	
Multicollinearity Condition Number			14.2589	

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

Appendix Table 1 Estimates for models with dependent variable the log of the sum of Phase 1 SBIR funds awarded to a given Life Sciences Firm in year t. (standard errors in parentheses). Compared to Table 3, the number of non-LSF SBIR winners in the zip code of the origin firm is added as a control variable.

Variable Code	Variable Description	OLS Estimates with White's standard errors	GEE Estimates with standard errors clustered at the firm level	GEE Estimates with standard errors clustered at the state level
Intercept	Intercept	-3.0190 ***	-3.0189 ***	-3.0189 ***
		(0.0337)	(0.0452)	(0.0310)
SBIR_0.1	SBIR winners located 0.1 miles from the origin firm	0.0474 ***	0.0474 ***	0.0474 ***
		(0.0093)	(0.0103)	(0.0064)
SBIR_0.5	SBIR winners located 0.5 miles from origin firm (net of winners in other radii)	0.0062	0.0062	0.0062
		(0.0088)	(0.0096)	(0.0072)
SBIR_1	SBIR winners located 1 mile from the origin firm (net of winners in other radii)	0.0159 **	0.0159 **	0.0159 **
		(0.0064)	(0.0067)	(0.0067)
SBIR_1.5	SBIR winners located 1.5 miles from the origin firm (net of winners in other radii)	0.0283 ***	0.0283 ***	0.0283 ***
		(0.0070)	(0.0085)	(0.0056)
SBIR_2	SBIR winners located 2 miles from the origin firm (net of winners in other radii)	-0.0007	-0.0007	-0.0007
		(0.0076)	(0.0077)	(0.0084)
SBIR_2.5	SBIR winners located 2.5 miles from the origin firm (net of winners in other radii)	0.0082	0.0082	0.0082
		(0.0072)	(0.0083)	(0.0073)
NON_LSF_SBIR	non - LSF SBIR winners in the zip code of the origin firm	-0.0103 ***	-0.0103 ***	-0.0103 ***
		(0.0031)	(0.0039)	(0.0029)
NON_SBIR_0.1	non - SBIR winners located 0.1 miles from the origin firm	0.0266	0.0266	0.0266 ***
		(0.0196)	(0.0215)	(0.0093)
NON_SBIR_0.5	non - SBIR winners located 0.5 miles from origin firm (net of non - SBIR winners in other radii)	-0.0027	-0.0027	-0.0027
		(0.0081)	(0.0091)	(0.0126)
NON_SBIR_1	non - SBIR winners located 1 mile from the origin firm (net of non - SBIR winners in other radii)	-0.0050	-0.0050	-0.0050
		(0.0076)	(0.0086)	(0.0043)
NON_SBIR_1.5	non - SBIR winners located 1.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0072	-0.0072	-0.0072
		(0.0083)	(0.0108)	(0.0067)
NON_SBIR_2	non - SBIR winners located 2 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0125	-0.0125	-0.0125
		(0.0085)	(0.0094)	(0.0099)
NON_SBIR_2.5	non - SBIR winners located 2.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0011	-0.0011	-0.0011
		(0.0066)	(0.0077)	(0.0044)
VCFs_0.1	Venture Capital Firms located 0.1 miles from the origin firm	-0.0046	-0.0046	-0.0046
		(0.0444)	(0.0485)	(0.0478)
VCFs_0.5	Venture Capital Firms located 0.5 miles from the origin firm (net of venture capital firms in other radii)	0.0115	0.0115	0.0115
		(0.0070)	(0.0080)	(0.0085)
VCFs_1	Venture Capital Firms located 1 mile from the origin firm (net of venture capital firms in other radii)	-0.0068	-0.0068	-0.0068
		(0.0070)	(0.0076)	(0.0052)
VCFs_1.5	Venture Capital Firms located 1.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0038	-0.0038	-0.0038
		(0.0048)	(0.0068)	(0.0034)
VCFs_2	Venture Capital Firms located 2 miles from the origin firm (net of venture capital firms in other radii)	0.0001	0.0001	0.0001
		(0.0058)	(0.0066)	(0.0065)
VCFs_2.5	Venture Capital Firms located 2.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0047	-0.0047	-0.0047
		(0.0050)	(0.0068)	(0.0044)
Universities	Number of research universities located in the same Metropolitan Statistical Area with the origin firm	0.0016	0.0016	0.0016
		(0.0010)	(0.0011)	(0.0009)
Establishments	Number of non-LSF establishments in the same zip code with the origin firm (thousand)	0.0447 ***	0.0447 ***	0.0447 ***
		(0.0145)	(0.0172)	(0.0120)
PreviousSBIR	Average SBIR funds awarded to the origin firm in the five years preceeding award year (2006 thousand $	0.0028 ***	0.0028 ***	0.0028 ***
		(0.0002)	(0.0002)	(0.0003)
Last	Number of years since the last SBIR grant awarded to the origin firm since award year	-0.0033	-0.0033	-0.0033
		(0.0058)	(0.0058)	(0.0059)
Patents	Total number of patents awarded to the origin firm by 2006	0.0000	0.0000	0.0000
		(0.0002)	(0.0001)	(0.0001)
BioPharma	Dummy variable that equals 1 for biopharmaceutical firms	0.0713 ***	0.0713 ***	0.0713 **
		(0.0204)	(0.0238)	(0.0277)
Age	Age of origin firm at SBIR award(s) year	-0.0063 **	-0.0063	-0.0063
		(0.0032)	(0.0038)	(0.0040)
AgeSquare	(Age of origin firm at SBIR award(s) year)^2	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Size	Variable that is increasing with the number of the employees at the origin firm	0.0003	0.0003	0.0003
		(0.0035)	(0.0041)	(0.0034)
After_94	Dummy variable that equals 1 if the dependent variable corresponds to a year later than 1994	0.8259 ***	0.8259 ***	0.8259 ***
		(0.0269)	(0.0419)	(0.0326)
Observations			4236	
R-Square			0.3764	
Adjusted R-Square			0.3721	
White's Test			872.1 ***	
Multicollinearity Condition Number			14.6975	

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

Appendix Table 2

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Appendix Table 2 Estimates for models with dependent variable the log of the sum of Phase 1 SBIR funds awarded to a given Life Sciences Firm in year t. (standard errors in parentheses). Compared to Table 3, the product of the density of SBIR winners and a dummy variable that takes the value of 1 for observations before 2000 are added as interaction terms in the analysis.

Variable Code	Variable Description	OLS Estimates with White's standard errors		GEE Estimates with standard errors clustered at the firm level		GEE Estimates with standard errors clustered at the state level	
Intercept	Intercept	-3.0113	***	-3.0113	***	-3.0113	***
		(0.0335)		(0.0450)		(0.0311)	
SBIR_0.1	SBIR winners located 0.1 miles from the origin firm	0.0480	***	0.0480	***	0.0480	***
		(0.0094)		(0.0102)		(0.0058)	
SBIR_0.5	SBIR winners located 0.5 miles from origin firm (net of winners in other radii)	-0.0026		-0.0026		-0.0026	
		(0.0089)		(0.0099)		(0.0079)	
SBIR_1	SBIR winners located 1 mile from the origin firm (net of winners in other radii)	0.0144	**	0.0144	**	0.0144	**
		(0.0065)		(0.0070)		(0.0069)	
SBIR_1.5	SBIR winners located 1.5 miles from the origin firm (net of winners in other radii)	0.0226	***	0.0226	***	0.0226	***
		(0.0072)		(0.0085)		(0.0059)	
SBIR_2	SBIR winners located 2 miles from the origin firm (net of winners in other radii)	-0.0017		-0.0017		-0.0017	
		(0.0079)		(0.0080)		(0.0096)	
SBIR_2.5	SBIR winners located 2.5 miles from the origin firm (net of winners in other radii)	0.0119		0.0119		0.0119	
		(0.0076)		(0.0087)		(0.0088)	
NON_SBIR_0.1	non - SBIR winners located 0.1 miles from the origin firm	0.0291		0.0291		0.0291	***
		(0.0200)		(0.0219)		(0.0100)	
NON_SBIR_0.5	non - SBIR winners located 0.5 miles from origin firm (net of non - SBIR winners in other radii)	-0.0029		-0.0029		-0.0029	
		(0.0082)		(0.0091)		(0.0135)	
NON_SBIR_1	non - SBIR winners located 1 mile from the origin firm (net of non - SBIR winners in other radii)	-0.0058		-0.0058		-0.0058	
		(0.0077)		(0.0086)		(0.0045)	
NON_SBIR_1.5	non - SBIR winners located 1.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0059		-0.0059		-0.0059	
		(0.0083)		(0.0105)		(0.0061)	
NON_SBIR_2	non - SBIR winners located 2 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0157		-0.0157		-0.0157	
		(0.0086)		(0.0095)		(0.0107)	
NON_SBIR_2.5	non - SBIR winners located 2.5 miles from the origin firm (net of non - SBIR winners in other radii)	-0.0058		-0.0058		-0.0058	
		(0.0064)		(0.0071)		(0.0034)	
VCFs_0.1	Venture Capital Firms located 0.1 miles from the origin firm	-0.0016		-0.0016		-0.0016	
		(0.0435)		(0.0474)		(0.0499)	
VCFs_0.5	Venture Capital Firms located 0.5 miles from the origin firm (net of venture capital firms in other radii)	0.0109		0.0109		0.0109	
		(0.0067)		(0.0075)		(0.0085)	
VCFs_1	Venture Capital Firms located 1 mile from the origin firm (net of venture capital firms in other radii)	-0.0043		-0.0043		-0.0043	
		(0.0071)		(0.0075)		(0.0049)	
VCFs_1.5	Venture Capital Firms located 1.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0009		-0.0009		-0.0009	
		(0.0047)		(0.0066)		(0.0035)	
VCFs_2	Venture Capital Firms located 2 miles from the origin firm (net of venture capital firms in other radii)	-0.0005		-0.0005		-0.0005	
		(0.0058)		(0.0066)		(0.0063)	
VCFs_2.5	Venture Capital Firms located 2.5 miles from the origin firm (net of venture capital firms in other radii)	-0.0026		-0.0026		-0.0026	
		(0.0050)		(0.0067)		(0.0049)	
Universities	Number of research universities located in the same Metropolitan Statistical Area with the origin firm	0.0018		0.0018		0.0018	**
		(0.0010)		(0.0011)		(0.0009)	
Establishments	Number of non-LSF establishments in the same zip code with the origin firm (thousand)	0.0241		0.0241		0.0241	**
		(0.0131)		(0.0151)		(0.0101)	
PreviousSBIR	Average SBIR funds awarded to the origin firm in the five years preceeding award year (2006 thousand $	0.0028	***	0.0028	***	0.0028	***
		(0.0002)		(0.0002)		(0.0003)	
Last	Number of years since the last SBIR grant awarded to the origin firm since award year	-0.0039		-0.0039		-0.0039	
		(0.0058)		(0.0058)		(0.0058)	
Patents	Total number of patents awarded to the origin firm by 2006	0.0000		0.0000		0.0000	
		(0.0002)		(0.0001)		(0.0001)	
BioPharma	Dummy variable that equals 1 for biopharmaceutical firms	0.0735	***	0.0735	***	0.0735	***
		(0.0204)		(0.0237)		(0.0281)	
Age	Age of origin firm at SBIR award(s) year	-0.0061		-0.0061		-0.0061	
		(0.0032)		(0.0038)		(0.0039)	
AgeSquare	(Age of origin firm at SBIR award(s) year)^2	0.0001		0.0001		0.0001	
		(0.0001)		(0.0001)		(0.0001)	
Size	Variable that is increasing with the number of the employees at the origin firm	0.0003		0.0003		0.0003	
		(0.0035)		(0.0041)		(0.0033)	
After_94	Dummy variable that equals 1 if the dependent variable corresponds to a year later than 1994	0.8290	***	0.8290	***	0.8290	***
		(0.0269)		(0.0417)		(0.0327)	

Appendix Table 2 continued Estimates for models with dependent variable the log of the sum of Phase 1 SBIR funds awarded to a given Life Sciences Firm in year t. (standard errors in parentheses). Compared to Table 3, the product of the density of SBIR winners and a dummy variable that takes the value of 1 for observations before 2000 are added as interaction terms in the analysis.

Variable Code	Variable Description	OLS Estimates with White's standard errors	GEE Estimates with standard errors clustered at the firm level	GEE Estimates with standard errors clustered at the state level
D2000*SBIR_0.1	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_0.1	-0.0530	-0.0530	-0.0530
		(0.0374)	(0.0357)	(0.0307)
D2000*SBIR_0.5	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_0.5	0.0407	0.0407	0.0407 **
		(0.0240)	(0.0243)	(0.0165)
D2000*SBIR_1	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_1	-0.0280	-0.0280	-0.0280
		(0.0186)	(0.0185)	(0.0216)
D2000*SBIR_1.5	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_1.5	0.0128	0.0128	0.0128
		(0.0206)	(0.0202)	(0.0130)
D2000*SBIR_2	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_2	0.0109	0.0109	0.0109
		(0.0226)	(0.0227)	(0.0178)
D2000*SBIR_2.5	Dummy variable that takes the value of 1 for observations before 2000 * SBIR_2.5	-0.0260	-0.0260	-0.0260
		(0.0142)	(0.0147)	(0.0243)
Observations			4236	
R-Square			0.3762	
Adjusted R-Square			0.3711	
White's Test			998.3 ***	
Multicollinearity Condition Number			14.5028	

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