DO LOCATION CHARACTERISTICS HAVE DIFFERENT SURVIVAL VALUES FOR HIGH AND LOW- TECHNOLOGY DE NOVO ENTERPRISES ?

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ABSTRACT

The importance of sectors characterized by high knowledge and technological intensity is growing in the new economy. The creation and maintenance of competitive advantage in high-technology sectors depend to a large degree on innovation. Since diffusion of innovation tends to be local, location characteristics matter. We argue that new high-technology firms can improve their survival probabilities by entering locations that stimulate and support innovation. These characteristics include urban diversity, competitive industrial structure, and clustering. In contrast, clustering, competition and diversity have lower survival value for low-technology firms, as the benefits accruing from higher innovation levels are less valuable. Indeed, the costs of urban congestion, and the pressure of competition on prices may result in negative impacts on survival. We test our hypotheses using an extensive longitudinal data base which covers *all de novo* entrants into the Canadian manufacturing sectors. The results indicate that clustering has a higher survival value for high-technology firms. Urban diversity and competition have positive effect on the survival of high-technology firms and negative effect on low- technology firms.

Introduction

Knowledge plays an important part in determining the competitive advantage of many firms in the new economy. The relative importance of knowledge, however, varies considerably among sectors. This is reflected in significant inter-sectoral differences in the levels of expenditures on R&D, the importance of skilled employees, and the rates of innovation (Acs and Audretsch (1988), Hadlock, Hecker and Gannon (1991), Agarwal and Audretsch (2001), OECD (1996)).

Several authors have examined the relationship between the level of knowledge intensity (often reflected in the presence of high-level of innovative technological activity) and entry and post entry performance. Early work by Mahmood (1992) showed that hazard rates in high-technology industries were higher than in low-technology industries. Similarly Audretsch and Mahmood (1993) have found survival to be negatively affected by high-technology environment. Much of the recent literature focused on the effects of technological activity on market structure (Gort and Klepper (1982), Klepper and Simons (2000), Pakes and Ericson (1998)). Two opposing forces characterize the effects of innovative technological activity. High-technology products have high rates of obsolescence and thus create opportunities for new entry and reduce the competitive advantage of incumbents. High levels of innovative technological activity, however, increase uncertainty and thus deter entry and reduce the probability of survival. Recent work addressed the impact of technological activity on survival rates in the context of the life cycle of product markets (Agarwal (1996), Agarwal and Gort (1996), Jovanovic and MacDonald (1994)). In particular the focus was on the circumstances under which entrants, especially smaller ones, have a relative survival advantage (Agarwal, Sarkar, and Echambadi, (2002), Sarkar, Echambadi, Agarwal and Sen (2003)).

"Diffusion of knowledge and ideas tends to be local rather than global" (Aharonson, Baum and Feldman (2004a)). Thus the strategic choice of where to locate is especially critical for de novo entrants in knowledge intensive sectors. These firms may strategically locate so as to access the relevant networks through which ideas and knowledge flow. They may also seek environments which stimulate creativity and encourage cross fertilization. Access to pools of skilled employees is also an important factor which may determine the abilities of new firms to overcome entry barriers, rapidly mature and ensure long term profitability and survival.

Choice of a location was shown to affect survival prospects of entrants to all manufacturing sectors (Dumais, Ellison and Glaeser (2002), Dunne, Klimek and Roberts (2004), Pe'er and Vertinsky (2006a), Shaver and Flyer (2000)). However, since knowledge is a unique resource, more prone to appropriation and spillovers, the benefits and costs of various location externalities accruing to firms may vary considerably as a function of the knowledge intensity of their sector. Innovation is an important means of protecting from erosion core competencies derived from proprietary knowledge. It is therefore likely that knowledge intensive firms would benefit more from locating in environments which stimulate innovation and support innovative activity. Innovation is less important to firms in sectors where competitive advantage is derived from other factors such as economies to scale or access to less expensive inputs. Thus, for example, it is possible that firms in knowledge intensive sectors would benefit from environments characterized by urban diversity that stimulate cross fertilization and creativity while in other sectors lower rents and wages, proximity to markets or quality of infrastructure may confer competitive advantage .

Because of the importance of innovation to high-technology sectors and informed by recent literature that emphasizes the relationships of location attributes and innovation (Audretsch and

Feldman (1996), Baptista and Swann (1998), Pe'er and Vertinsky (2006a), Romanelli (1989)), we explore in this paper whether survival rates of new high-technology manufacturing enterprises are affected by various location attributes in different ways than survival rates of low-technology enterprises. We are especially interested in the impacts on survival of co-location, the diversity of the urban environment, the local industrial structure, and local resource recoverability. We control for differences in the current and initial profiles of resources and capabilities, industry growth, economic region idiosyncrasies and time fixed effects.

We have used extensive longitudinal database which covers all de novo entrants into the Canadian manufacturing sector during the period 1984-1998. The results confirm that the survival rates of high-technology firms are lower compared to low-technology firms at every age. Maturity has less survival advantage in high-technology than in low-technology industries reflecting the effects of faster product obsolescence in high-technology sectors. Localization economies and urban diversification are more important for survival in the high-technology sectors. A market structure characterized by many small firms is more welcoming than a concentrated local environment in the high-technology sectors as it enhances the flow of information while maintaining high levels of inter-firm rivalry that stimulate innovation. In contrast, rivalry has negative impact on survival in the low-technology sectors. We also confirm the findings of Sarkar *et al*.(2003), Shane (2001), and Almeida, Dokko and Rosenkopf (2003) that smaller size is less of a disadvantage in high-technology than low-technology sectors and that the quality of human resources has higher survival value for high-technology firms.

The next section discusses the literature and develops the hypotheses. The third section describes the methodology. It is followed by a discussion of the results and conclusions.

Related Literature and Hypotheses Development

A firm that depends on innovation for survival must consider several factors in choosing a location. It must choose a location where mechanisms exist that permit it to access new ideas and information necessary to sustain innovation. It may wish to enter a location where finding strategic partners with complementary resources is facilitated by proximity and the existence of well developed and extensive inter-firm and interpersonal networks (Stuart and Sorenson (2003), Aharonson, Baum and Feldmand (2004b), Kalnins and Chung (2004)). Since much of new knowledge is not codified, access to a pool of mobile skilled employees who can bring to the firm the tacit knowledge acquired by working for rivals is highly desirable. Having access to employees who can bring to the firm ideas developed in other sectors may stimulate inter-sectoral transfers of knowledge and cross fertilization (Jacobs (1963), Glaeser (1999)).

Porter (1990, 1998) highlighted the importance of clustering in stimulating and supporting innovative activities. Clusters facilitate the emergence of networks and specialized markets of skilled employees, encourage mobility and face to face contacts, all mechanisms through which new ideas and knowledge flow (Stuart and Sorenson (2003), Rosenthal and Strange (2003)). The benefits and costs of knowledge spillovers depend on the value of knowledge received or spilled by a firm. New firms that need to further develop their knowledge base may asymmetrically benefit from involuntary transfers of knowledge while more mature firms may see their competitive advantage being eroded (Shaver and Flyer (2000), Pe'er and Vertinsky (2006b)).

Clusters contribute also in other ways to the survival of new enterprises. They provide advantages of backward and forward linkages associated with large local markets. These are especially important for high-technology industries that require high precision of matching crucial inputs and intermediate goods between highly specialized demanders and suppliers (Marshall (1920)). High-technology startups may require also special infrastructure and services including, for example, specialized shared laboratory services, or sectoraly dedicated private equity firms. These are likely to be found near concentration of similar firms.

While all new entrants seek legitimacy (Stinchcombe (1965)), firms in traditional sectors have less difficulty to gain it as their products are well known and the type of activity they engage in is well understood by suppliers, buyers and financial institutions. Entrants to sectors characterized by high levels of innovation who face difficulty in gaining legitimacy may find it less challenging to gain it in locations with high concentration of similar firms as the visibility of the type of activities they engage in and/or their products is higher.

Hypothesis 1: *The positive impact of localization economies on the survival of new high-technology enterprises is higher than on the survival of new low-technology entrants.*

Localization economies stem from specialization i.e. concentration of similar firms in a location, *within* sector information spillovers, and the emergence of pools of specialized production factors.

Innovation, however, may also occur because of flow of ideas and information *between* sectors. Jacobs (1969) argued that urban diversity fosters cross fertilization of ideas and therefore innovation and growth. The evidence supports the idea that diversity may stimulate growth but only in innovative high-technology sectors. Henderson, Kuncoro, and Turner (1995), for example, examining growth in the U.S from 1970-1987 found that a city's employment diversity had a positive impact on growth in high-technology sectors where technologies were rapidly evolving, while specialization had a positive impact on growth in sectors with mature, stable technologies. Similar results were found in France by Duranton and Puga (2001).

Hypothesis 2: *Urban diversity is likely to have a positive impact on the survival of new high-technology firms and negative impact on the survival of low-technology new enterprises.*

Concentration of firms of similar type amplifies rivalry and competition (Porter (2000)). A high level of competition may facilitate innovation. Furthermore, there is evidence that a competitive market structure i.e. the presence of many small companies, creates a more welcoming environment for new entrants and magnifies the flow of information between them (Pe'er and Vertinsky (2006a), Rosenthal and Strange (2003)). Nevertheless, high levels of competition also represent pressures on prices and entrepreneurial profit margins. The importance of the impacts of a competitive industrial structure on innovation and on prices depends on the nature of the industry of the entrant and its technological characteristics (Agarwal and Gort (1996), Gort and Klepper (1982)).

Small firms in the high-technology sectors may benefit from a competitive structure that stimulates innovation and facilitates their access to local networks. These firms are likely to be more differentiated than low-technology firms and thus be less sensitive to pressure on prices. The impact of price pressures on the survival of low-technology firms is likely to negate any benefits which may result from knowledge spillovers.

Hypothesis 3: *A competitive local market structure has a positive impact on the survival of new high-technology firms and negative impact on the survival of new low-technology firms.*

Lower exit costs are generally associated with higher exit rates. If failing accrues high costs, firms will delay their entry until they are more confident about their prospects and therefore would be less likely to fail. Moreover, once entered, firms will try to stay as long as they can to avoid the high costs of exit (Dixit (1982)). New high-tech firms, however, face higher uncertainty and risks with respect to their technologies, market acceptance and future prospects. Market entry may be perceived as an experiment which can reveal their true prospects (Jovanovic (1982)). Decision to enter a high-technology sector involve the acceptance of higher probability of failure and therefore is more sensitive to the price of failure.

Low-technology firms, on the other hand, can assess their prospects with more confidence. Thus, the benefits of experimentation are relatively lower and therefore the costs of failure have less impact on the decision to enter. Lower costs of exit would not induce low-technology firms to enter and accept a higher risk of failure in the same way they would in high-technology firms. We expect, therefore, that the negative impact on survival rates of lower costs of failure (sunk costs) would be more significant for high-technology than for low-technology firms.

Hypothesis 4: *Lower exit costs have a stronger negative impact on survival rates in high-technology sectors compared to low-technology sectors.*

Methodology

Data

The data set used to estimate our model is T2-LEAP which is a merger of two different Canadian databases. The first database, the Longitudinal Employment Analysis File (LEAP), is used to identify new entrepreneurial entry and exit, 3-digit SIC code[1], number of employees, and their location coordinates. The second database is The Corporate Tax Statistical Universe File (T2SUF). This database is used to assess firm specific annual financial variables such as equity, assets, sales and closing inventories, converted to constant Canadian dollars using a 1985 price index.

[1] Firms may produce products belonging to different 3-digit SIC codes, however, our data include only the primary sector in which a firm operates.

T2-LEAP is a unique, firm-level database that includes all incorporated employers in Canada. The database tracks the employment and payroll characteristics of individual firms from their year of entry to their year of exit. The employment record of each business is derived from administrative taxation records that each Canadian employer must file[2]. The payroll data are associated with a Revenue Canada employer identification number. Accordingly, firms enter the LEAP database in the year they first hire employees, and record their last entry in the database in the last year they have employees. For each year, total payroll and employment are calculated. The latter is the average annual count of employees within the firm, or Average Labor Units (ALU). This payroll and employment information is then organized longitudinally; each observation in the database corresponds to a particular firm whose employment, payroll and industry characteristics are recorded annually.

The longitudinal nature of LEAP allows entry and exit times to be measured with precision. Births (entrants) in any given year are firms that have current payroll data, but did not have payroll data in the previous year. In our empirical estimation, we include de novo entrants (also referred as new entry, greenfield, or independent)[3] and births of establishments that are owned by a firm that had establishments in previous years (also referred as dependent, subsidiary) (Helfat and Lieberman (2002)). De novo entry accounts for 82% to 91% of all newly created establishments, depending on the sector. Similarly, exits in any given year are identified by the absence of current payroll data, where such data had existed in the previous year. LEAP distinguishes *'real' birth* or death from *'false'* ones. Real births and deaths reflect the creation of new establishments and the failure of existing ones. False births and deaths can reflect organizational restructuring within a firm, a change in the name of the firm, change in location[5] spin-offs or merger and acquisitions. While almost every study undertaken analyzing entry and

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[2] Every employer in Canada is required to register a payroll deduction account (for the purpose of unemployment insurance), and issue a T4 slip to each employee that summarizes earnings received in a given fiscal year. The LEAP database includes every business that issues a T4 taxation slip.

[3] We exclude from our sample spin-offs that started as subsidiaries or divisions of incumbents and later transformed to independent establishments (also known as parent spin-offs). We cannot, however, differentiate between new entry and firms which started by executives of an incumbent leaving to start their own firms (also known as entrepreneurial spin-offs).

[5] We excluded firms for which location change was observed. However, our results do not change when excluding only those firms that moved to other locations 10 miles or more from their founding locations.

exit suffers from false classification (Caves (1998), Geroski, (1995), and Sutton (1996)), LEAP identifies false births and deaths using a method of 'labor tracking'[6].

A firm is considered to have survived year *t* if year *t* is not the year in which the firm is unincorporated, if it has assets greater than zero in year *t+1*, and if the firm has one or more employees in year *t+1*. For a firm to survive it must meet all of these criteria, otherwise it is recorded as exiting during year *t*[7]. A firm is added to our sample in year *t* if it is incorporated in that year and hires its first employees at that year.

T2LEAP contains business operating in all sectors of the economy. Our database covers the manufacturing sector between the years 1984 and 1998. Aside from allowing us to identify exits, our database permits us to compute a number of firm level covariates which we will use to test the hypotheses formulated above.

High-technology definition

The distinction between high-technology and low-technology industries is fundamental to our analyses. We experimented with three industry level definitions that were widely used in the literature. First, we used the index developed by Vagra (1998). The index combines three criteria: (1) the total number of innovations per 1,000 employees (Acs and Audretsch (1988); (2) an above average ratio of Research and development (R&D) spending to sales at the industry sector (3-digit SIC code) (Acs (1996), Smith, Acs, and FitzRoy (2002)); and (3) an above average percentage of scientists, engineers and engineering technicians of total industry occupations (Glasmeier, Markusen, and Hall (1983)). Second, we used the industry sector's (3-digit SIC code) percentage of research and development employment (Hadlock, Hecker and Gannon (1991)). This measure was employed by Agarwal (1996), Agarwal and Audretsch (2001), Gort, Jensen and Lee (2002)) among others. Third, we used the OECD (1996) classification defined as R&D expenditures as a share of gross output or value added. In each of the above classification methods a threshold index

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[6] This means that if, for example, firm A merged with firm B in year t, then a new firm, C, is created and given a synthetic history aggregated from the histories of firms A and B. The individual histories of A and B disappear from the data base and firm C represents their joint operations both before and after year t.

[7] Firms that appear to cease operations for one or more years and then start up again in subsequent years are dropped from the data set. Adding employment greater than one and assets greater than zero to the existing measures of exit in T2LEAP, corrects for cases in which firms did not legally unincorporated in the same year their operations ceased, and for cases when production had ended but a low level of employment was retained while the firm was shutting down.

level divides low and high-technology sectors. The results obtained using these alternative methods were robust. We report the results obtained using the first method which is based on a multidimensional index that from a theoretical point of view is superior to the two uni-dimensional ones.

Variables

Dependent Variable:

Length of Firm Survival For each firm-year observation, FIRM SURVIVAL was coded as 1 if the firm survived in a given year and as 0 otherwise.

Independent Variables:

Some of our independent variables are generated by dividing firm-specific characteristics to the average characteristics of all incumbents operating in its region within the same industrial sector. We create concentric rings with radius of twenty miles around each firm for a given year. Radius of 20 miles was chosen (hereinafter critical chosen radius) based on findings of pervious studies showing that agglomeration externalities attenuate rapidly beyond that distance (e.g., Abrahamson, Baum and Feldman (2004a,b); Keller (2002); Rosenthal and Strange (2003))[8]. Similarly, several industry level covariates (such as: local market competitiveness and local entry rate) are calculated within the same concentric rings around a firm. Our covariates, except from firm-specific initial characteristics, are updated annually.

Location Characteristics

Local Density As a measure of LOCAL DENSITY (localization economies) we use two alternative methods. First, we aggregate the employment (number of firms) in the 3-SIC code sector within the concentric circle around the firm (the count of number of firms in a region was used by Abrahamson, Baum and Feldman (2004), Sorenson and Audia (2000), Baum and Mezias

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[8] The distance between any two firms A and B, is adjusted to the earth's curvature using spherical geometry and is computed as:

$$d(A,B) = 3437 \times \left\{ \arccos\left[\sin(latitude_A) \times \sin(latitude_B) + \cos(latitude_A) \times \cos(latitude_B) \times \cos\left(\left| longitude_A - longitude_B \right|\right)\right]\right\}$$

where latitude and longitude are measured in radians, the constant is the earth's radius and the linear distance units are in miles

(1992) among others). Second, as a robustness check we use the ratio of employment (firms) in the 3-SIC code sector to the total number of manufacturing employees (firms) in the circle. Previous studies such as Feser and Bergman (2000), Glassman and Voelzkow (2001), Porter (2001), Shaver and Flyer (2000), used similar ratio. However, they segmented the data into political jurisdictions (state, metropolitan statistical area) which may bisect clusters, and thus may misrepresent industrial concentrations.

Urbanization Economies As a measure for URBANIZATION ECONOMIES we use the inverse Herfindahl index calculated at the economic region where the firm is located with 2-digit industries (this measure was used in Henderson (1995) among others). Increases in this index generally indicate a more diverse urban environment and thus potential benefits from cross-fertilization.

Local Market Competitiveness (Structure) As an indicator of LOCAL MARKET COMPETITIVENESS we use the number of establishments per worker in the focal sector within the critical chosen radius around the firm (this measure was used in Glaeser *et al.* (1992) and Rosenthal & Strange (2003)). As this ratio increases the environment in a given industry and in a given location is thought to become more competitive (i.e., the market is populated by large number of firms).

Local Entry Rate We compute the two year average LOCAL ENTRY RATE to the focal sector within the critical chosen radius. High sectoral entry rates may suggest that resources can migrate to new firms, increasing the level of investment recoverability and decreasing exit barriers. When resources are immobile (e.g., infrastructure, heavy machinery) or specialized (i.e., tailored to specific industry), high entry rates will increase the demand for second hand assets and thus increase the salvage value.

Firm Specific Attributes

Size The RELATIVE SIZE (current and initial) of a firm is calculated as the size of the firm relative to the industry's average for a given year. The industry average reflects the importance of scale economies and provides a measure of the Minimum Efficient Scale (MES) in the industry. A ratio of 1 or higher suggests that the firm operates at an efficient scale. Lower ratios indicate that the firm is operating at a suboptimal size. To measure INITIAL RELATIVE SIZE we divided the firm's size by the average size of all entrants to the sector in the year when entry was observed.

Growth. GROWTH of a firm in terms of sales (Z_t) in year *t* relative to year *t-2* is measured by arc growth rate.

(1) $$Z_t = \frac{z_t - z_{t-2}}{(z_t + z_{t-2})/2}$$

Since this measure is defined with respect to the average sales of the firm rather than sales in the initial year, it has the advantage of being bounded in the interval [-2,2], thus moderating the effect of mismeasurment of initial sales and consequently a large error in growth rate (Brander *et al*. 1999).

Quality of Human Resources Higher wages tend to reflect a greater investment in certain labor-related enhancements, such as training and firm-specific human capital (Mincer, 1958). The literature on wage efficiency shows that firms tend to pay a wage rate above the market clearing wage to attract and retain high-quality labor and to provide incentives for workers to exert more effort (Lemieux, 2005). As an indirect measure of the initial and current quality of human capital available to a firm, we employ RELATIVE QUALITY OF HUMAN CAPITAL (lag 1) defined as the average wage paid by the firms divided by the sector average wages paid by all other (de novo entrants) in the ***same critical chosen radius*** in the same year to ensure that our measures are comparable across different external conditions (Dutta *et al.*, 2005).

Leverage LEVERAGE is the ratio of debt to assets. Debt is defined as assets (book value) less equity. Equity consists of common and preferred shares and accumulated retained earnings (or losses).

Productivity The current and initial effective deployment of resources is measured by the PRODUCTIVITY of the firm. Our database does not contain sufficient data for classical measures of Total Factor Productivity (TFP); however, it is possible to calculate Approximate Total Factor Productivity (ATFP). As originally suggested by Griliches (1990), and more recently by Hall

(1999), this measure of productivity is derived from a simple Cobb-Douglas production function. Suppose that firm *i* has a certain productivity level A_i and produces output Y_i using capital K_i and labour L_i. The firm's production function is:

(2) $Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}$.

If we solve for productivity, A_i, and take the natural log of both sides, the equation can be rewritten as:

(3) $\ln(A_i) = \ln\left(\frac{Y_i}{L_i}\right) - \alpha \ln\left(\frac{K_i}{L_i}\right)$.

Equation (3) describes the efficiency of the firm at turning inputs into outputs. This is comprised of the firm's labor productivity and the amount of capital each worker has at their disposal. Labor productivity is measured as total sales divided by the number of employees (ALU). No measure of capital per worker is present in T2LEAP, however, a measure of total assets is available. We use total assets minus closing inventory and divide the result by the number of employees. Removing closing inventories leaves us with a good measure of the efficiency with which workers turn inputs into outputs, using their available resources[9]. The optimal capital share α, varies significantly from industry to industry in the manufacturing sector. The Annual Survey of Manufacturing is used to derive this share. The natural log of ATFP for a given firm is defined as:

(4) $\ln(ATFP_i) = \ln\left(\frac{sales_i}{alu_i}\right) - \alpha \ln\left(\frac{assets_i - inventories_i}{alu_i}\right)$

where alu_i is the average labor units (i.e., total employees) of the firm, $sales_i$ is its total sales, $assets_i$ is its total assets, and $inventories_i$ is the closing inventories of the firm.

Subsidiary We use a categorical variable to indicate if a firm is part of a multi-unit organization (with SUBSIDIARY equals 0 for single-unit firm and 1 for multi-unit).

Age We classify firms to four age groups. Firms in their first and second years of operation are classified NEW. Firms in their third and fourth years of operation are classified YOUNG. Firms in

[9] As a measure of capital we use total assets minus closing inventory. The value of assets is drawn from the firm's balance sheet and consists of capital assets like land, building and machinery; short-term financial assets like cash; long-term financial assets like bonds; and intangible assets like goodwill and reputation.

their fifth and sixth years of operation are classified MIDDLE. Firms in their seventh or later year of operation are classified OLDER (the omitted category).

Other Controls

Industry Growth We use two measures for INDUSTRY GROWTH : average percentage change in employment over 3 years in the 3-digit SIC sector, or the 3 year average of sectoral percentage sales growth.

Macroeconomic Conditions We use time dummies to control for macroeconomic conditions.

Industry-Specific Characteristics We employ industry fixed effects in all of our estimations. Industry specific characteristics that may affect entrepreneurial enterprises' profitability are similar to those affecting incumbents' profits.

Econometric Model

To test our hypotheses we estimate the hazard facing entrants overtime operating in high-technology versus low-technology industry sectors. Because of the structure of our data (right censoring and annual data about entry), we need to employ a statistical model that is capable of accommodating data with incomplete discrete durations as well as entries in different times (i.e., cohorts of entrants). There are several empirical approaches that can be applied (e.g., see surveys by Kiefer (1988), Lancaster (1990)). We choose to use the semi Cox proportional hazards model since it does not assume a particular distributional form for the probability of exit (such as required by probit and logit) or firm age (required by tobit[10]). The basic (static) version of the Cox model can be extended to allow for time-varying covariates along with time-invariant ones. Specifically, the Cox proportional model estimates the hazard $h(t)$ -- the probability that a firm with covariates vector X_{t-1} exits in t, conditional on the fact that it survived to period $t-1$.

(5) $h(t) = P(\text{exit at } t \mid \text{survive to } t\text{-}1) = P(T = t \mid T \geq t)$ for $t=1,\ldots K$

Consequently, the probability of reaching the tth interval (year) is provided by the survival function

(6) $$S(t) = \prod_{j=1}^{t-1} \left[1 - h(j)\right]$$

[10] For the tobit model, it has been shown that if the underlying disturbances are not normally distributed the estimator is inconsistent.

In order to account for the effects of the covariates we define the hazard rate

(7) $\log\ h\left(t \mid Y_{t-1}\right) = \lambda_t + \beta Y_{t-1}$

where the parameters λ_t identify the baseline hazard function providing the annual exit probability for a firm whose current covariates (Y_{t-1}) assume a zero value[11]. The β vector represents the regression coefficients measuring the impact of the set of explanatory variables included in the vector Y_{t-1}. We model the probability of an event (exit) between time *t-1* and *t* as a function of state variables observed at time *t-1*.

To study differences in the survival values of location attributes in high and low-technology sectors we stratified the baseline hazard rate into high and low- technology sectors, and include in the model interaction terms between the stratification variable and covariates representing location attributes. We control for differences in the impacts of firm level characteristics on survival in high and low-technology sectors. Since previous empirical research suggested that differences in resources and capabilities that existed in founding have persistent impacts on survival chances (Dunne, Roberts and Samuelson (1989), Audretsch (1995), Swaminathan (1996), Geroski *et al.* (2002), Klepper (2002))[13], we include them as controls in our models. We also control for industry, time, and economic region fixed effects. Specifically the model is formulated as:

(8)

$$\log h(t \mid X_{t-1}; X_0; L_{t-1}; s_1) = \lambda_t + \left(\beta_0 X_{t-1} + \chi_0 X_0 + \delta_0 L_{t-1}\right) + s_1\left(\beta_1 X_{t-1} + \chi_1 X_0 + \delta_1 L_{t-1}\right)$$

where the hazard function is calculated for a firm with lagged covariate vector X_{t-1}, initial covariates X_0, that belongs to a given technological sector (i.e., stratum; $s_1 = 1$ for firms in high-technology sectors and zero elsewhere). Firm characteristics include relative size, growth, relative quality of human capital, leverage, and productivity. The vector L_{t-1} includes the following location characteristics: density, urban diversity market competitiveness and entry rate. The model

[11] Thus, λ_1 gives the probability of exit within the first year of activity, λ_2 gives the probability of exit in the second year provided that the firm did not exit during the first year. Note, λ varies with time but not across firms.

[13] Passive learning models predict a significant effect on initial conditions even at higher ages. The active learning models predict that the effects of initial conditions diminish faster with age.

preserves proportionality of hazards functions within each stratum while letting the hazard ratio vary between strata as well as introducing non-proportionality between hazards functions of firms from different strata. Testing the interaction terms corresponds to testing structural differences between firms from different strata in a very general framework. The model is estimated by maximum likelihood methods.

Empirical Results

Table 1 and Figure 1 present survival rates for entrants in high-technology vis-à-vis low-technology industries. The data suggest that hazard rates are significantly higher in the high-technology than the low-technology sectors. The survival rate is higher for low-technology than for high-technology firms in every age. These differences increase with age. In order to investigate whether the differences between the survival rates are statistically significant, we test for equality using Wilcoxon and Log-Rank tests. Table 1 shows that according to both tests, firms in different levels of technology intensity confront statistically different hazard rates. Sample correlations between the independent variables are reported in Appendix A.

Insert Table 1 about here

Insert Figure 1 about here

Our empirical strategy includes two types of models. First, we estimate a simple model of survival where technological intensity of a sector is included as a dummy variable. Second, we model the impact of technological intensity by including a set of interactive terms between the covariates representing location characteristics and the dummy variable representing the technological intensity of the sector. In both models we include firm characteristics as well as industry, economic region and time fixed effects. We use the second model to test our hypotheses.

Exit of new firms

The results of our first set of models are presented in Table 2. These specifications assume that the probability of failure of low-technology and high-technology firms differs only by a proportional factor. The reported standard errors in all of our specifications are robust- having been adjusted for clustering by firm. Since our primary interest lies in the differences between the determinants of failure among firms operating in various levels of technological intensity we use the specification presented in this table as our base model and will provide only succinct discussion of the results.

Column (1) represents the unconditional impact of technological intensity on the probability of exit. The coefficient estimate of HIGH-TECH (dummy variable which assumes the value of 1 if a firm is classified as belonging to a technology intensive sector and 0 otherwise) is positive and highly significant; indicating that high-technology entrants face higher hazard rates than low-technology firms. Columns (2) – (4) add firm-specific current and initial attributes. The coefficients of the firm level variables are consistent with previous findings. Specifically, firm's relative size (e.g., Agarwal, Gort (1996), Mata and Portugal (2002)), relative quality of human capital , leverage and productivity (Pe'er and Vertinsky (2006b))– are all significant determinants of survival. Larger firms, with higher quality of human capital, lower leverage and higher productivity, experience lower hazards. Leverage increases the hazard facing new entrants even when controlling for efficiency or productivity. Entrants which are subsidiaries of larger firms (SUBSIDIERY) have survival advantage over de-novo entrants.

Column (3) adds the firm's initial characteristics profile. The significant coefficients imply that apart from the current conditions initial endowments of resources and capabilities have an impact on survival. Specifically, entrants with higher initial quality of human capital, higher initial productivity, and lower initial leverage have survival advantage. A likelihood ratio test for the model including initial characteristics (column 3) versus the model using only current characteristics (column 2) supports the inclusion of initial conditions as a more appropriate specification. Specification (4) adds past growth and quadratic growth term to account for a possible nonlinear effect. Due to uncertainty, financial constraints and adjustment costs, most firms operate in less than optimal size during their initial stages (Penrose (1959)). Therefore, past growth has an important positive impact on survival as it reflects the ability of new small firms to overcome initial constraints of size. The survival advantage of growing firms has a diminishing effect as observed by the positive coefficient on the quadratic growth term. This may suggest the importance of the pace of growth and the well documented negative relationship between size and growth (Geroski (1995), Cabral (1995)).

Column (5) adds location characteristics. The coefficients imply that increases in LOCAL MARKET COMPETITIVENESS and in LOCAL ENTRY RATE are negatively associated with survival. High entry rates are associated with lower exit barriers which decrease the threshold for voluntary exit and increase the propensity of weaker firms to enter and experiment. Market competitiveness represents the presence of many small firms and a more competitive environment which can create pressures on prices and profit margins. DENSITY – our measure of localization economies - has a positive impact on survival while the coefficient of URBANIZATION ECONOMIES is not statistically significant. These results are consistent with previous finding about benefits from agglomerative externalities (e.g. Ellison and Glaeser (1997), Henderson (2000), Rosenthal and Strange (2003b)). Localization economies reflect the ability of new entrants to share supply channels of intermediate inputs, supporting services developed by existing firms, and a labor market pool. Urbanization effects include tradeoffs between the benefits of locating in an urban diverse environment and the cross fertilization it may foster, and congestion costs.

The specification in Column (6) employs probit model for a robustness check. Age dummies included in this specification show that learning-by-doing increases the probability of survival at a decreasing rate.

Insert Table 2 about here

Testing for structural differences in the survival value of location attributes as a function of the technological intensity of the industry

The models tested in Table 3 add interaction terms between levels of technological intensity and the other covariates to the specifications presented in Table 2. This formulation allows us to test for structural differences between the impacts of the covariates and thus test our hypotheses as a function of the technological intensity of the sector the firm belongs to. Firm-specific attributes (columns 7-9) and location characteristics (column 10) are added sequentially to the model. The likelihood ratio test suggests that model 11 in Table 3 is more appropriate than model 5 in Table 2. We start by presenting the empirical results of each step followed by a discussion.

The coefficients of the first-order covariates provide estimates of the factors influencing the hazard rate of low-technology firms. The specifications in column (7) include current firm-specific characteristics; column (8) adds initial characteristics. The story told by the first-order covariates is straightforward. Low-technology firms that have larger current and initial size, better initial and current quality of human capital, lower initial and current leverage, higher initial and current productivity, and entrants that are subsidiaries have survival advantages. Our main interest lies in the differences (if any) between survival patterns of firms in industries with different levels of technological intensity.

The second-order interaction term of RELATIVE SIZE with HIGH-TECH (column 8) is not statistically significant suggesting that the positive impact of current size on survival is identical for high-technology and low-technology firms. The significant and positive coefficient of the interaction term between INITIAL RELATIVE SIZE and HIGH-TECH suggests that an increase in initial relative size has a weaker (yet positive) effect on the likelihood of survival of technology intensive firms than on low-tech firms. Entrants into technology intensive sectors tend to differentiate their offerings from those of incumbents by occupying narrower niches (Porter (1979), Caves and Porter (1977)). This strategy decreases the disadvantages confronting small high-technology entrants due to lack of economies to scale, and allows coexistence without attracting much incumbents' aggressive reactions (Geroski (1995)). No differences were found in the impact of GROWTH (column 9) between the two sectors. Growth had a positive impact on survival but at a declining rate.

Insert Table 3 about here

The next firm-level characteristic included in our estimation is the relative quality of human capital. As expected, the coefficients confirm that both the initial quality and the current quality of human capital decrease the probability of failure. The impact of INITIAL RELATIVE QUALITY OF HUMAN CAPITAL seems to be important and permanent. The analysis reveals noticeable structural differences in the impacts of the quality of human capital on high and low technology firms. Increases in the current and initial qualities of human capital have stronger positive effects on the likelihood of survival for high-technology firms.

Both initial and current levels of leverage (INITIAL LEVERAGE, LEVERAGE lag1) have negative effects on the survival of entrants. However, the lower negative effect of INITIAL LEVERAGE for technology intensive firms implies that financial constraints at the initial stages are less binding in the high-technology sectors where intangible assets (ideas) can attract additional financing despite of a high leverage. Current PRODUCTIVITY has similar positive effect on survival for high and low technology firms but there are differences in the impact of INITIAL PRODUCTUVITY. Given the innovative nature of high-technology products, the expected lead time to production is longer and thus low productivity in the initial stages does not signal weakness.

Firms that are subsidiaries of multi-unit organizations (SUBSIDIERY) confront lower hazards in both technological intensity categories, reflecting preferential access to parent's funding, reputation, distribution and marketing logistics, greater option for resource reallocation, professional networks, accumulated know-how, and patents.

Industries which are growing offer an environment that supports survival. INDUSTRY NET ENTRY has positive effect on the survival of firms in high-tech sectors and no significant effect on low-tech ones. The share of products in *formative stages* in technology intensive sectors is higher than their share in low-tech sectors. These products are characterized by '…relatively primitive design, manufactured on comparatively unspecified machinery, and marketed through a variety of exploratory techniques. Volume is typically low.' (Williamson (1975: 215)). Thus, an increase in three-years average entry rates to high-technology sectors may suggest the beginning of a maturation process characterized by reduced uncertainty regarding various aspects such as market demand, and dominant design resulting in higher survival prospects (Sarkar *et al.* (2003)).

Column 10 adds interactions between technological intensity of the sector and location characteristics and provides the answer to our key research questions. The likelihood ratio test statistic for the model with the interaction effects of location characteristics and technological intensity (Column 10) versus the model which included all control variables (Column 9) is well above the critical value suggesting that there are important differences in survival values of location characteristics as a function of the technological intensity of the sector. Localization economies (LOCAL DENSITY) have positive effect on survival of new entrants with a stronger effect on firms in technology intensive sectors supporting Hypothesis 1. As hypothesized (Hypothesis 2) URBANIZATION ECONOMIES have positive effect on survival of technology intensive firms and negative effects on low-technology firms. As hypothesized (Hypothesis 3) LOCAL MARKET COMPETITIVENESS has a negative impact on survival for low-tech firms and positive impact on survival prospects of high-tech entrants. No support was found to hypothesis 4. Sunk costs affected equally survival prospects of high and low-technology firms. Higher entry signal lower entry and exit costs allowing weaker firms to enter and experiment. They also reduce the threshold for voluntary exit.

Discussion and Conclusion

This study shows that location attributes matter in different ways to the survival of firms depending on the technological intensity of the sector. Most of the empirical research on the impacts of location characteristics on performance of new ventures is based on case studies of individual districts (e.g., Saxenian, 1994, Porter, 1998, 2000), or specific industrial sectors (e.g., footwear industry – Sorenson and Audia, 2000; hotel – Chung and Kalnins, 2001, biotechnology – Stuart and Sorenson, 2003). Case studies of industrial districts suffer from a selection bias on the dependent variable as they focus on enterprises that enter clusters. Sectoral studies reflect the specific context of the industry chosen. Our study covers a population which includes all manufacturing sectors in all locations using longitudinal data.

The study finds that in high-technology sectors location characteristics that either stimulate or support innovative activities have significant survival benefits for new ventures. These benefits compensate for some negative externalities that are associated with these location characteristics. The results suggest that the benefits of locating in clusters, which include knowledge spillovers, the existence of specialized labor markets, the existence of "firms in downstream industries, producers of complementary products, specialized infrastructure providers, government and other institutions providing specialized training, education, information, research and technical support" are more important in technological intensive industries (Porter (1998: 199)). High-technology ventures compared to ventures in traditional sectors rely more on their ability to utilize external resources and capabilities through outsourcing and partnerships which are easier to form in clusters. High-technology firms also require access to valuable and up-to-date information about trends in technology (Cohen and Levinthal (1994)), activities, offerings and suppliers of competitors, which flow in cluster networks and more generally exposure to knowledge spillovers which proximity to other similar firms facilitates. Moreover, entrants who are capable to assimilate this knowledge and align their products or services early in their lives with the demands of the market, are likely to overcome issues of 'limited legitimacy' and 'liability of newness' which are more severe in the high-technology sectors (Aldrich and Fiol (1994), Stinchombe (1965)).

Urban diversity with opportunities for inter-sectoral cross fertilization of ideas appears to strengthen high-technology firms while the costs of congestion that such environment creates reduce the survival prospects of low-technology firms. Employment diversity and an urban setting with its amenities and opportunities for cross fertilization are important stimuli to innovation activities, key to success in the high-technology sectors. In contrast, specialization is key to efficiencies in low-technology traditional firms.

A more competitive market structure, i.e., markets characterized by the existence of many small firms rather than a few large ones, may enhance information spillovers and permit easier access to inter-firm networks on the one hand while increasing competitive pressures on prices on the other hand. We found that a competitive market structure has net survival benefits for high-technology firms and negative impact on the survival of low-technology companies. Information spillovers and professional networks are especially important for sectors where innovation is essential (e.g., Aharonson *et al.* 2004, Stuart and Sorenson, 2003). A high level of competition may stimulate innovation and the adoption of 'best practices' (Porter 1998). Furthermore, high-technology firms tend to find shelters from competition by occupying highly specialized niches. The tradeoff between higher competition that results in pressures on prices and entrepreneurial profit margins and the benefits of networking and information spillovers results in a negative balance for low-technology firms. Low-technology firms tend to be less differentiated than high-technology firms and thus are exposed to fiercer competition while the advantages of innovation stimulating environments provide them less competitive advantage.

Table 1 – Life-table estimates of survival rates

year	high-tech	low-tech
1	93.69	94.59
2	87.51	89.67
3	83.09	85.36
4	79.08	81.85
5	75.73	78.67
6	72.09	75.82
7	69.14	73.36
8	66.85	71.47
9	64.20	69.56
10	62.37	67.70
11	60.71	66.16
12	59.27	64.99
13	57.73	64.17
14	57.51	63.59

test of equality of survival functions across samples

Wilcoxon (DF=1)	Chi-Square=47.17
	Pr>Chi-Square 0.0000
Log-Rank (DF=1)	Chi-Square=60.07
	Pr>Chi-Square 0.0000

Figure 1 - Survival of new entrants operating in high-technology and low-technology

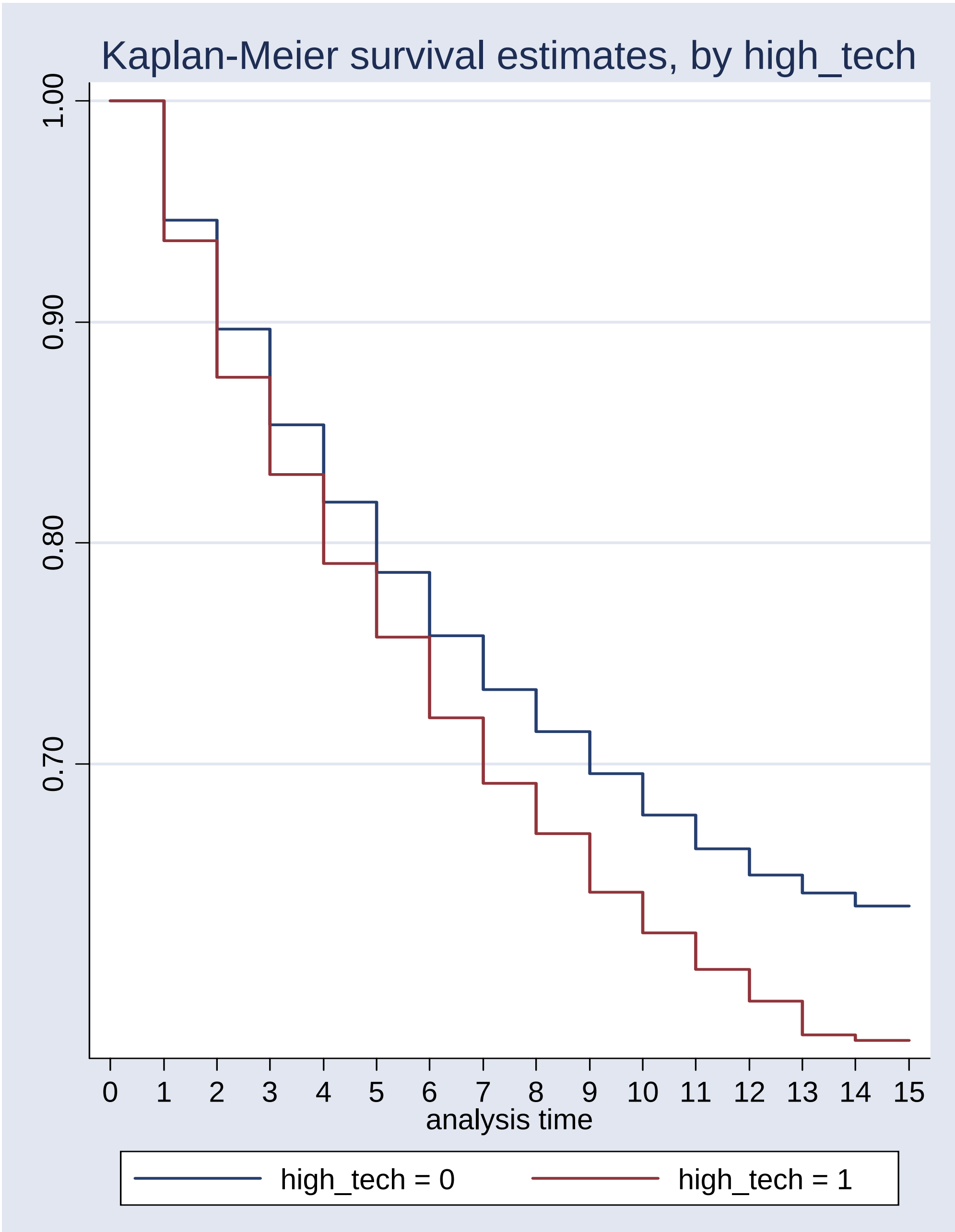

Table 2 - Cox Hazard Model - unconditional impact of high-technology sectors - lagged and initial covariates

	1	2	3	4	5	6
High-Tech	0.1761***	0.1236***	0.1311***	0.1555***	0.1608***	0.0797***
	0.0226	0.0228	0.0231	0.022	0.0221	0.012
Relative size (lag1)		-0.6814***	-0.8251***			
		0.0507	0.0576			
Initial relative size			-0.1275***	-0.1505***	-0.1524***	-0.1284***
			0.013	0.0159	0.0153	0.0122
Growth				-1.1402***	-1.1416***	-0.4945***
				0.0407	0.0411	0.0086
(growth) ^2				0.2016***	0.2030***	0.3100***
				0.0245	0.0247	0.0061
Relative quality of HC (lag1)		-0.7725***	-0.5438***	-0.3677***	-0.3595***	-0.1624***
		0.0653	0.0756	0.0778	0.0772	0.0456
Initial relative quality of HC			-0.5220***	-0.7831***	-0.7739***	-0.3547***
			0.0832	0.0798	0.0792	0.0455
Leverage (lag1)		0.8392***	0.5735***	0.3407***	0.3424***	0.2339***
		0.022	0.0307	0.0297	0.0297	0.0166
Initial leverage			0.3757***	0.4305***	0.4273***	0.2538***
			0.0308	0.0299	0.0296	0.0161
Productivity (lag1)		-0.2298***	-0.1043***	0.014	0.0554	-0.0395***
		0.012	0.0162	0.0164	0.0164	0.0079
Initial productivity			-0.1635***	-0.1658***	-0.1689***	-0.0757***
			0.0141	0.01363	0.0135	0.007
Subsidiary		-0.8802***	-0.8336***	-1.2472***	-1.2639***	-0.6576***
		0.0346	0.0356	0.0383	0.0385	0.0208
Density					-0.0218***	-0.1739***
					0.0061	0.0477
Urbanization Economies					-0.0042	-0.0031
					0.0031	0.0018
Local market competitiveness					0.0009**	0.0008
					0.0005	0.0008
Local entry rate (2YA)					0.0038*	0.0006
					0.0021	0.0005
industry net entry (3YA)					0.0025	0.0127
					0.0589	0.0323
New						0.3112***
						0.0209
Young						0.1987***
						0.0188
Middle						0.1225***
						0.0205
No. of subjects	46,966	46,966	46,966	46,966	46,966	46,966
No. of observations	244,528	244,528	244,528	244,528	244,528	244,528
No. of failures	10,567	10,567	10,567	10,567	10,567	10,567
Time at risk	245,773	245,773	245,773	245,773	245,773	
LogLikelihood	-110,666	-105,793	-104,370	-101,559	-101,233	-36,995

Comments:
standard errors adjusted for clustering on the firm
all specifications include time, economic region and 2 digit SIC dummies
*: *p<0.10, ** p<0.05, ***p<0.01*

Table 3 - The determinants of firm exit: Semi-proportional Cox hazard model with interaction terms between high-technology dummy and other covariates

Controls	7	8	9	10
relative size (lag1)	-0.7034***	-0.8397***		
	0.0526	0.0607		
relative size (lag1)x High-tech	0.1019	0.0594		
	0.1414	0.1611		
initial relative size		-0.1233***	-0.0770**	-0.0771**
		0.0145	0.033	0.033
initial relative size x High-tech		0.0709**	0.0591***	0.0590***
		0.0347	0.0251	0.0254
growth			-1.1421***	-1.1425***
			0.0413	0.0417
growth x High-tech			0.0191	0.0208
			0.0375	0.0387
(growth)^2			0.1997***	0.2003***
			0.0249	0.0251
(growth)^2 x High-tech			0.0181	0.0202
			0.0242	0.0242
relative quality of HC (lag1)	-0.753***	-0.5540***	-0.3787***	-0.3683***
	0.0646	0.0838	0.0881	0.0894
relative quality of HC(lag1)x High-tech	-0.1050**	-0.0348***	-0.0594***	-0.0548***
	0.051	0.0166	0.0163	0.0166
initial relative quality of HC		-0.4783***	-0.4625***	-0.4631***
		0.0922	0.0901	0.0926
initial relative quality of HC x High-tech		-0.1788***	-0.1786***	-0.1788***
		0.0722	0.072	0.0715
leverage (lag1)	0.8457***	0.5589***	0.3146***	0.3166***
	0.0245	0.034	0.03412	0.0339
leverage (lag1) x High-tech	-0.0295	0.0699	0.1175	0.1135
	0.0465	0.0665	0.0699	0.0697
initial leverage		0.4054***	0.4667***	0.4631***
		0.0342	0.0336	0.0332
initial leverage x High-tech		-0.1472**	-0.1691***	-0.1636***
		0.0676	0.0719	0.0713
productivity (lag1)	-0.2303***	-0.1011***	-0.1171***	-0.1165***
	0.0127	0.0169	0.02	0.022
productivity (lag1)x High-tech	0.0068	-0.0186	-0.0188	-0.0201
	0.0197	0.0098	0.011	0.0291
initial productivity		-0.1709***	-0.1681***	-0.1720***
		0.0151	0.015	0.0149
initial productivity x High-tech		0.0412**	0.0408**	0.0421**
		0.0196	0.0203	0.0207
Subsudiary	-0.8689***	-0.8145***	-1.2304***	-1.2435***
	0.0382	0.0394	0.0422	0.0424
Subsidiary x High-tech	-0.0597	-0.0912	-0.0807	-0.0829
	0.0887	0.0912	0.0977	0.0979
H1				
Local density				-0.2017***
				0.0067
Local density x High-tech				-0.0842***
				0.0234
H2				
Urbanization economies				0.0062
				0.0044
Urbanization economies x High-tech				-0.0132***
				0.0246
H3				
local market competitiveness				0.0046***
				0.0018
local market competitiveness x High-tech				-0.0058***
				0.002
H4				
industry net entry (3YA)				-0.0886
				0.0886
industry net entry (3YA) x High-tech				-0.2301*

Appendix A – Correlation Table

		1	2	3	4	5	6	7	8	9	10
1	High-tech										
2	Initial relative size	-0.0015									
3	Growth	-0.0051	-0.0118								
4	(growth) ^2	-0.0071	0.0046	0.7829							
5	Relative quality of HC (lag1)	-0.0433	0.1688	-0.0635	-0.0122						
6	Initial relative quality of HC	-0.0471	0.1841	0.0282	0.0447	0.6012					
7	Leverage (lag1)	0.0253	-0.0399	-0.3575	-0.3932	0.002	-0.0228				
8	Initial leverage	0.029	-0.0774	-0.0628	0.0698	-0.431	-0.0363	0.4004			
9	Productivity (lag1)	-0.002	-0.0196	-0.3614	-0.4432	0.0824	0.041	0.3783	-0.0374		
10	Initial productivity	-0.0011	-0.054	0.0454	0.052	0.1012	0.1479	0.0024	-0.0004	0.3506	
11	Subsidiary	-0.0253	0.1872	-0.002	0.0594	0.1472	0.1666	-0.0456	-0.1313	0.0944	0.209

		1	2	3	4	5
1	High-tech					
2	Local density	0.0967				
3	Urbanization Economies	0.3126	-0.1582			
4	Local market competitiveness	0.0055	-0.041	0.0083		
5	Local entry rate (2YA)	-0.0183	-0.1688	0.0354	0.0188	
6	industry net entry (3YA)	-0.0147	-0.0633	-0.0084	-0.0054	0.0381

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