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Abstract

If localization economies are present, firms within denser industry concentrations should exhibit higher levels of performance than more isolated firms. Nevertheless, research in industrial organization that has focused on the influences on firm survival has largely ignored the potential effects from agglomeration. Recent studies in urban and regional economics suggests that agglomeration effects may be very localized. Analyses of industry concentration at the MSA or county-level may fail to detect important elements of intra-industry firm interaction that occur at the sub-MSA level. Using a highly detailed dataset on firm locations and characteristics for Texas, this paper analyses agglomeration effects on firm survival over geographic areas as small as a single mile radius. We find that greater firm density within very close proximity (within 1 mile) of firms in the same industry increases mortality rates while greater concentration over larger distances reduces mortality rates.

JEL Classification: R12, O18.
Keywords: Firm Survival, Agglomeration, Localization, and Knowledge Externalities.

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1 Introduction

Marshall hypothesized nearly a century ago that knowledge spillovers and shared human capital are localized and help to explain why certain industries that are not otherwise tied to geographically specific inputs or demand tend to concentrate spatially. Geographic proximity of kindred firms should foster human interaction, inter-firm labor mobility, and the exchange of knowledge. As an industrial concentration grows and the localized knowledge base expands, the embedded firms enjoy aggregate economies of scale which, in turn, should contribute to relatively higher growth rates of the geographically concentrated industry.

If these localization economies bestow advantages on firms in spatially concentrated industries, one would naturally expect that entrants would have a preference toward spatial proximity to like firms. Rosenthal and Strange (2003) find evidence that localization influences entrants' location decisions although the effect diminishes rapidly over space. One would not only expect to see a relatively higher rate of firm entry, however. The cost advantage derived from localization economies should lead to higher industry performance and lower hazard rates, *ceteris paribus*, for kindred firms within the spatial concentration. Indeed, Henderson (2003) finds that industrial localization at the county-level has strong productivity effects in the high tech industries.

The objective of this paper is to estimate the effect of spatial concentration on the probability of firm survival for a set of high technology industries in Texas. These relatively new industries have exhibited a strong tendency to cluster. Using a highly detailed establishment-level data set for Texas, we are able to observe key firm-level characteristics, including NAICS-6 industry classification, size, ownership status, entry and exit dates (in case of mortality), and exact address. We then utilise, *inter alia*, exact firm-level variations in intra-industry spatial concentration within concentric rings to test the proposition that industrial localization influences the likelihood of establishment exit. This has the advantage of enabling us to observe exact measures of spatial concentration over precise distances independently of arbitrary jurisdictional boundaries. Unlike previous industry studies in this realm, we eliminate the own-firm contribution to the concentration measures to correctly identify the potential for localization effects. We find evidence that greater localization within very small geographic areas contributes to firm mortality while localization effects over a larger geographic area reduce firm mortality.

It is surprising that the literature on failure rates has paid relatively scant attention to the effect of agglomeration economies on survival and exit rates for industries that tend to specialise geographically. This is particularly so since there has been an emphasis in this literature on the role of internal economies of scale in firm survival and growth. Due to data limitations, much of the earlier analyses utilized industry exit rates, since firm-specific characteristics were unavailable. However, even with firm-level data, analyses have been rather more interested in ownership status, market conditions, technology uncertainty, and internal sources of decreasing long run average costs (Audretsch and Mahmood, 1994). The role of internal economies of scale and their effect on firm profitability and exit probabilities have been primarily investigated within the context of the cost disadvantage inherent in operation at less than minimum efficient scale (see, for example, Audretsch, 2002). We are aware of a small number of studies that look at industrial localization as a variable for explaining firm exits (Staber, 2001; Folta *et al.*, 2006; Shaver and Flyer, 2000). However, the present study differs significantly in its use of exact and continuous measures of the geographic distribution of establishments.

2 Literature Review

The literature on firm survival has largely ignored agglomeration effects. Dunne *et al.* (1988, 1989) use plant-level panel data from the Census of Manufactures to analyze entry and exit from 4-digit SIC industries at the establishment and multi-plant firm levels between the five year intervals of the Census. While they include concentration of ownership by way of multi-plant operation, their model does not include any measure of spatial concentration of the given industry within the specific market regions. In a similar vein, Baldwin and Gorecki (1991) analyze entry and exit with particular attention to the effects of firm characteristics at time of entry on prospects for survival. Others have investigated exit rates relative to size, scale, organizational structure (Audretsch, (1991)), technology (Winter, (1984)), market growth (Bradburg and Caves, (1982)) and pre-entry experience (see, Helfat and Lieberman

(2002) for a review). Audretsch and Mahmood (1994, 1995) estimate hazard functions using firm-specific data, but their treatment of scale economies focuses on internal factors while recognition of the technological environment is limited to higher costs due to higher levels of R&D or greater technological uncertainty in more technologically advanced and dynamic industries. Dunne *et al.* (2005) are primarily interested in the role of producer experience in firm survival.

The few studies that have looked at spatial concentration and firm failure rates have concluded that higher concentration is associated with higher mortality (Folta *et al.*, 2006; Shaver and Flyer, 2000; Staber, 2001). As Shaver and Flyer (2000) point out, if firms are heterogeneous, knowledge spillovers will likely benefit weaker firms more than stronger firms. If weaker firms' competitiveness is bolstered by spatial proximity to stronger firms, particularly strong firms may perceive that they have more to lose than to gain by close proximity to competitors. The implication is that spatial concentrations may tend to attract weaker firms and repel entrants that have stronger intellectual properties to commercialise. Although Folta *et al.* (2006) advise caution in the use of survival as a single measure of firm performance within industry concentrations, they suggest that the higher mortality rates for firms in denser concentrations may be due to higher performance expectations and lower exit costs. They also point out, as does Henderson *et al.* (1995), that net agglomeration economies may be non-linear. In the early growth phase of an industry cluster, positive agglomeration economies dominate. However, congestion effects become relatively more important as the concentration grows and matures.

The role of agglomeration economies has been carefully investigated in the context of firm entry and growth. Rosenthal and Strange (2003) find that localization helps to explain entry patterns. Of rather more interest has been research into the effect of agglomeration economies on local or regional employment growth rates at the industrial level, seeking to determine whether localization or urbanization effects, or both, are present [Glaeser et al. (1992), Henderson et al. (1995), Combes (2000)]. More recently, researchers have considered effects at the firm level. Henderson (2003) finds that greater localized firm counts in the high tech industries has significant productivity effects at the firm level. Fafchamps (2004), looking at manufactuirng firms in Morocco, concludes that agglomeration has an effect on firm growth rates, but it is not working through productivity.

Combes (2000) notes that localized information spillovers occur when firms have complementary pieces of information that are exchanged through localized relationships. The greater the number of firms, the greater the likelihood that complementarities occur. He describes these pieces of information as relating to firm or market organization and input or output innovations, the latter being referred to as a technological externality. One might think that innovations in any of these realms might suffice to inspire an entrepreneur and result in a start-up. Henderson *et al.* (1995) envision the magnitude of localized knowledge externalities at any given time as the result of a dynamic process, the Marshall-Arrow-Romer (MAR) externality. That is, a shared, localized knowledge base accumulates through time as collective learning and growth of experience takes place.[1] This dynamic element would presumably also characterize the extent of knowledge and experience of individual firms.

If important knowledge spillovers are present, one can then easily imagine why start-up firms would choose to locate among kindred firms. By definition, new firms lack experience. Thus, if the relevant spillovers are, as Henderson *et al.* (1995) suggest, a non-excludeable knowledge base (technical and market "know-how" that accrues through time) that is shared by all localized firms, the entering firm could expect to be up to speed quicker by embedding itself in an existing concentration. New firms' contributions to the knowledge base would occur as the firms gain unique, substantive experience and so acquire, or enable others to acquire, unique bits of knowledge that circulate within the locality. The key observation for us is that new firms would apparently have much more to gain by entering into a spatially concentrated environment than incumbent firms gain from their entry. Indeed, if entry into the locality sharpens competition for inputs and the extension of shared knowledge in an increasingly competitive environment has the effect of accelerating the pace of innovation, rates of return to R&D will fall, as pointed out by Combes (2000). The marginal effect of rival firm density may be negative. On the other hand, each potential start-up would have to balance the benefits from gaining access to the knowledge spillovers with the costs of the leakage of its own intellectual property, or, more generally, its R&D, due to its imperfect excludeability. In the absence of any entry barriers, entry would occur up to the point where risk-adjusted expected profits would be equalized

[1] Glaeser et al. (1992) refer to these dynamic localization effects as Marshall-Arrow-Romer (MAR) externalities.

across localities. Higher expected profits that accrue to economies of scale available from location in a denser concentration would have to be balanced by greater risk.

Moreover, given the relatively greater riskiness of new firms compared to more mature firms, co-location with similar firms may enhance the new firms' ability to attract employees. This would be the case if, for example, workers consider the higher risk of failure associated with employment in a new firm to be mitigated by virtue of its location within a spatial concentration of similar firms. That is, if workers believe that localized social and professional networking increases their labor mobility, they would prefer, all else equal, to work for a firm within an industry concentration. Indeed, Freedman (2008) finds greater spatial concentration in the software publishing industry results in greater mobility of labor.

Krugman (1991) poses the question, "how far does a technological spillover spill?"[2] Most of the earlier studies of knowledge externalities were conducted at relatively aggregated industry levels and over relatively large geographic areas. Mansfield (1995), among others, uses U.S. states as the geographic division while counties and Metropolitan Statistical Areas have been common geographical boundaries for analysis. Henderson (2003) concludes that plants in clusters located in different counties within the same MSA do not benefit from clusters beyond their own, other than from access to shared sources of production inputs. Using finer spatial focus, Wallsten (2001) finds that knowledge spillovers are limited to a radius on the order of 1/10 of a mile (or about two city blocks). This suggests that the effective locality is a neighborhood, not even a city, and certainly significantly smaller than counties and MSAs. Rosenthal and Strange (2003) provide a relevant quote in Saxenian (1994) from a technology industry employee in Silicon Valley who said, "The joke is that you can change jobs and not change parking lots." Looking at start-up firms at the Zip Code level, they conclude that agglomeration economies attenuate rapidly up to a distance of one mile.

Complicating the matter further is the relevance of time. Jaffe *et al.* (1993) find a temporal component to the localization of knowledge. In high tech industries, the rate of product innovation and market evolution is extraordinarily rapid. If important elements of localized knowledge have a

[2] Krugman (1991), page 485.

brief shelf life and knowledge diffuses slowly through space, there is a premium on close proximity since its eventual diffusion beyond the locality is largely irrelevant.

If own-industry knowledge spillovers dissipate very rapidly across space, the search for localization externalities needs to be conducted within a finely grained geographical focus. Significant localization effects may not reach a threshold for detection if the spatial unit under observation is the MSA while the appropriate geographical area is sub-metropolitan in size. Measures of urban specialization across the larger geography will understate the actual and relevant industrial density and perhaps overstate the role of industrial diversity. Employment location quotients as a specialization measure, for example, tend toward 1 as the geographic extent of the measurement region is expanded. This has clear implications for observational distinctions between MAR and Jacobs-type externalities.[3]

In the analysis that follows, we analyze the effect of agglomeration economies on high-tech firm survival. We do not have an a priori hypothesis of the effects of industrial density on survival. Combes (2000) notes, "Since competition generates opposite effects on the level of local R&D and innovations, its effect is also indeterminate on local technological spillovers." Using variation in firm-specific measures of spatial density, within circles of varying radii, we seek too analyze the effect of localization on high tech firm hazard rates.

3 Empirical Model and Data

The high-technology industries considered in this paper have come to represent the new "knowledge economy." These industries are ideal candidates to benefit from the presence of specialized, high skill labor inputs and knowledge spillovers. Indeed, one of our criteria for designation as a high-tech industry is the relatively high employment of scientists and engineers in its labor force. The other criterion is relatively high levels of industry R&D. (These criteria are discussed in more detail below.)

We adapt the model found in Rosenthal and Strange (2003) to the question of firm survival. That is, if prices are normalized to 1, profit-maximizing establishment j's profits in industry i in period t

[3] See Jacobs (1969).

can be expressed as

$$\pi_{jit}(x,\epsilon) = \max_{z} a(x_{jit})f(z)(1+\epsilon_{ij}) - c(z) \tag{1}$$

where $a(x)$ is a shift term that depends on a vector $x = (x_l, x_u, x_j)$ consisting of both localization and urbanization variables as well as other characteristics that are particular to firm j. The vector x_l contains localization effects as captured by firm density measures, as explained below. Both the production (revenue) technology $f(z)$ and the cost function $c(z)$ depend on a vector of factor inputs z. Production technology is common to all firms in the industry. A firm will remain active in the market as long as long as $\pi_{jit} > 0$ and will exit if $\pi_{jit} < 0$, assuming that current period profits will persist. We assume ϵ_{ijt} is a random draw for each firm in a given industry in each period and is independent and identically distributed across establishments in each industry according to the cumulative distribution function $H(\epsilon_i)$.

Thus, given the solution to (1), z', the firm will exit in a given period if

$$\epsilon_{ijt} < \frac{c(z')}{a(x_{jit})f(z')} - 1 \tag{2}$$

There is then a probability $h(t) = H(\epsilon_{jt})$ that a firm will exit the industry in any given period t. If agglomeration economies vary positively with spatial density, i.e., greater density results in a higher value of $a(x)$, greater spatial density will correspond to a lower value of $H(\epsilon_j)$, all else equal. Therefore, the probability is higher that the firm will survive the period.

We estimate probabilities of firm failure using a Cox proportional hazards model. The basic Cox proportional hazards model can be written as follows:

$$h(t) = h_0(t)\exp(x^{'}\beta + z^{'}\psi) \tag{3}$$

where $h(t)$ is the conditional hazard rate and $h_0(t)$ is the unspecified baseline hazard function. The vectors of covariates that are establishment specific are denoted by x and the market condition variables are denoted by z.

In order to gauge the geographic extent of localization effects, we use an approach similar to Rosenthal and Strange (2003). However, we compute alternative spatial density measures within concentric rings of 0-1, 1-5, 5-10, and 10-25 mile radii around each firm's exact location for every high-tech firm in Texas during the period of the study. Unlike Rosenthal and Strange (2003), the density measures are based on the actual physical addresses of firms and employment. After geo-coding each establishment by physical address, we compute the distance between each establishment and all other establishments both in the same industry and in all other industries.[4] Therefore, as Duranton and Overman (2005) point out, space is treated as continuous so that the measures of the distribution of activity are independent of any city, county or other arbitrary jurisdictional division. We limit our analysis to a maximum radius of 25 miles since that corresponds roughly to the typical Texas county. In Texas, nearly all counties are square and half of the diagonal distance within a county is an average of about 23 miles. Since the geographic areas over which these measures are computed are identical for all firms, no additional spatial normalization is necessary. Freedman (2008) using a data set similar to ours, calculated the location quotient for each establishment by drawing concentric circles with radii of 5, 10, and 25 miles around each firm.

We compute local densities using both location quotients (LQ) and count data in terms of employment. The conventional LQ is a measure of an industry's presence in a particular location compared to the general spatial distribution of economic activity. For a given industry, the LQ is calculated as the ratio of its share of total employment in a sub-region relative to that industry's share of total employment in the broader region. In our case, we compute the LQ for each ring around each firm relative to the State of Texas. A firm and its employment are excluded from density measures in any ring in which the firm is located.

The calculated rivals' LQ can be expressed using the following equation.

$$LQ_{rji} = \left(\frac{E_{rji}/E_{rj}}{E_i/E} \right) \tag{4}$$

[4] The distances were computed under the assumption the world is flat, using trigonometric functions with latitude and longitude as arguments. The distances are typically small enough that curvature of the earth introduces relatively small errors.

Where, E_{rji} is the number of employees around establishment j in industry i (by six digit NAICS codes) and E_{rj} is the total number of employees in all industries around establishment j within radius r for $r_l < r \leq r_u$. The values r_l and r_u are the lower and upper values of the radii defining the four concentric rings defined above. E_i is the total number of employees in Texas for industry i and E is the total number of employment for all non-farm industries in Texas.

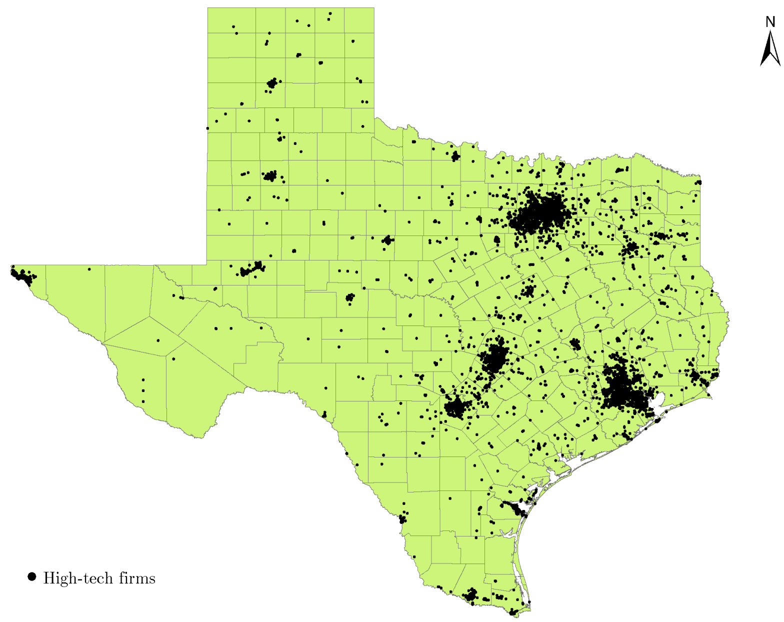
We obtained the firm-level data for Texas from the Quarterly Census of Employment and Wages (QCEW) from the Texas Workforce Commission. This data set provides firm-specific monthly employment and quarterly total wages reported by establishment as required under the Texas unemployment insurance (UI) program. Each record includes the specific location (address) of the establishment, business start-up date (the date on which UI liability begins), and the relevant six-digit NAICS code. Furthermore, separate establishments (branches or franchises) of the same firm are separately identified and reported in separate records. This panel data set is comprized of observations from Q3:1999 through Q2:2007.[5]

Definition of the high-technology sector is necessarily somewhat arbitrary. This paper utilises the set of high tech industries specified by the American Electronics Association (now known as TechAmerica) in 2003 –roughly the mid-point of the timeframe for this study– and based on the 2002 NAICS scheme. It includes 49 industries identified at the NAICS-6 level. The American Electronics Association's prinipal selection criterion is that an industry be a "maker/creator of technology, whether it be in the form of products, communications, or services." See Table A1 for a list of industries that constitute the high tech sector in this analysis. In our data set, we have more than 20,000 technology firms (more than 25,000 establishments) and 380,000 total observations. From these, we identify separately the entrants with previous experience.[6] Figure 1 illustrates the location of high-tech establishments in Texas and shows their spatial concentration along Interstate 35. One can also note a sprinkling of high-tech establishments across the less urban areas of the state. Figures 2 and 3 illustrate the intra-urban spatial distribution of software publishing establishments in the Austin and Dallas Metropolitan

[5] It should be pointed out that the authors obtained these data under an agreement of confidentiality and disclosure of the actual data is subject to certain restrictions.

[6] Entrant with previous experience is a firm that enters the market but has previously been in the industry under prior ownership.

Figure 1: High-Tech Firm Locations in Texas



Statistical Areas. Spatial clustering at this level is also evident.

The software publishing industry accommodates firms whose activities are diverse in terms of the nature of the software they produce. Given the large number (approximately 2,000) of software publishing establishments in Texas and the necessity of examining each establishment in order to determine its place in the software product space, it is difficult to sort establishments by product characteristics in order to view the spatial distribution by this particular sub-category. We have, however, included in Tables 1 and 2 some micro-characteristics of co-located establishments. Table 1 considers a sample of the software publishing firms that are located in the same building and the order in which their appearance at that location took place. We do not identify the cities in order to ensure anonymity of the firms. While the establishments are almost all involved in applications software publishing, we conclude that eight of the sets of establishments in the fifteen buildings are composed of potentially direct rivals or establishments in a similar product space. In all cases, the establishment with the longer tenancy has more employees and, on average, a higher average payroll. Table 2 illustrates

Figure 2: Spatial Distribution of Establishments for Software Publishers in Austin MSA

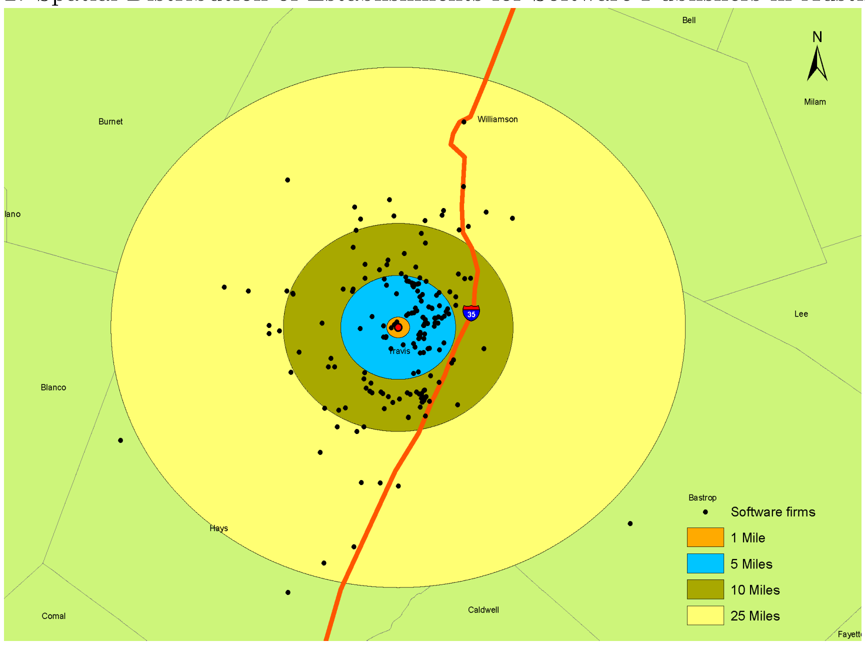
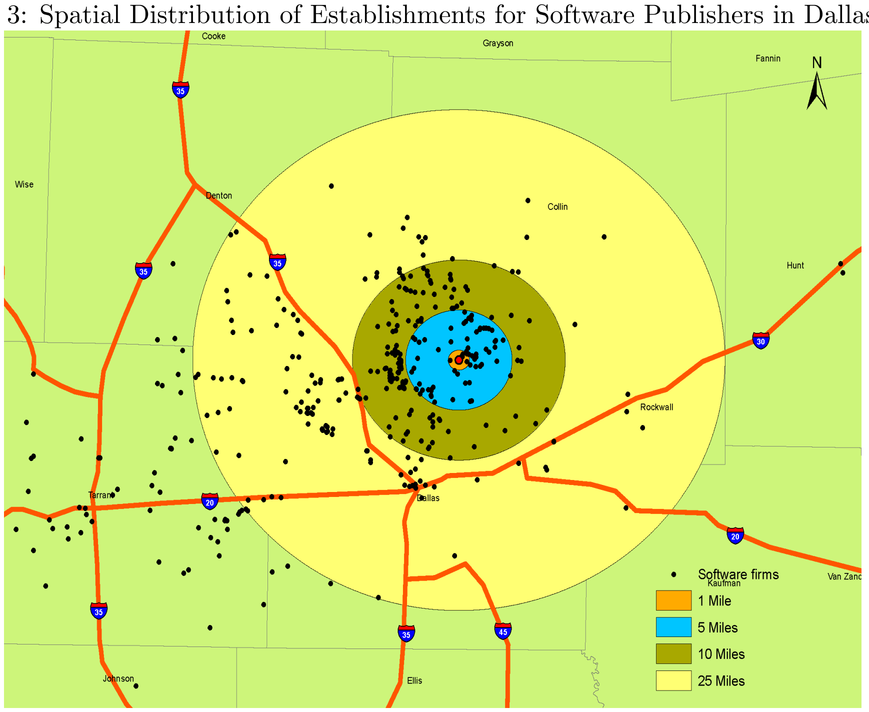


Figure 3: Spatial Distribution of Establishments for Software Publishers in Dallas MSA



the characteristics of the 31 establishments located within 5 miles of a randomly selected software publishing firm indicated as firm 1. We note, again, that nearly all of the establishments are involved in the production of applications software. It is also worth noting that about one-third, or more, are involved in business software development, four are in communications and utility management software, two in game development, and two clearly publishing in healthcare industry-related software.

In the case of the broader set of high tech industries, transportation costs as an agglomerating force and access to geographically specific natural resources are not particularly relevant. High-tech firms are not typically tied to local or regional market demand and do not have significant upstream industrial linkages other than, perhaps, research universities, expert consultants, and specialized funding sources. Of these upstream linkages, we control for the level and proximity of university research by including a dummy variable for the local presence of a research university or institution. Local presence is defined as being in the same county as the establishment. A research university or institution is identified as one which has received at least $10 million in federal research support during any federal fiscal year during the period of this analysis. Using this criterion, there are ten counties in Texas which qualify as hosting a research complex. Data on annual university R&D expenditures were obtained from the National Science Foundation. The annual NSF data actually span two calendar years since the federal fiscal year begins in October. In order to convert these annual R&D expenditures into quarterly data, we use a fourth of a fiscal year's total for quarters 1-3, and a fourth of the given fiscal year's total for quarter 4 of the previous calendar year.

In order to measure the urbanization effect, we compute urban density for all non-farm industries, excluding the industry in which the firm under observation is located, using analogous measures as were used for localization effects. However, in this case, we only compute density measures for the number of establishments and employment for the entire area within a 25 mile radius. We compute these measures as both LQ's and count data. We also compute a Herfindahl Index to capture the industrial diversity in the 25 mile circle. The Herfindahl Index is the sum of squared employment shares at the 4-digit NAICS. We include this measure to capture the possibility that urban industrial diversity generates external effects (Jacobs-type) that are relevant to firm survival probabilities. A

Table 1: Selected same location firm information.

City	Building	Occupying order	Average quarterly Employment	Average quarterly Wage	Category
A	1	1	142.33	21,044.57	Develop computer games software.
		2	135.33	12,810.72	Computer games software interactive.
	2	1	65.33	26,045.01	Global provider of web-based software for member and donor-based non-profits.
		2	4.00	26,610.75	Electronics and computer software.
	3	1	113.67	23,581.33	Creates & develop games for PCs, game consoles, online, and wireless markets.
		2	73.33	18,417..89	Provides superior quality market data and analytical products.
B	1	1	79.00	20,064.86	Provider of leading healthcare and emergency software.
		2	2.00	32,375.00	Data systems designers
C	1	1	4.67	30,660.86	Optimum operations planning, scheduling, and economic forecasting.
		2	2.00	3,000.00	Develop user-friendly mainframe computer information retrieval systems.
	2	1	12.00	25,313.58	3D modeling technologies, software development, and architectural engineering services.
		2	11.33	27,875.47	Computer graphics.
	3	1	75.00	29,160.27	Comprehensive software solutions for the infrastructure lifecycle.
		2	57.00	29,750.68	Comprehensive software solutions for the infrastructure lifecycle.
	4	1	38.00	16,851.82	Digital signal processors designed specifically for used in real-time.
		2	13.33	7,473.72	Develop software that will reduce costs and increase skills.
	5	1	21.33	20,672.16	Investment management & derivative management accounting software.
		2	5.00	10,645.40	Produce pitch books, information memorandums, and data rooms.
	6	1	22.33	19,526.06	Produce benefit administration software systems
		2	21.00	23,719.24	Graphic designers
D	1	1	634.67	49,496.77	Develop software and services.
		2	10.67	30,309.09	Insurance consultants & counselors and computer software & services.
E	1	1	56.67	44,502.83	Develop identity management software and services.
		2	7.00	17,737.29	Provides complete identity management solutions.
	2	1	208.67	11,516.01	Develop computer games software.
		2	1.67	6,546.60	Software solutions for franchise management and IT outsourcing.
F	1	1	5	21,450.00	Helpdesk and computer software.
		2	24.67	49,403.11	Develop software and services.
		3	12.00	29,009.75	Spatial data and mapping software.
	2	1	4	20,404.50	Provides unified communication and collaboration services.
		2	3	18,415.00	No information
Averages		**1**	**95.69**	**27,841.24**	
		2 & 3	**23.84**	**19,167.46**	

Table 2: Rival information within five miles.

Firm	Category	Liability date	Distance (in miles)	Average quarterly Employment
1	Develop computer games software.	1999-04	–	208.67
2	Software solutions for franchise management and IT outsourcing.	2005-06	.000	1.67
3	Business Software.	2000-01	.210	4.00
4	Develop identity management software and services.	1990-09	.589	7.00
5	Develop software and services.	2005-03	.589	56.67
6	Aircraft software.	1994-10	.712	2.00
7	Method and apparatus for controlling electrical power.	2005-07	1.404	2.00
8	Software traning	1982-02	1.433	2.00
9	Business sollutions software.	1994-03	1.789	18.00
10	Property appraisal software	1998-04	1.976	79.33
11	Develop computer games software.	1991-09	2.097	144.33
12	Material handling equipment software development, training, and support.	2001-07	2.339	18.00
13	Utilty management software	2001-11	2.515	13.00
14	Business Consulting Services	2006-08	2.793	5.00
15	Software specializes in managing benefits, payroll and human resources.	2006-04	3.113	31.33
16	Voice over IP softswitch platform delivers and various telephone services.	2007-04	3.175	26.00
17	High quality premium tax software.	1995-10	3.362	35.00
18	Computer repair and advanced computer services	1993-06	3.419	7.00
19	Packaging software	1990-09	3.420	15.00
20	Prepackaged security software services.	2001-01	3.525	26.00
21	Data Systems	1997-01	3.569	4.00
22	Asset management solutions software.	2005-12	3.702	3.00
23	Healthcare software.	1990-12	3.756	50.33
24	Helpdesk and computer software.	1983-12	4.104	5.00
25	Spatial data and mapping software.	2004-01	4.104	12.00
26	Develop software and service.	2006-01	4.104	24.67
27	No information	1991-06	4.283	3.00
28	Provides unified communication and collaboration services.	2005-01	4.283	4.00
29	Health care supply chain management software	2006-02	4.323	138.67
30	Coommunication systems software	2001-07	4.495	2.00
31	Business administration software.	2006-01	4.642	12.00
32	Business process outsourcing and IT Outsourcing.	1990-09	4.975	7.00

positive coefficient on this variable can be interpreted to mean that less industrial diversity (higher HHI) tends to generate higher mortality. In that case, establishments in regionally specialized areas would have higher mortality rates, *ceteris paribus*, than establishments located in industrially diverse urban areas.

In addition to the localization and urbanization effects, the set of establishment-specific variables also includes age of the firm in months, average payroll, and relative size of the firm. Regional measures include the county unemployment rate, proportion of county population between 24-54 years, and rural land price.

Age of the firm in months is the period of time since UI liability began. This is reported for all firms. Therefore, despite the fact that the data set starts in 1999, we can observe the actual start-up date for all firms. Average payroll is the firm's total payroll for the quarter divided by average monthly employment for the quarter. This method for approximating wage rates is fairly common in the labor economics literature (Freedman, 2008; De Silva *et. al.* 2010; Dube 2007, 2010). Relative size of the firm is the ratio of its current employment to its industry's total employment within a 25 mile radius.

The proportion of the county population between 24-54 years old is taken from the Census Bureau's Annual Population Estimates. This variable serves as a proxy for the technological savvy of the workforce and assumes younger workers are more comfortable with rapidly evolving technologies. While educational characteristics would be preferable, they are not available for a majority of Texas counties. To account for factor costs, we use the yearly median rural land price in each of 33 land market regions in Texas for the counties comprising the region as reported by the Texas A&M Real Estate Center. As a second measure, we use the average quarterly payroll for the individual firm. The county unemployment rate for the final month in each quarter, as reported by the Texas Workforce Commission, is also included to provide an indication of the overall economic conditions in the local county.[7]

While some studies of industry exit attempt to capture financial market conditions by including

[7] The TWC unemployment rate is the average rate for the calendar year. We average consecutive years beginning with year 1999-2000 since that best overlaps our definition of a year as running from third quarter through second quarter of the following calendar year.

the prime rate, it seems unlikely that high tech firms rely in critical ways on bank financing (Audretsch and Mahmood, 1995). The key measure of access to financial resources should capture conditions in either venture capital or public equity markets. We attempt to capture these influences by including the NASDAQ index at the previous quarterly close. The NASDAQ has been more closely associated with the technology sector than other stock exchanges. We assume that a rising index reflects greater market willingness to provide equity funding.

Since firms can have more than one establishment, establishment-level observations for each industry are not likely to be independent over time. Note, the sample consists of 25,279 establishments with 389,343 observations that capture current quarterly firm characteristics until they fail or are right censored. Therefore, we use clustered standard errors by firm.[8] We assume that the error term is independent across firms but not necessarily within a firm over time.[9]

4 Results and Discussion

Table 3 contains summary statistics for both localized density measures at the NAICS-6. The second column reports the proportion of firms for which the average LQ of its rivals is greater than 1 as calculated for each radius band (donut). The third column reports the density measures based on number of rivals. Note the pattern that is observed in both columns as distance increases; the densities first decrease and then tick up across the 5-10 and 10-25 mile rings. This would be consistent with an urban spatial pattern of discrete sets of commercial buildings distributed across a metropolitan region. Table 4 reports the summary statistics of the variables used in this study.

Table 5 contains the results of the proportional hazard estimations using rivals' LQ dummy and rival firm count density measures. Column 1 reports results for the LQ estimation without any other firm or county controls. This is intended as a simple test of our hypothesis that localization affects firm survival. Column 3 reports the results for the estimations using firm count as the density measures.

Estimation results based on the different measures of intra-industry firm densities do not differ in

[8] In regressions we do not consider self-employed workers (firms).
[9] We use the Breslow-Peto approximation to break ties.

Table 3: Agglomeration measures by radius.

Radius	For All TX Firms	
	Rivals' Employee Based $LQ > 1$	Number of Rival Firms
$1 \leq$ mile	.550	11.655
	(.498)	(46.495)
$> 1 - 5 \leq$ miles	.023	.717
	(.149)	(2.681)
$> 5 - 10 \leq$ miles	.034	1.317
	(.182)	(4.627)
$> 10 - 25 \leq$ miles	.062	5.868
	(.241)	(14.673)
	For All MSA Firms	
$1 \leq$ mile	.543	11.948
	(.498)	(47.128)
$> 1 - 5 \leq$ miles	.023	.734
	(.150)	(2.713)
$> 5 - 10 \leq$ miles	.035	1.350
	(.182)	(4.685)
$> 10 - 25 \leq$ miles	.063	6.015
	(.244)	(14.818)
	For All Non-MSA Firms	
$1 \leq$ mile	.788	1.639
	(.409)	(5.444)
$> 1 - 5 \leq$ miles	.011	.123
	(.104)	(.980)
$> 5 - 10 \leq$ miles	.023	.179
	(.150)	(1.272)
$> 10 - 25 \leq$ miles	.021	.844
	(.143)	(6.556)

Standard deviations are in parentheses

Table 4: Summary statistics.

Variable	Mean (Standard deviation)
Startups	.234
	(.423)
Employment ratio: $25 \leq$ miles	.190
	(.274)
Employment based HHI: $25 \leq$ miles (4 digit NAICS)	.396
	(.206)
Firm with prior experience	.322
	(.467)
Average number of employees per firm	44.304
	(345.170)
Current quarterly average wage rate	15,925.56
	(13,033.78)
Average age in months	112.811
	(144.78)
County unemployment rate	5.4986
	(1.225)
Average total population in counties between ages 24 and 54	66,1356.10
	(51,5557.50)
Other firm density: $25 \leq$ miles	50,929.45
	(32,642.30)
County amenity LQ	.963
	(.221)
Undeveloped land price	601.375
	(265.446)
NASDAQ	2097.142
	(670.513)
Probability of being located in an MSA county	.972
	(.166)
Probability of being located in an knowledge center county	.713
	(.452)

Table 5: Hazard estimates for high-tech firms in Texas (all firms).

Variable	(1)	(2)	(3)	(4)	(5)
Startups	.549***	.386***	.629***	.584***	.590***
	(.045)	(.058)	(.044)	(.059)	(.060)
Rivals' $LQ > 1$ dummy: $1 \leq$ mile	.224**	.117**			
	(.046)	(.048)			
Rivals' $LQ > 1$ dummy: $> 1 - 5 \leq$ miles	-.291*	-.365**			
miles	(.186)	(.184)			
Rivals' $LQ > 1$ dummy: $> 5 - 10 \leq$ miles	-.283*	-.374**			
miles	(.148)	(.148)			
Rivals' $LQ > 1$ dummy: $> 10 - 25 \leq$ miles	.038	-.072			
miles	(.091)	(.093)			
Log number of rivals: $1 \leq$ mile			.401***	.416***	.417***
			(.013)	(.015)	(.018)
Log number of rivals: $> 1 - 5 \leq$ miles			.062	.081	.091
			(.058)	(.058)	(.058)
Log number of rivals: $> 5 - 10 \leq$ miles			.074	.057	.059
			(.052)	(.052)	(.052)
Log number of rivals: $> 10 - 25 \leq$ miles			-.151***	-.164***	-.144***
			(.033)	(.035)	(.035)
Employment ratio within 25 miles		-1.095***		-.731***	
		(.117)		(.113)	
Employment based HHI: 25 $\leq$ miles					-.372**
(4 digit NAICS)					(.151)
Firms with prior experience		-.196***		-.202***	-.251***
		(.052)		(.052)	(.052)
Current quarterly average wage		-.151***		-.182***	-.186***
rate (Log)		(.035)		(.034)	(.035)
Age in months (Log)		-.055**		.015	.009
		(.018)		(.019)	(.019)
County unemployment rate		.032		.043**	.044**
		(.020)		(.019)	(.019)
Total population in county between		-.019		-.080**	-.087**
ages 24 and 54 (Log)		(.037)		(.039)	(.039)
Unban density: 25 $\leq$ miles (Log)		.022		-.029	-.016
		(.032)		(.034)	(.034)
County amenity LQ		-.086		-.028	-.034
		(.110)		(.105)	(.104)
Undeveloped land price (Log)		.070		.308***	.306***
		(.053)		(.055)	(.054)
NASDAQ (Log)		-.119		-.241**	-.242**
		(.090)		(.083)	(.083)
MSA county		.147		.264*	.243
		(.162)		(.161)	(.160)
Knowledge center county		.119		.040	.047
		(.082)		(.086)	(.086)
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	24646	24646	24646	24646	24646
Number of failures	2240	2240	2240	2240	2240
Wald χ^2	592.886	47624.944	1487.810	1600.900	97400.904

*** Denotes statistical significance at the 1 percent level, ** denotes statistical significance at the 5 percent level, and * statistical significance at the 10 percent level. Robust standard errors clustered by firms are in parentheses

substantive ways. Both measures produce coefficient estimates that are positive and highly significant for the radius up to 1 mile. The signs on the coefficients for both intra-industry density measures become both negative and significant as the rings become more distant.

The positive and significant coefficients on both of the intra-industry density measures for the area within a radius of one mile implies that greater concentration over a relatively short distance is associated with higher failure rates, not lower. This effect, however, appears not to extend beyond one mile. This result is similar to the results of Shaver and Flyer (2000) and Folta *et al.* (2006). It is inconsistent with the assumption that greater concentration results in net positive localization economies for these industries. This is suggestive of more vigorous competition among firms (both in product space and for inputs) as a result of closer spatial location that, as Rosenthal and Strange found in the case of the effects of density on entry, attenuates quite rapidly. Firms that are located somewhat more apart –further than one mile– enjoy the benefits of the agglomeration without the competitive effects. While suggestive, however, it provides no direct evidence that knowledge externalities are present and negative.

The estimates of the coefficients of the variables from the LQ and count density regressions are qualitatively nearly identical. Firms with higher employment shares (larger firms) within 25 miles have a higher rate of survival. Firms with prior experience (or firms that changed hands) have relatively lower hazard rates. This observation is in line with Dunne *et al.* (2005). Results indicate that relatively 'older' firms have a lower hazard rate. Workforce characteristics are significant with expected signs.

The urban density variable is positive. This indicates that greater spatial density of firms in other industries contributes to mortality, suggesting that net total urbanization forces have a negative influence on firm survival. As one might easily imagine, greater urban density brings both benefits and costs. While providing greater diversity and specialization of inputs, greater urban density means greater congestion costs and higher factor costs as real estate prices and commercial lease rates are bid up. From experience, the authors of this paper know that commuting times during rush hour in Austin, TX were extraordinary during the decade of the 1990s and into the new century as the city's transportation infrastructure struggled to catch up to regional growth driven by the high tech sector. In industries where high levels of human capital are key, the negative coefficient on average quarterly wages could be explained by the fact that Texas firms that pay higher wages are able to retain more talented workers and enjoy higher levels of performance. Since the QCEW data base only reports the number of employees for whom unemployment insurance is paid and total payroll, another possibility is that the average payroll increases due to additional hours worked for a given number of insured employees when business is good. On the other hand, the sign on the HHI variable is positive, suggesting that firms benefit from greater industrial diversity.

The sign on the lagged NASDAQ variable is as expected and quite significant. As a bellwether of technology firms' ability to raise capital, a rising NASDAQ index is consistent with higher survival rates. The high tech sector has been characterized by high levels of firm start-ups that relied on venture capital inputs for initial growth phases and public equity market offerings (IPO) to establish longer term viability. Finally university R&D expenditures appear to have no effect on hazard rates, echoing the results of De Silva and McComb (2010).

There may be selection issues in the above estimations. Higher failure rates would be observed if a disproportionate share of the localized firms are weak relative to the universe of firms in the industry and more likely to fail for reasons otherwise unrelated to spatial density. This problem would be exacerbated if existing clusters attract more entry, and entrants, as new firms, are more likely to fail. To avoid this problem, we focus only on firms that had been in operation for at least 36 months prior to the beginning of the period under analysis. In this sample, we exclude any firm that entered during the period from Q3:1997 through Q2:2000. These "established" firms, which we term "incumbent firms," have demonstrated some degree of sustained ability to compete within the industry. By limiting the sample to these "incumbent firms," it is our view that the question of selection bias is mitigated.

Table 6 reports results from both the LQ and count density estimations for "incumbent firms" only. It can be seen that qualitative results for localization effects do not change. The estimated coefficients for density within 1 mile, for both density measures, are positive and statistically significant. Note that the estimate of the coefficient of the dummy variable for rivals' LQ greater than one suggests a

Table 6: Hazard estimates for high-tech firms in Texas that entered before July 1997.

Variable	(1)	(2)	(3)	(4)	(5)
Rivals' $LQ > 1$ dummy: $1 \leq$ mile	.341***	.190**			
	(.086)	(.089)			
Rivals' $LQ > 1$ dummy: $> 1 - 5 \leq$	-.257	-.365			
miles	(.387)	(.386)			
Rivals' $LQ > 1$ dummy: $> 5 - 10 \leq$	-.839**	-.932**			
miles	(.344)	(.343)			
Rivals' $LQ > 1$ dummy: $> 10 - 25 \leq$	-.545**	-.710***			
miles	(.208)	(.210)			
Log number of rivals: $1 \leq$ mile			.490***	.526***	.523***
			(.023)	(.027)	(.035)
Log number of rivals: $> 1 - 5 \leq$ miles			-.141	-.121	-.113
			(.135)	(.136)	(.138)
Log number of rivals: $> 5 - 10 \leq$ miles			-.118	-.142	-.138
			(.098)	(.100)	(.101)
Log number of rivals: $> 10 - 25 \leq$ miles			-.158**	-.161**	-.148**
			(.066)	(.069)	(.070)
Employment ratio within 25 miles		-1.195***		-.618**	
		(.201)		(.195)	
Employment based HHI: $25 \leq$ miles					-.399
(4 digit NAICS)					(.321)
Firm controls	No	Yes	No	Yes	Yes
Market controls	No	Yes	No	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	9134	9134	9134	9134	9134
Number of failures	694	694	694	694	694
Wald χ^2	715.097	1277.943	1484.502	2475.291	144958.02

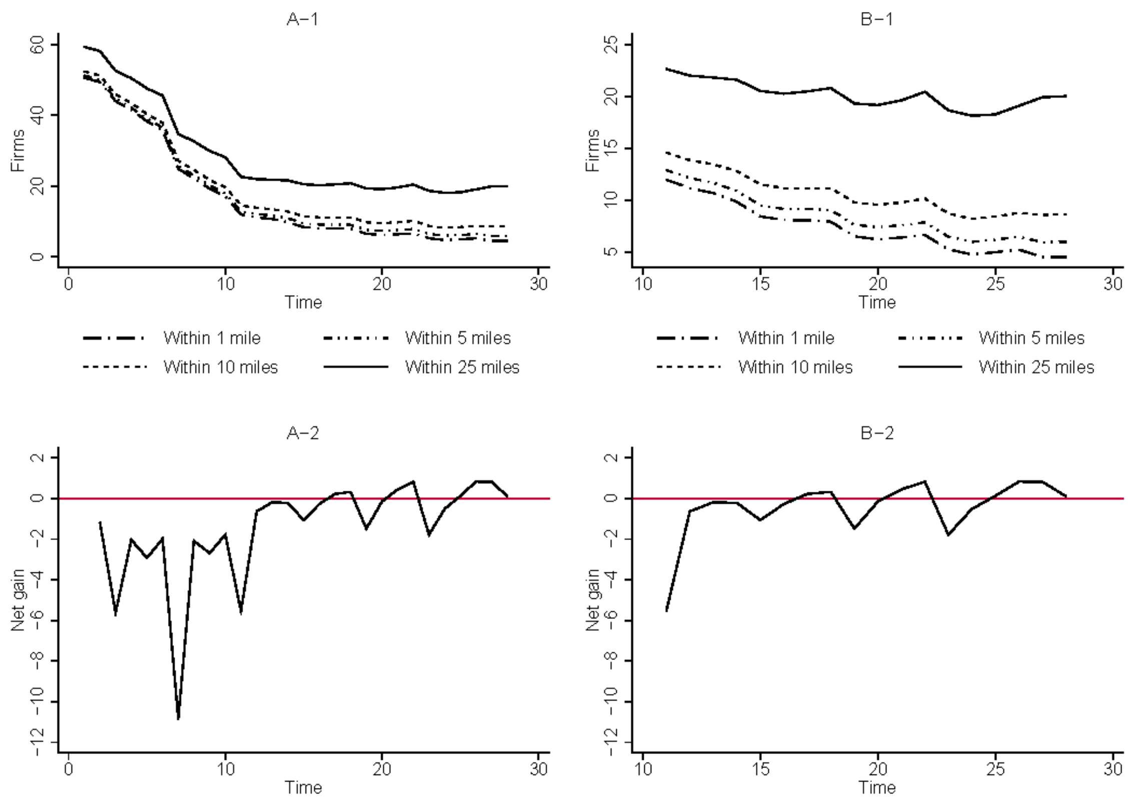
*** Denotes statistical significance at the 1 percent level, ** denotes statistical significance at the 5 percent level, and * statistical significance at the 10 percent level. Robust standard errors clustered by firms are in parentheses

separate effect of the greater density on mortality of about 24%. The estimates, where significant, change sign as distance increases beyond the immediate ring. As would be expected, the relative size of the firm has a negative and significant relationship with mortality rates as reported in columns 2 and 4 of Table 6. We also examined these exit probabilities using simple probit regressions and found, once again, that qualitative results are unchanged. We do not report these estimates, but they can be provided upon request.

We report hazard rates for "entrant firms" in Table 7 where "entrant firms" denotes firms that entered between Q3:2000 and Q2:2004. This allows us to track entrants for at least three years. More importantly, we are able to observe density measures in the cluster at the time the firm enters the industry. The results on initial density measures, in our view, are consistent with the Rosenthal and Strange (2003) finding that localization economies have a positive influence on entrants' location decisions, although the effect diminishes rapidly over space. It woould appear, as we reasoned above, that density offers new firms initial opportunities for greater profits but bears higher longer-term risk, particularly as the degree of spatial concentration increases. Greater density in the more distant rings again appears to reduce hazard rates. We also examine the exit probabilities using simple probit regressions and find that the qualitative results are the same. These results can be provided upon request.

The high tech sector experienced a significant contraction during the period 2000-2002 following the bursting of the "dot.com" bubble in March 2000. Although we control for market conditions by including the NASDAQ variable, anecdotal evidence suggests that the latter part of the decade of the 1990s was characterized by relatively abundant venture capital and the ability of unprofitable Internet-related firms, in particular, to locate external sources of financing. As figure 4 Panel A1and A2 illustrate, while the number of high tech firms declined sharply duirng the period 2000-2002 both in terms of net births/deaths, this decline also resulted in a thinning of the spatial concentration on the high tech industries in Texas. This is seen by the sharp decrease in the average numbers of firms in the same industry within rings proximate to each firm. This is of course consistent with our finding that mortality rates are higher in denser concentrations. However, by the start of 2003, the total number

Figure 4: High tech firm densities and net gains by radius



of firms and the level of spatial concentration within the industries appear to have stabilized, as can be seen in Figure 4 Panels B1and B2.

This contractionary period undoubtedly reduced heterogeneity among firms within industries as weaker firms were weeded out and provides some additional opportunity to control for unobserved firm heterogeneities. We re-estimate the model using only post-2002 observations on firms that survived the shakeout, i.e., firms that were still in operation in the first quarter of 2003. The results of this estimation are contained in Table 8. As can be seen, the qualitative result on the positive association of higher mortality with greater density within one mile still holds.

Table 7: Hazard estimates for high-tech firms in Texas after 2002:Q4.

Variable	(1)	(2)	(3)	(4)	(5)
Startups	.898***	.250***	.863***	.258***	.262***
	(.048)	(.068)	(.048)	(.068)	(.069)
Rivals' $LQ > 1$ dummy: $1 \leq$ mile	-.068	-.092			
	(.048)	(.050)			
Rivals' $LQ > 1$ dummy: $> 1 - 5 \leq$ miles	-.266	-.347			
	(.192)	(.192)			
Rivals' $LQ > 1$ dummy: $> 5 - 10 \leq$ miles	.023	-.018			
	(.143)	(.143)			
Rivals' $LQ > 1$ dummy: $> 10 - 25 \leq$ miles	.010	-.061			
	(.102)	(.103)			
Log number of rivals: $1 \leq$ mile			.380***	.369***	.368***
			(.021)	(.022)	(.024)
Log number of rivals: $> 1 - 5 \leq$ miles			.067	.056	.055
			(.056)	(.056)	(.057)
Log number of rivals: $> 5 - 10 \leq$ miles			-.018	-.007	-.010
			(.054)	(.053)	(.054)
Log number of rivals: $> 10 - 25 \leq$ miles			-.070**	-.118**	-.092**
			(.035)	(.037)	(.038)
Employment ratio within 25 miles		-.776***		-.625***	
		(.116)		(.116)	
Employment based HHI: $25 \leq$ miles					-.323**
					(.152)
Firm controls	No	Yes	No	Yes	Yes
Market controls	No	Yes	No	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	17753	17753	17753	17753	17753
Number of failures	1884	1884	1884	1884	1884
Wald χ^2	1545.071	95806.795	1770.763	2083.284	2112.119

*** Denotes statistical significance at the 1 percent level, ** denotes statistical significance at the 5 percent level, and * statistical significance at the 10 percent level. Robust standard errors clustered by firms are in parentheses

5 Conclusions

The results of this analysis, although consistent with Folta *et al* (2006), Shaver and Flyer (2000), and Staber (2001), run contrary to conventional beliefs of economists on the net effects of localization economies. This study makes an important contribution in this realm by virtue of the relatively greater geographic and establishment-level detail that is employed. Indeed, the narrow spatial analysis is important. The negative localization effect on establishment survival is confined to a radius of only one mile or less. This "close quarters" effect would be obscured in an analysis at the MSA or county level.

We find these results on localization to be quite plausible and suggestive of the presence of highly localized knowledge externalities that have the effect of enhancing competition among the very closely-located firms. However, we recognise that our model cannot empirically identify the separate effects of localization. We realize, as do Shaver and Flyer (2000), that knowledge spillovers spill both ways. It is quite possible that firms with relatively strong intellectual property or higher levels of R&D might perceive that there is more to lose than to gain by a location next door to their rivals or potential rivals or that the availability of knowledge spillovers would tend to attract weaker firms. We control for this possibility by estimating the model using only observations on firms that had been in operation for at least three yrears.

Marginal proximity (between 1 and 25 miles) to the densest industry concentration appears to offer positive net localization economies. As industry density beyond the one mile radius increases, the effect of density on mortality changes sign. Location near, but not in, a dense spatial concentration might offer key advantages while mitigating continuous knowledge outflows associated with continuous inter-firm worker interactions. The potential labor draw probably extends to at least 25 miles in even the most congested metropolitan areas while the nearby industry concentration ensures access to networks of specialized venture capitalists and other specialized business services providers. Access to these key production inputs is not likely affected significantly by locating just "off to the side." This may offer an explanation for why Glaeser *et al.* (1992), in their analysis of industry growth at the MSA-level, found no evidence of MAR-type dynamic localization externalities in the high-tech industries at the MSA-level.[10]

Despite negative localization economies, start-up firms may be attracted to denser concentrations. Newer firms are riskier than established firms and are probably less attractive, *ceteris paribus*, to potential employees due to the higher likelihood of firm mortality. Location in a dense concentration can help to offset employee risk. That is, if geographic proximity increases worker mobility, as Freedman (2008) finds, individuals may be more willing to take a job if the hiring firm is embedded in a dense concentration. Co-location of similar firms in the same office tower or campus facilitates inter-firm employee networking through frequent casual encounters, lunches at the same restaurants, etc. Workers are able to acquire current employment market information through this localized network at relatively low cost and use existing personal relationships to advantage in competition for employment openings. Thus, the same elements that contribute to knowledge spillovers between firms can benefit riskier firms in terms of their employment of workers.

Without offering any explanation for how a spatial industry concentration comes into existence, new firm entry may partially depend on the firm exits. Rosenthal and Strange (2003) cite Carlton (1983) as referring to the firm *birth potential* of an area and suggesting that firm failures provide localized ingredients for start-ups by releasing factors of production, most notably labor and entrepreneurial proclivities. Higher failure rates may well contribute to higher start up rates in highly localized and dense industry concentrations.

[10] Glaeser *et al.* (1992) found little evidence of MAR-type externalities across a broader range of industries.

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Appendix A

Table A1: High-Tech Industry Classifications

NAICS	Description	NAICS	Description
325411	Medicinal Chemicals and Botanical Products	334512	Automatic Environmental Controls
325412	Pharmaceutical Preparations	334513	Industrial Process Control Instruments
325413	In Vitro and In Vivo Diagnostic Substances	334514	Totalizing Fluid Meter & Counting Devices
325414	Biological Products, Except Diagnostic Substances	334515	Electricity Measuring & Testing Equipment
333295	Semiconductor Machinery	334516	Analytical Laboratory Instruments
333314	Optical Instrument & Lens	334517	Irradiation Apparatus
333315	Photographic & Photocopying Equipment	334519	Other Measuring & Controlling Instruments
334111	Electronic Computers	335921	Fiber Optic Cables
334112	Computer Storage Devices	511210	Software Publishers
334113	Computer Terminals	517110	Wired Telecommunications Carriers
334119	Other Computer Peripheral Equipment &	517211	Paging Services
	Electromedical Equipment	517212	Cellular & Other Wireless Telecommunications
334210	Telephone Apparatus	517310	Telecommunications Resellers
334220	Radio & TV Broadcasting & Wireless Communications	517410	Satellite Telecommunications
	Equipment	517510	Cable & Other Program Distribution
334290	Other Communications Equipment	517910	Other Telecommunications
334310	Audio & Video Equipment	518111	Internet Service Providers
334411	Electron Tubes	518112	Web Search Portals
334412	Bare Printed Circuit Boards	518210	Data Processing, Hosting, & Related Services
334414	Electronic Capacitors	541330	Engineering Services
334413	Semiconductor & Related Devices	541380	Testing Laboratories
334415	Electronic Resistors	541511	Custom Computer Programming
334416	Electronic Coils, Transformers, & other Inductors	541512	Computer Systems Design
334417	Electronic Connectors	541513	Computer Facilities Management
334418	Printed Circuit Assembly	541519	Other Computer Related Services
334419	Other Electronic Components	541710	R & D in the Physical, Engineering, & Life Sciences
334510	Electromedical & Electrotherapeutic Apparatus	541711	Commercial Physical & Biological Research
334511	Search, Detection, Navigation, Guidance, Aeronautical,	611420	Computer Training
	& Nautical Systems & Instruments		