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Geographic concentration and high tech firm survival

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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 suggest 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.

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 establishments. 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 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 establishment 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 establishment-level characteristics, including NAICS-6 industry classification, size, ownership status, entry and exit dates (in case of mortality), and exact address. We then utilize, *inter alia*, exact establishment-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-establishment 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 establishment mortality while localization effects over a larger geographic area reduce establishment 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 specialize geographically. This is particularly so since there has been an emphasis in this literature on the role of internal economies of scale in establishment survival and growth. Due to data limitations, much of the earlier analyses utilized industry exit rates, since establishment-specific characteristics were unavailable. However, even with establishment-level data, analyses have

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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 single plant 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 (Bradburd 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 establishments are heterogeneous, knowledge spillovers will likely benefit weaker establishments more than stronger establishments. If weaker establishments' competitiveness is bolstered by spatial proximity to stronger establishments, particularly strong establishments 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 establishments and repel entrants that have stronger intellectual properties to commercialize. 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 manufacturing firms in Morocco, concludes that agglomeration has an effect on firm growth rates, but it is not working through productivity. [1]

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. [2] 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-excludable 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 excludability. In the absence of any entry barriers, entry would occur up to the point where risk-adjusted expected profits would be equalized 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, Freeedman (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?”[3] Most of the earlier studies of knowledge externalities were conducted at relatively aggregated industry levels and over relatively large geographic areas. Mansfield (1995), among

[1] A recent article by Frenken et al. (2011) provides a good survey on clusters and their effects on industrial dynamics.

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

[3] Krugman (1991), page 485.

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. Saxenian (1994) provides a relevant quote from a technology industry employee in Silicon Valley who said, "The joke is that you can change jobs and not change parking lots." Rosenthal and Strange (2003), looking at start-up firms at the Zip Code level, conclude that agglomeration economies attenuate rapidly up to a distance of 1 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 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. [4]

In the analysis that follows, we analyze the effect of agglomeration economies on high-tech establishment 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 establishment-specific measures of spatial density, within circles of varying radii, we seek to analyze the effect of localization on high tech establishment 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, the importance of well educated and creative workers in this highly dynamic sector is one of its salient features.

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

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

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 $_{ijt}$ is a random draw for each firm in a given industry in each period and is independent and identically distributed across firms in each industry according to the cumulative distribution function $H(\epsilon_i)$.

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

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

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.

Although the discussion thus far has been cast in terms of the *firm*, our analysis, more precisely, takes place at the establishment level. We estimate probabilities of establishment failure using a Cox proportional hazards model. The basic Cox proportional hazards model can be written as follows:

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

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, using an establishment-level dataset, we compute alternative spatial density measures within concentric rings of 0–1, 1–5, 5–10, and 10–25 mile radii around each establishment's exact location for every high-tech establishment in Texas during the period of the study. Unlike Rosenthal and Strange (2003), the density measures are based on the actual physical addresses of establishments 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. [5] 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 establishments, no additional spatial normalization is necessary. Freeedman (2008) using a data set similar to ours, calculated the location quotient for each establishment within concentric circles with radii of 5, 10, and 25 miles around each establishment.

We compute local densities using both (employment) location quotients (LQ) and count data in terms of establishments. 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

[4] See Jacobs (1969).

[5] 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.

share of total employment in the broader region. In our case, we compute the *LQ* for each ring around each establishment relative to the State of Texas. An establishment and its employment are excluded from density measures in any ring in which the establishment is located. Therefore, all measures of the own-industry *LQ* are referred to as rivals' *LQ*, where the use of the term rival, in most cases, signifies rivalry in competition for localized resources. In some cases, the localized firms will also be rivals in output markets.

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

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

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 employment for all non-farm industries in Texas.

We obtained the establishment-level data for Texas from the Quarterly Census of Employment and Wages (QCEW) from the Texas Workforce Commission. This data set provides establishment-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. Note that a firm could have many establishments (branches or franchises) and they are identified and reported in separate records. This panel data set is comprised of observations from Q3:1999 through Q2:2007.[6] As in Dunne et al. (1989), we define an establishment exit as the last period where we observe a UI account number in the data set. In the case of a single-establishment firm, this would also imply disappearance of the EIN (Enterprise Identification Number). For multi-establishment firms, if at least one establishment survives, so does the EIN.

Definition of the high-technology sector is necessarily somewhat arbitrary. This paper utilizes 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 principle 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.[7] Fig. 1 illustrates the location of high-tech establishments in Texas and shows their spatial concentration along Interstate 35 from the Dallas/Fort Worth Metroplex down to San Antonio and in the Houston metropolitan area. One can also note a sprinkling of high-tech establishments across the less urban areas of the state. Fig. 2 illustrates the intra-urban spatial distribution of software publishing establishments in the Austin Metropolitan Statistical Area. Spatial clustering at this level is also evident.

In the case of the high tech industries, transportation costs as an agglomerating force and access to geographically specific natural resources are not particularly relevant. High-tech establishments 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 following fiscal year's total for quarter 4 of each calendar year.

In order to measure the urbanization effect, we compute urban density for all non-farm industries, excluding the industry in which the establishment 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 establishment survival probabilities. A 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 establishment in months, average payroll, and relative size of the establishment. Regional measures include the county unemployment rate, proportion of county population between 24 and 54 years, and rural land price.

Age of the establishment in months is the period of time since UI liability began. This is reported for all establishments. Therefore, despite the fact that the data set starts in 1999, we can observe the actual start-up date for all establishments. Average payroll is the establishment'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 (Freeedman, 2008; De Silva et al., 2010; Dube et al., 2007, 2010). Relative size of the establishment is the ratio of its current employment to its industry's average establishment employment in the state.

The proportion of the county population between 24 and 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 establishment. 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.[8]

[6] 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.

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

[8] 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.

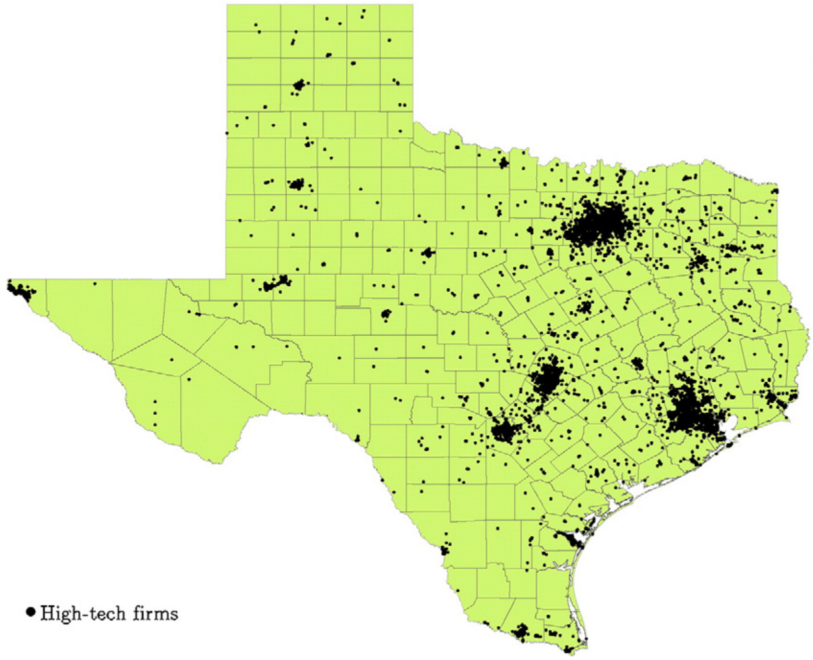

Fig. 1. High-tech establishments locations in Texas.

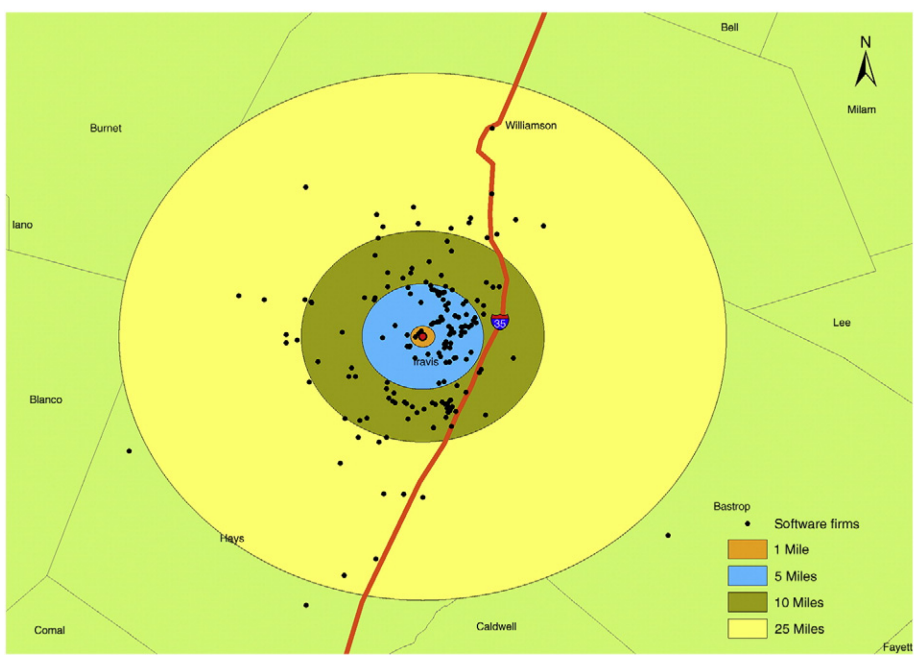

Fig. 2. Spatial distribution of establishments for software publishers in Austin MSA.

While some studies of industry exit attempt to capture financial market conditions by including 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 some establishments are part of multi-establishment firms, 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 establishment characteristics until they fail or are right censored. Therefore, we use clustered standard errors by firm.[9] We assume that the error term is independent across firms but not necessarily within a firm over time.[10] Establishments that are part of a multi-establishment firm may have different mortality rates, all else equal, than stand-alone establishments. We use the log of the number of

[9] In regressions we do not consider self-employed workers (firms).

[10] We use the Breslow–Peto approximation to break ties.

establishments associated with each Enterprise Identification Number (EIN) in Texas to control for this influence. While it would be ideal to control for all multi-establishment operations, which would identify association with firms that have other establishments outside of Texas, we are unable to do so since our dataset is restricted to Texas establishments.

4. Results and discussion

Table 1 contains averages for both localized density measures at the NAICS-6. The second column reports the average *LQ* based on the employment of rival establishments as calculated for each radius band (donut). The third column reports the density measures based on number of rivals. Not surprisingly, the *LQ* measure is quite high for the 1 mile rings since the average establishment is located in a one-mile concentration with nearly a dozen rivals. The presence of any rivals in an employment area as small as 1 mile in radius reflects substantial localization relative to the State of Texas. It is worthwhile to point out the tight geographic distribution of activity that is discerned with continuous spatial measures and which would not be observed at the county or MSA-level. 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 2 reports the summary statistics of the variables used in this study.

Table 3 contains the results of the proportional hazard estimations using rivals' *LQ* and rival establishment count density measures. Column 1 reports results for the *LQ* estimation without any other establishment or county controls. This is intended as a simple test of our hypothesis that localization affects establishment survival. Column 3 reports the results for the estimations using establishment count as the density measures. The log number of rivals is based on the total number of rival establishments in the ring plus 1. In this way, the measure is always defined and is zero for a ring in which no rivals are present.

Table 1
Agglomeration measures by radius.

Radius	For all TX establishments	
	Rivals' employee based *LQ*	Number of rival establishments
1 ≤ mile	69.364	11.655
	(1391.222)	(46.495)
> 1–5 ≤ miles	.209	.717
	(4.829)	(2.681)
> 5–10 ≤ miles	.229	1.317
	(5.684)	(4.627)
> 10–25 ≤ miles	.482	5.868
	(6.458)	(14.673)
	For all MSA establishments	
1 ≤ mile	63.861	11.948
	(1371.518)	(47.128)
> 1–5 ≤ miles	.209	.734
	(4.869)	(2.713)
> 5–10 ≤ miles	.225	1.350
	(5.614)	(4.685)
> 10–25 ≤ miles	.485	6.015
	(6.450)	(14.818)
	For all non-MSA establishments	
1 ≤ mile	257.652	1.639
	(1939.547)	(5.444)
> 1–5 ≤ miles	.181	.123
	(3.201)	(.980)
> 5–10 ≤ miles	.360	.179
	(7.722)	(1.272)
> 10–25 ≤ miles	.376	.844
	(6.740)	(6.556)

Standard deviations are in parentheses.

Table 2
Summary statistics.

Variable	Mean (Standard deviation)
Startups	.234
	(.423)
Establishment with prior experience	.322
	(.467)
Current quarterly average wage rate	15,925.56
	(13,033.78)
Average age in months	112.811
	(144.78)
Number of branches	15.477
	(64.918)
Relative establishment size	1.17545
	(5.5537)
Employment based HHI: 25 ≤ miles (4 digit NAICS)	.396
	(.206)
County unemployment rate	5.4986
	(1.225)
Average total population in counties between ages 24 and 54	66,1356.10
	(51,5557.50)
Other establishment density: 25 ≤ 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)

Estimation results based on the different measures of intra-industry establishment densities do not differ in 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. There is an important difference in interpretation of the different density measures. Since the *LQ* captures employment density within the industry, it can be quite high even though the ring may contain only one or two other establishments. In fact, for the small area within a 1 mile radius, the *LQ* will typically be well above 1 if there is at least one other firm.[11] Moreover, an establishment located adjacent to a large establishment might appear to be in a dense one-mile concentration even though there is, in fact, only one or two other establishments in the locale. This measure effectively aggregates the rival establishments' employment, making no distinction in terms of the number of establishments. On the other hand, the count density measure does not capture rival firm size, only their number. While our preference leans toward the count density measure, using both measures provides different perspectives that yield a consistent conclusion.

The positive and significant coefficients on both of the intra-industry density measures for the area within a radius of 1 mile imply that greater concentration over a relatively short distance is associated with higher failure rates, not lower. The effect, however, appears not to extend beyond 1 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 establishments (both in product space

[11] As noted, the *LQ* measure within one-mile rings in cases of dense concentrations of establishments (own-industry) tends to be quite high. The range of the measured *LQ*'s is from zero to over 50,000. As a consequence, the estimated coefficient is quite small, although significant at .01.

Table 3
Hazard estimates for high-tech firms in Texas (all firms).

Variable	(1)	(2)	(3)	(4)	(5)
Startups	.655***	.516***	.730***	.718***	.723***
	(.042)	(.055)	(.042)	(.056)	(.056)
Rivals' *LQ*:	.000***	.000***			
1 ≤ mile	(.000)	(.000)			
Rivals' *LQ*:	−.025	−.028*			
> 1 − 5 ≤ miles	(.016)	(.015)			
Rivals' *LQ*:	−.109*	−.107*			
> 5 − 10 ≤ miles	(.062)	(.063)			
Rivals' *LQ*:	−.001	−.001			
> 10 − 25 ≤ miles	(.002)	(.002)			
Log number of rivals:			.386***	.426***	.407***
1 ≤ mile			(.013)	(.014)	(.017)
Log number of rivals:			.044	.088	.080
> 1 − 5 ≤ miles			(.055)	(.055)	(.055)
Log number of rivals:			−.039	−.055	−.060
> 5 − 10 ≤ miles			(.047)	(.048)	(.048)
Log number of rivals:			−.093**	−.052	−.062*
> 10 − 25 ≤ miles			(.032)	(.034)	(.034)
Relative		−.010		−.020**	
establishment size		(.006)		(.007)	
Employment based					−.242*
HHI: 25 ≤ miles					(.144)
(4 digit NAICS)					
Establishments with		−.413***		−.335***	−.368***
prior experience		(.056)		(.054)	(.054)
Log number of		.176***		.146***	.147***
establishments in		(.018)		(.016)	(.016)
EIN					
Current quarterly		−.215***		−.241***	−.246***
average wage rate		(.035)		(.034)	(.035)
(Log)					
Age in months (Log)		−.064***		.008	.005
		(.018)		(.018)	(.018)
County		.032		.035*	.035
unemployment		(.019)		(.018)	(.018)
rate					
Total population in		.022		−.048	−.049
county between					
ages 24 and 54		(.036)		(.037)	(.037)
(Log)					
Unban density: 25		.022		−.048	−.051
≤ miles (Log)		(.036)		(.033)	(.033)
County amenity *LQ*		.055		.102	.099
		(.095)		(.093)	(.093)
Undeveloped land		.030		.297***	.299***
price (Log)		(.050)		(.053)	(.053)
NASDAQ (Log)		−.170*		−.255**	−.258**
		(.089)		(.082)	(.082)
MSA county		.056		.281*	.284
		(.158)		(.157)	(.156)
Knowledge center		.004		−.063	−.063
county		(.077)		(.082)	(.081)
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	24,625	24,625	24,625	24,625	24,625
Number of failures	2434	2434	2434	2434	2434
Wald χ^2	29,689.352	30,003.631	2338.370	2376.560	35,464.165

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

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. Establishments that are located somewhat farther apart – further than 1 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. Establishments with higher employment shares (larger establishments) within 25 miles have a higher rate of survival. Establishments with prior experience (or establishments that changed hands) have relatively lower hazard rates. This observation is in line with Dunne et al. (2005). Results indicate that relatively 'older' establishments have a lower hazard rate. Workforce characteristics are significant with expected signs. The positive and significant coefficient estimate for the log number of branches within each EIN is of some interest. While one might postulate a number of reasons for this finding, we find plausible, as did Folta et al. (2006) in their firm-level analysis, the possibility that establishment exit costs are lower for high tech firms whose establishments tend to be located within spatial concentrations. For many of these industries, establishment fixed costs are low, intra-firm reallocations across establishments may be readily accomplished, and terminated employees may have relatively shorter intervals between jobs. Another interesting conjecture is that high tech firms, particularly those that have lower entry and exit costs, locate branches within different spatial concentrations in order to take advantage of diverse pools of localized knowledge. As the firms learn the value of localization in the different clusters, they reallocate resources accordingly by closing and perhaps expanding some establishments. At the very least, closing establishments within a multi-establishment firm has quite different implications than closing an establishment when that implies mortality of the firm itself.

The coefficient on the urban density variable is not statistically significant. 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. Industrial diversity, as measured by the HHI, appears weakly to influence mortality rates of high tech firms in Texas. Thus, it can be inferred that net total urbanization forces have a slight influence on establishment survival. 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 establishments 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.

The sign on the lagged NASDAQ variable is negative and quite significant in the count density estimations. 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 establishment start-ups that relied on venture capital inputs for initial growth phases and public equity 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 (2012).

There may be selection issues in the above estimations. Higher failure rates would be observed if a disproportionate share of the localized establishments are weak relative to the universe of establishments 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 establishments, are more likely to fail. To avoid this problem, we focus only on establishments 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 establishment that entered during the period from Q3:1997 through Q2:2000. These "established" establishments, which we term "incumbent establishments," have demonstrated some degree of sustained ability to compete within the industry. By limiting the sample to these "incumbent establishments," it is our view that the question of selection bias is mitigated.

Table 4 reports results from both the *LQ* and count density estimations for "incumbent establishments" 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. The estimates, where significant, change sign as distance increases beyond the immediate ring. As would be expected, the relative size of the establishment 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 establishments" in Table 5 where "entrant establishments" denotes establishments 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 establishment 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 would appear, as we reasoned above, that density offers new establishments initial opportunities for greater profits but bears higher longer-term risk, particularly as the degree of spatial concentration increases. Thus, one can theorize that positive marginal benefits to entrants from localization generate negative marginal benefits to the existing concentration in the form of increased competition for resources and output markets. 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.

Table 5
Hazard estimates for high-tech firms in Texas after 2002:Q4.

Variable	(1)	(2)	(3)	(4)	(5)
Startups	.910***	.393***	.866***	.387***	.402***
	(.048)	(.066)	(.048)	(.066)	(.066)
Rivals' *LQ*: 1 ≤mile	−.000	−.000			
	(.000)	(.000)			
Rivals' *LQ*: >1−5 ≤miles	−.036	−.038			
	(.028)	(.026)			
Rivals' *LQ*: >5−10 ≤miles	−.037	−.031			
	(.031)	(.029)			
Rivals' *LQ*: >10−25 ≤miles	−.000	−.001			
	(.001)	(.001)			
Log number of rivals: 1≤mile			.376***	.414***	.383***
			(.021)	(.022)	(.023)
Log number of rivals: >1 −5 ≤miles			.028	.031	.021
			(.056)	(.056)	(.056)
Log number of rivals: >5 −10 ≤miles			−.010	−.001	.011
			(.053)	(.053)	(.053)
Log number of rivals: > 10−25 ≤miles			−.080**	−.057	−.076**
			(.034)	(.036)	(.037)
Relative establishment size		−.027***		−.036***	
		(.012)		(.012)	
Employment based HHI: 25 ≤miles					−.407**
					(.151)
Establishment controls	No	Yes	No	Yes	Yes
Market controls	No	Yes	No	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	17,748	17,748	17,748	17,748	17,748
Number of failures	1936	1936	1936	1936	1936
Wald χ^2	82,725.992	1913.096	2226.378	3067.023	73,894.678

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

Table 4
Hazard estimates for high-tech firms in Texas that entered before July 1997.

Variable	(1)	(2)	(3)	(5)	
Rivals' *LQ*: 1≤mile	.000***	.000**			
	(.000)	(.000)			
Rivals' *LQ*: >1−5 ≤miles	−.008	−.003			
	(.023)	(.018)			
Rivals' *LQ*: >5−10 ≤miles	−.256**	−.216**			
	(.110)	(.095)			
Rivals' *LQ*: >10−25 ≤miles	−.002	−.003			
	(.004)	(.004)			
Log number of rivals: 1≤mile			.473***	.499***	.455***
			(.023)	(.029)	(.035)
Log number of rivals: >1−5 ≤miles			.094	.182	.163
			(.116)	(.118)	(.118)
Log number of rivals: >5−10 ≤miles			−.080	−.125	−.135
			(.095)	(.098)	(.097)
Log number of rivals: >10−25 ≤miles			−.189**	−.141**	−.161**
			(.064)	(.069)	(.070)
Relative establishment size		−.010		−.023***	
		(.009)		(.012)	
Employment based HHI: 25 ≤miles					−.576*
					(.320)
(4 digit NAICS) establishment controls	No	Yes	No	Yes	Yes
Market controls	No	Yes	No	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Number of establishments	9117	9117	9117	9117	9117
Number of failures	718	718	718	718	718
Wald χ^2	137,187.93	96,632.26	163,343.93	135,720.54	153,641.65

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

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 Fig. 3 Panel A1and A2 illustrate, while the number of high tech establishments and firms declined sharply during the period 2000–2002 both in terms of net births/deaths, this decline also resulted in a thinning of the spatial concentration of the high tech industries in Texas. This is seen by the sharp decrease in the average numbers of establishments in the same industry within rings proximate to each establishment. This is consistent with our finding that mortality rates are higher in denser concentrations. However, by the start of 2003, the total number of establishments and the level of spatial concentration within the industries appear to have stabilized, as can be seen in Fig. 3 Panels B1and B2.

This contractionary period undoubtedly reduced heterogeneity among establishments within industries as weaker establishments were weeded out and provides some additional opportunity to control for unobserved establishment heterogeneities. We re-estimate the model using only post-2002 observations on establishments that survived the shakeout, i.e., establishments that were still in operation in the first quarter of 2003. The results of this estimation are contained in Table 5. As can be seen, the qualitative result on the positive association of higher mortality with greater density within 1 mile still holds for the count density variables. The effect of the LQ on mortalilty variable vanishes. This may be attributable to a post-

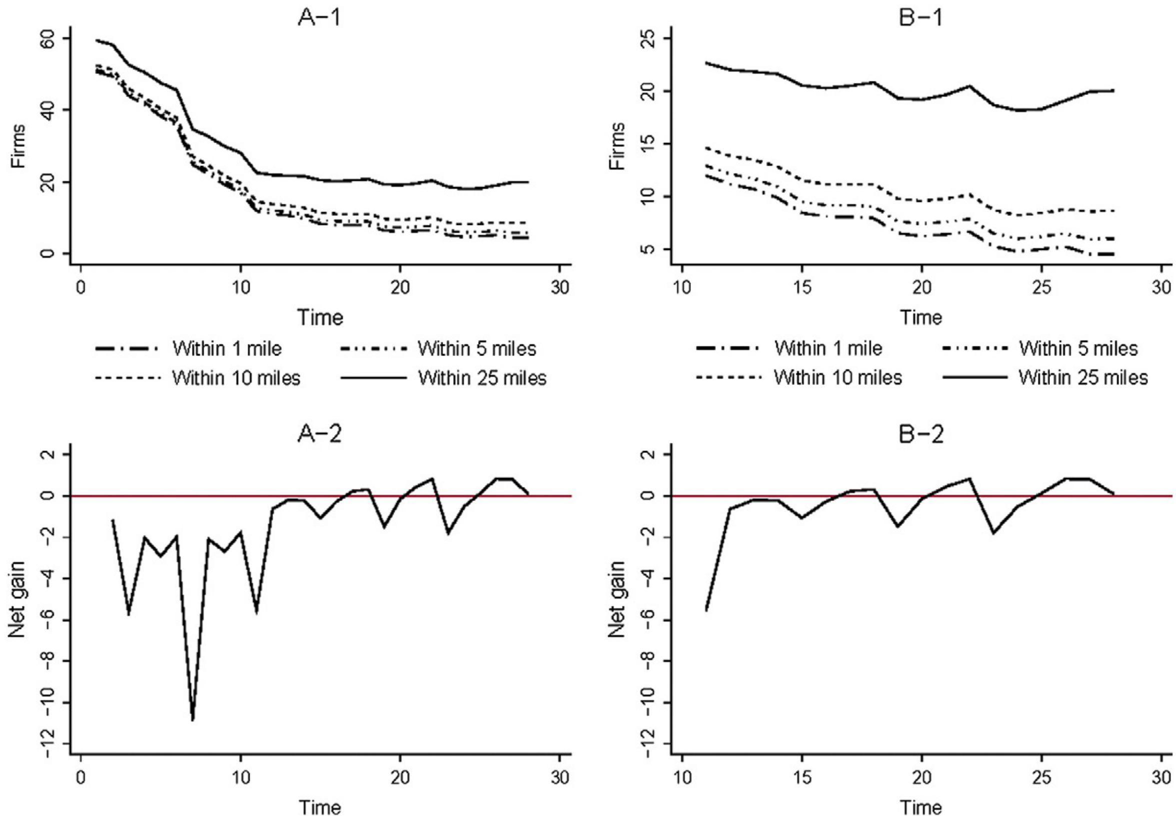

Fig. 3. High tech firm densities and net gains by radius.

2002 employment equilibrium in which there was relatively little variation in the LQ measures.

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 1 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 externalities that have the effect of enhancing competition among the very closely-located establishments. 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 establishments 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 establishments. We control for this possibility by estimating the model using only observations on establishments that had been in operation for at least three years.

Marginal proximity (between 1 and 25 miles) to the densest industry concentration appears to offer positive net localization economies. As industry density beyond the 1 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-establishment worker interactions that occur in close quarters. 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. [12]

Despite negative net localization economies, start-up establishments may nevertheless be attracted to denser concentrations. Ready access to the localized knowledge base may provide critical information for an inexperienced firm to survive the period following its launch. Newer establishments are riskier than incumbent establishments and are probably less attractive, *ceteris paribus*, to potential employees due to their higher likelihood of establishment mortality. Employment in a dense concentration can help to offset employee risk. That is, if geographic proximity increases worker mobility, as Freeedman (2008) finds, individuals may be more willing to take a job with a new enterprise if the hiring establishment is embedded in a dense concentration. Co-location of similar establishments in the same office tower or campus facilitates inter-establishment 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

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

competition for employment openings. Thus, the same elements that contribute to knowledge spillovers between establishments can benefit riskier establishments in terms of their employment of workers.

This finding may provide some support for the argument that higher rates of entry are the other side of the coin from higher mortality rates. Carlton (1983) noted that firm failures provide localized ingredients for start-ups by releasing factors of production, most notably labor and entrepreneurial proclivities. This is consistent with the view that there is an internally dynamic process at work in which higher failure rates contribute to higher start up rates in highly localized and dense industry concentrations.

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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, & Nautical Systems & Instruments	611420	Computer Training

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