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Essays on Entrepreneurship across Space: How Cities Support the Emergence, Survival, and Capital Acquisition of Entrepreneurs

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ESSAYS ON ENTREPRENEURSHIP ACROSS SPACE:

How Cities Support the Emergence, Survival, and Capital Acquisition of Entrepreneurs

By

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Thomas Hyclak

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Dedication

To my loving wife April and incredible son Liam

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God has truly blessed me with loving friends, family, and now an academic career. May He continue to bless all of you in your endeavors as He has me.

Disclaimer

Certain data included herein are derived from the Kauffman Firm Survey and Kauffman Index of Entrepreneurial Activity of the Ewing Marion Kauffman Foundation, Kansas City, MO. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the Ewing Marion Kauffman Foundation.

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Abstract

Michael Porter (1990) declared that entrepreneurship is "at the heart of national advantage." Edward Lazear (2002) more recently proclaimed that, "the entrepreneur is the single most important player in a modern economy." Audretsch and Thurik (2001) explain that the shifting emphasis on entrepreneurship can be explained by comparative advantage that now lies in knowledge-based economic activities. This growing literature has presented local, state, and federal policy makers with a compelling way through entrepreneurship programs to gain back jobs lost to globalization and outsourcing (Audretsch et al., 2006). While the effects of entrepreneurs on growth have been studied, the benefits of cities for new firms is less researched. We consider how cities encourage entrepreneurship, support entrepreneur survival, and enhance new firm financing.

Chapter 1 analyzes the effect of cities on the individual decision to start a firm. Specifically, we consider how several agglomeration theories may encourage individuals to launch a new firm. We contribute to the expanding literature on entrepreneurship by using the Kauffman Index of Entrepreneurial Activity (KIEA) for 1998-2011, considering individual startup decisions, while controlling for individual motivations, and examining the importance of the local industry conditions to new firm launches across several industries. We find that individuals in regions with entrepreneurial social and institutional structures are more likely to launch a new firm, while industry concentration and diversity are only significant in denser locations. The presence of small and new firms in a region creates an environment conducive to entry and is consistent across industry sectors.

Chapter 2 explores the effect of local industrial conditions on a startup's probability of shutdown using the Kauffman Firm Survey (KFS). We contribute to the expanding literature on entrepreneurship by considering shutdowns and positive-exits separately, using a comprehensive model including firm and local industry conditions, and estimating shutdown determinants for high-tech and manufacturing startups. We find strong evidence that the determinants of shutdown are significantly affected along these three dimensions. We test the effect of cluster, Jacobs, and Chinitz agglomerations on new firm shutdowns, but find that new firm shutdowns are not prevented

by any source of agglomeration. While concentrated clusters and dense regions promote persistence for manufacturing firms, a regional structure with a large share of small firms (i.e. Chinitz hypothesis) promotes survival for non-manufacturing startups. An environment with a large share of small firms also decreases the risk of shutdown for low-tech startups, while higher industry MES and research expenditures decrease the risk of shutdown.

Finally, chapter 3 considers the effects of local industry conditions on external capital acquisition of new firms, using the Kauffman Firm Survey (KFS). While survival and growth has been the predominant measure of performance, Gompers and Lerner (2001) emphasize that access to external finance is necessary for entrepreneurs to establish a competitive advantage. We contribute to the entrepreneurial financing literature by accounting for heterogeneity in financing methods and repeated transactions, exploring how local industry conditions affect new firm financing, and considering how the determinants of financing differ for high-tech and low-tech firms. We find that the region in which a firm operates significantly affects the funding chances of new firms. New firms are at a greater risk of external equity and debt infusions in regions that specialize in certain industries and in industries with lower wages. While the chance of equity financing is greater in regions with an entrepreneurial culture and small supplier network (Landier model and Chinitz hypothesis), the probability of debt financing is greater in regions with concentrated clusters (Porter) and lower university research expenditures. Interestingly, these effects are mirrored for low-tech startups, while high-tech startups are only affected by the industry's wage and region's specialization.

Chapter I

The Influence of Local Social and Industrial Characteristics on Emergent Entrepreneurship

1 Introduction

Some areas seem to have local social and industrial conditions conducive for individuals to start a new firm (e.g. Silicon Valley and New York City), while other regions have conditions that deter entry (e.g. Pittsburgh (Chinitz, 1961) and Detroit). We add to the growing literature on entrepreneurship by considering the effect of various sources of agglomeration on an individual's probability of starting a new firm, using the Kauffman Index of Entrepreneurial Activity (KIEA).

The connection between entrepreneurship and urban growth is a stylized fact in economics. Through increased competition and innovation pressures, new entrants encourage existing firm improvements and future regional growth (Fritsch and Mueller, 2004; van Stel et al., 2010). This research has addressed the challenges of regional and national stagnation and has generated a myriad of studies on entrepreneurship. Many of these empirical studies focus on the effects of either industry or region characteristics, but rarely both (Geroski, 1995; Reynolds et al., 1994). Understandably, these studies also often omit individual motivations as very few datasets contain such information and aggregate data into startup rates at the industry or region level. However, leaving out these variables that are important determinants of starting a firm (Wennekers, 2006) may significantly bias results. While various sources of agglomeration have been hypothesized to affect startups, it remains unclear whether each source is equally important or if a particular source may capture multiple theories because of limitations in data or modeling techniques. By modeling multiple sources of agglomeration together, we attempt to reveal the relative contribution of each agglomeration theory.

Section 2 presents previous literature on the determinants of entrepreneurial entry and the hypotheses tested in this study. We consider the effect on entrepreneurship of agglomerations: Marshallian industry concentration, Jacobs urbanization, and the Chinitz hypothesis. Individuals may launch firms near customers and suppliers or where they can learn from surrounding firms. Marshall suggested that industry concentration may encourage knowledge spillovers, while Jane Jacobs (1970) proposed that industry diversity enhanced knowledge spillovers and innovation in startups. Finally, the Chinitz (1961) hypothesis suggests that the presence of small and independent firms leads to social and institutional structures that encourage entrepreneurship.

The next section summarizes the KIEA dataset and explores the entrepreneurship measure used in this paper. The KIEA identifies a wide range of startups as they occur. Alternative datasets contain a coarse measure for entrepreneurship (e.g. number of startups by industry and region) and only include employer, incorporated, or industry-specific startups. The KIEA contains individual level observations from the Current Population Survey (CPS) from 1998–2011. A dynamic measure of entrepreneurship is created in which less-devoted entrepreneurs are excluded, but the entrepreneur need not be incorporated or have employees. The KIEA also includes individual data from CPS, geographic location, and detailed industry classification allowing industry and region variables from the County Business Patterns (CBP) to be matched to entrepreneurs in the KIEA.

Section 4 presents the empirical framework and estimates for the effect of agglomeration sources on startup decisions for individuals controlling for individual motivations and industry characteristics. We find that the Chinitz hypothesis is the only source of agglomeration that significantly affects the probability of an individual to launch a new firm. A presence of small and new firms in a region creates an environment conducive to entry and is consistent across industry sectors. The Chinitz variables appear to explain startups better than the hypotheses of Marshall and Jacobs.

Finally, section 5 concludes with a summary of results, policy implications, and future research ideas.

2 Determinants of Entrepreneurship

We are interested in how local industrial, social, and institutional conditions affect individuals choosing between starting a new firm, being (un)employed, or exiting the labor force. Specifically, we examine alternative agglomeration theories, while controlling for individual motivations. Labor-market theory assumes that individuals choose the mode of employment based on the benefits and costs of each choice (Storey, 1994; Douglas and Shepherd, 2002). We first examine how agglomeration may affect emergent entrepreneurship and then consider individual and industry motivating characteristics.

2.1 Agglomeration

One of the basic benefits to agglomerating is that firm productivity can improve through lower transportation costs if customers and suppliers are colocated. Individuals may launch a new firm near other firms to partake in these external cost savings. The key agglomerating mechanism in New Economic Geography is the savings from cheaper shipping costs (Fujita et al., 1999). Sugar, for example, was refined in New York City in the nineteenth century rather than the tropics because of the large costs in transporting refined sugar (Glaeser and Kerr, 2009).

2.1.1 Marshallian Agglomeration

Concentration of firms within an industry may also encourage startups through labor pooling and knowledge spillovers (i.e. localization economies). The labor hired in the first few years, vital to any new firm's success, may be constrained by the quality of the labor force in the surrounding region (Dahl and Klepper, 2007). Specialized workers may be required in certain industry startups and are more likely to pool around agglomerated firms. Labor pooling amongst clustered firms can smooth the effect of firm-specific shocks on individual workers (Marshall, 1890). Workers can easily change jobs when their employer is affected by a negative shock, making workers more productive under such insurance (Krugman, 1991). Large labor pools in a city may also facilitate matching between startups and employees (Helsley and Strange, 1990). Hence, new and existing firms needing similar specialized labor are likely to colocate and benefit from a greater availability of workers or lower wages in thick labor markets (Glaeser and Kerr, 2009).

Concentrated industries may also promote entrepreneurship through the dissemination of existing and new knowledge. Glaeser et al. (1992) describe the Marshall-Arrow-Romer (MAR) knowledge spillovers that occur when industries are highly concentrated, leading to economic growth. Marshall (1890) explained that in concentrated industries, "the mysteries of the trade become no mystery, but are, as it were, in the air." Customers and suppliers who work closely can share issues with existing products or describe needs and wants for new products (Porter, 1990). Knowledge spillovers are highly localized (Rosenthal and Strange, 2003) and emphasized by studies on patent citations (Jaffe et al., 2000; Carlino et al., 2007).

Contrary to MAR spillovers, Jacobs (1970) proposed that vital knowledge flows to firms from outside their own industry. Under this view, variety and diversity will lead to greater knowledge transfer and promote innovation. Several studies have attempted to test whether concentration or diversity is better for regional growth, with mixed findings (Glaeser et al., 1992; Henderson et al., 1995).

2.1.2 Chinitz Agglomeration

Chinitz (1961) found that characteristics of suppliers, rather than industry concentration, explained entrepreneurial differences between Pittsburgh and New York. Chinitz described the supplier needs of entrepreneurs as highly localized, compared to those of large incumbent firms that could internalize these needs. The vertically integrated steel firms in Pittsburgh were not concerned with the input needs nor output capabilities of entrepreneurs. On the other hand, New York City's small supplier network to the fragmented garment industry provided entrepreneurs with specialized inputs. Small firms further exhibit a lack of division of labor, enabling employees to learn a breadth of managerial knowledge that may be useful for running a business (Reynolds et al., 1994). The Chinitz hypothesis suggests that the presence of small and independent firms leads to social and institutional structures that promote a culture of entrepreneurship (Glaeser and Kerr, 2009).

An entrepreneurial culture may be self-sustained and not limited to specialized input suppliers (Hofstede, 2001). The Silicon Valley encourages entrepreneur trials and emphasizes cooperation between young startups (Saxenian, 1994). Early semiconductors led the way for future entrepreneurs through open inter-firm communication and a vertically disintegrated industry structure.

Glaeser and Kerr (2009) describe agglomerations in entrepreneurship that lead to an entrepreneurial culture. The clustering of entrepreneurs creates social structure that reduce the stigma of failure and increase the likelihood that others take risks (Landier, 2004). Entrepreneurial support institutions may also cluster around concentrations of entrepreneurs (e.g. angel investors, small business incubators, and specialized legal or accounting services). Glaeser and Kerr (2009) find that the Chinitz effect explains a significant amount of the variation in entrepreneurship across space while an entrepreneurial culture may be embodied by the Chinitz effect.

2.2 Individual Characteristics

Considering local industrial, social, and institutional conditions alone ignores the individual motivations to become an entrepreneur that have been identified by previous studies and results in omitted variable bias. We include demographic information that can play an important role in determining whether an individual becomes an entrepreneur or not. Older individuals are more likely to be self-employed, but younger people prefer to be self-employed (Blanchflower et al., 2001). Storey (1994) finds the highest prevalence of incumbent business owners in the middle-aged cohort while in several countries, nascent entrepreneurs are between the ages of 25 and 34 (Wennekers, 2006). Various ethnic groups have been linked to higher rates of entrepreneurship as immigrants (Delmar and Davidsson, 2000; Jansen et al., 2003). Studies considering gender find that women are much less likely to be self-employed or involved in entrepreneurial activity (Acs et al., 2004; Reynolds et al., 2003; Blanchflower et al., 2001).

Education may have opposing effects; Le (1999) discusses the theoretically increased managerial ability and skills that are acquired throughout college, but higher levels of education will increase the quality of outside options. van der Sluis et al. (2008) may be the only study that has identified a positive effect of college dropouts and highly educated individuals.

Income levels can also produce mixed empirical results. Utility-maximizing individuals will select the best mode of employment based on several factors, such as income and risk attitude. In theory, higher-income employed individuals will be less willing to give up their current employment. On the other hand, lower-income employed individuals may choose to become entrepreneurs to increase income and improve working conditions (Douglas and Shepherd, 2002).

Finally, employed individuals are less likely to abandon steady streams of income. Unemployed individuals are more likely to be forced to start a new firm, or may not fit regular employment; Evans and Leighton (1989) find empirical evidence supporting this hypothesis. Individuals who did not switch industries in a CPS survey year may indicate previous employment and higher income.

2.3 Industry Factors

In order for firms to become profitable, new firms must reach minimum efficient scale (MES) (Audretsch, 1995). Survival is expected to be improved if this scale is smaller, as firms do not need as many resources to compete (Audretsch et al., 2000). Entrepreneurs that enter an industry with a size closer to the MES are more likely to survive, while smaller entrepreneurs will have difficulty reaching profitability. Larger MES industries also require larger upfront capital and may raise the cost of capital above existing firms' (Lyons, 1980). Finally, entrants may have difficulty attracting quality workers from larger existing firms.

Small firms may not be deterred from entering industries where scale economies are important (Audretsch, 1991). Industries in which the price level is above the minimum average cost may promote the existence of suboptimal capacity firms, i.e. startups. The further above minimum average cost the price is, the greater the probability of survival is (Weis, 1976).

3 Emergent Entrepreneurs

3.1 Measurement of New Launches

No consensus on how to measure entrepreneurship has been reached and each approach yield different interpretations. The number of individuals leading independent enterprises can be measured using self-employment rates (Evans and Jovanovic, 1989; Blanchflower and Oswald, 1998) or average firm size (Glaeser, 2007), but represent static measures. The dynamic nature of emergent entrepreneurship is captured by new product introductions (Audretsch and Feldman, 1996) or the founding of new firms (Glaeser and Kerr, 2009). Taking advantage of time series panel data, we adopt the latter by using an indicator for a change in labor status to self-employed using the Kauffman Index of Entrepreneurial Activity (KIEA) to measure new launches. A wide range of entrepreneurs are included (e.g. incorporated, unincorporated, employer, and non employer businesses) that are not picked up by datasets based on tax records (e.g. Longitudinal Business Database).

3.2 Data

The KIEA was developed by Robert Fairlie using the U.S. Bureau of the Census and the Bureau of Labor Statistics (BLS) Current Population Survey (CPS) covering the years 1998–2011. The KIEA presents a dynamic measure of business formation at the individual level because formation is captured once, when the individual changes primary work status and devotes a significant time to self employment. Hence, new business launches, rather than business ownership, is captured.

Another novelty is that casual entrepreneurs are removed by classifying entrepreneurs as those who devote more than 15 hours per week to self-employment. Finally, individual characteristics can be included from the CPS, such as geographic location, industry, and demographic information.

The CPS surveys more than 130,000 people in a four month period. Eight months later, the same households are re-interviewed in a second four-month period. The CPS uses a sampling methodology to make the survey nationally representative of the U.S. population, with a sample size of over 700,000 adults between the ages of 20 and 64. CPS respondents are then matched within a year to create a two-month panel. The primary goal of the CPS is to measure state and national unemployment rates and labor force characteristics. Precise estimates are made possible by using a national sample, including all fifty states and the District of Columbia. For all empirical exercises in this paper, the CPS sampling weights are employed to correct for non-response and post-stratification raking (Fairlie, 2012).

In order to measure entrepreneurship, individuals in the first interview who do not own a business as their main job are identified. Emergent entrepreneurs are identified if the same individuals own their own business in the second interview. In order to eliminate casual or part-time business owners, the individual must work more than fifteen hours per week and claim owning business as their primary job, or the work activity they devote the most hours to. Additionally, individuals in the first survey month who own their own business, but devote less than fifteen hours are not identified as entrepreneurs.

County Business Patterns (CBP) provides the basis of market and agglomeration measures used, including measures of employment, annual payroll, establishment counts, and establishment size distribution. Core-based Statistical Areas (CBSA) are defined using the 2000 U.S. Census to define areas of socioeconomic activity that are linked to an urban center. A CBSA must contain between 10,000 and 50,000 people for a micropolitan region, and over 50,000 for a metropolitan area. The county of the urban core, and any adjacent counties that share social and economic activity, based on commuting to work patterns, comprise the CBSA. These metropolitan area definitions are used to classify regions.

Industry codes developed by the OMB of U.S. Census Bureau, known as North American Industry Classification System (NAICS) codes, are used to define industries. NAICS codes use a nesting structure: The first two digits represent the economic sector, the third digit represents the sub sector, the fourth represents an industry group, the fifth represents a particular industry, and the sixth represents a national industry (different for some countries). Throughout this paper, analysis is conducted at the 3-digit (i.e. industry) NAICS code level.

3.3 Variables

Figure 1 presents the individual control variables provided by the KIEA. Figure 2 presents local industry measures calculated at the 3-digit NAICS and at the CBSA level using the County Business Patterns (CBP) dataset. We measure the colocation of firms using the employment density of a region. Density is calculated as the number of employees per square mile of land area. Unfortunately, this measure does not separate the importance of customers or suppliers in a particular industry. Glaeser et al. (1992) uses a location quotient (LQ) to measure MAR spillovers, which is the ratio of the percentage of employment in an industry within a region to the percentage of employment in the same industry across the entire U.S.. Jacobs spillovers are controlled for using the ratio of employment in the largest five industries to employment in the entire region (Glaeser et al., 1992). We include the share of small businesses to estimate the Chinitz effect and the concentration of entrepreneurs to estimate entrepreneur agglomerations.

We use Lackey and Wojan's (1999) measure for MES based on Eckard's (1994) suggestion that top firms are more likely to be operating near MES than small entrants. The average size of the top 50 U.S. firms for each industry is gathered using the 2007 Census of Manufacturing data. The MES variable is then the ratio of the region's average firm size for each three digit NAICS to the average firm size of the top fifty firms in each three digit NAICS. Values greater than one indicate that the region's industry has a higher average scale than the largest 50 U.S. firms in the respective industry. Finally, in order to control for outside options of individuals considering employment or starting a new firm, the average industry wage in a region is included.

Variable	Measurement
Education	Categorical dummies for educational attainment.
Income	Categorical dummies for income level.
Married	The individual is married.
Labor Force Code	Individual was previously unemployed or disabled/retired.
Race	Categorical dummies for race.
Female	Individual is female.
Native U.S.	The individual is native to the U.S..
Same Industry	Individual did not switch industries in survey year.
Age	The individual's age and age squared.
Home-Owner	The individual owns a home.

Figure 1: **DEFINITION OF KIEA INDIVIDUAL VARIABLES WITH EXPECTED SIGNS**

3.4 Summary Statistics

Table 1 shows individual characteristics for emergent entrepreneurs (upper statistic) and non-entrepreneurs (lower statistic). Entrepreneurs are more likely to be low income, and have some high school education, compared to non-entrepreneurs. About 25% of entrepreneurs worked in the same industry earlier in the year before they starting a business. 93% of employed individuals remained in the same industry, or did not change jobs. Home ownership rates and education levels appear to be quite similar amongst the two groups. About 52% of emergent entrepreneurs have medium incomes, while about 26% of entrepreneurs have high income. Finally, 22% of new entrepreneurs have low incomes compared to 16% for non-entrepreneurs.

Table 2 shows additional demographic information for entrepreneurs and non-entrepreneurs. There is little difference for most of the variables, except for gender and nativity. Only 41% of entrepreneurs are female, while 53% of non-entrepreneurs are female. Almost 78% of entrepreneurs are native citizens, compared to 84% of non-entrepreneurs. 80% of both sets of individuals are white and just over 40 years of age.

Table 3 shows the KIEA entrepreneurship index over time, adjusted for the CPS weights. The KIEA shows a slight drop after the DotCom bubble, but the rate returned to pre-contraction rates in 2002. Interestingly, the two largest increases occur from 2001–2002 and 2008–2009. On the surface, these may reflect a rising supply of entrepreneurs formerly unemployed. The number of entrepreneurs appears to be increasing over the time, primarily among men.

Variable	Definition
Localization Agglomerations (MAR)	Ratio of a region's share of employment in industry i relative to the nation's share of employment in that same industry. $lq = \frac{E_{ir}/E_r}{E_i/E}$ $E_{ir} =$ number employees in industry i and region r
Diversity Agglomerations (Jacobs)	Ratio of the region's employment in the five largest industries. (Smaller values indicate greater urbanization) $Jacobs = \frac{E_r^5}{E_r}$
Employment Density	Employment density or employment in region r per square mile of land area. $EmpDensity = \frac{E_r}{LandArea_r}$
Small Business Share (Chinitz)	Share of a region's employment in firms with fewer than 5 employees. $SmallBizShare = \frac{E_r^{1-5}}{E_r}$
New Firm Concentration (Chinitz)	Ratio of a region's share of entrepreneurial firms relative to the nation's share of entrepreneurial firms. $lq_E = \frac{F_r^E/F_r}{F^E/F}$
MES	Ratio of the region's average firm size for industry i to the average firm size of the top 50 firms in that same industry. $MES = \frac{E_{ir}/F_{ir}}{E_i^{50}/F_i^{50}}$ $F_{ir} =$ number of establishments in industry i and region r.
Average Wage	The payroll in industry i and region r per employee. $AvgWage = \frac{Payroll_{ir}}{E_{ir}}$

Figure 2: **DEFINITION OF KIEA REGION VARIABLES AND EXPECTED SIGNS**

Table 1: **KIEA INDIVIDUAL CHARACTERISTICS COMPARISON**

	Mean	Std. Err.	95% Conf. Interval	
Same Industry				
	0.933	0.000	0.932	0.933
	0.245	0.004	0.238	0.252
Home Owner				
	0.695	0.000	0.695	0.696
	0.685	0.004	0.678	0.693
Low Income				
	0.157	0.000	0.157	0.157
	0.219	0.003	0.212	0.226
Medium-low Income				
	0.335	0.000	0.335	0.336
	0.346	0.004	0.338	0.354
Medium-high Income				
	0.213	0.000	0.213	0.214
	0.171	0.003	0.165	0.177
High Income				
	0.294	0.000	0.294	0.295
	0.264	0.004	0.257	0.271
Some High School				
	0.120	0.000	0.119	0.120
	0.164	0.003	0.158	0.170
High School Diploma				
	0.303	0.000	0.303	0.304
	0.298	0.004	0.291	0.305
Some College				
	0.295	0.000	0.294	0.295
	0.266	0.004	0.259	0.273
Bachelors				
	0.191	0.000	0.191	0.192
	0.188	0.003	0.181	0.194
Grad Degree				
	0.091	0.000	0.091	0.091
	0.085	0.002	0.080	0.089

Note: Statistics are based on 2,404,524 observations from the Kauffman Index of Entrepreneurial Activity 1998-2011. The upper statistic is for non-entrepreneurs and lower statistic is for entrepreneurs, adjusted for Current Population Survey weights. Standard errors are estimated using Taylor linearization.

Table 2: **KIEA INDIVIDUAL CHARACTERISTICS COMPARISON**

	Mean	Std. Err.	95% Conf. Interval	
White				
	0.817	0.000	0.817	0.817
	0.844	0.003	0.838	0.851
Black				
	0.119	0.000	0.119	0.120
	0.092	0.003	0.087	0.097
Asian				
	0.020	0.000	0.020	0.020
	0.021	0.001	0.019	0.024
Other Race				
	0.044	0.000	0.044	0.044
	0.042	0.002	0.039	0.046
Age				
	40.661	0.005	40.651	40.672
	42.306	0.097	42.116	42.496
Female				
	0.525	0.000	0.524	0.525
	0.406	0.004	0.398	0.414
Native U.S.				
	0.839	0.000	0.838	0.839
	0.777	0.004	0.770	0.784

Note: Statistics are based on 2,404,524 observations from the Kauffman Index of Entrepreneurial Activity 1998-2011. The upper statistic is for non-entrepreneurs and lower statistic is for entrepreneurs, adjusted for Current Population Survey weights. Standard errors are estimated using Taylor linearization.

Table 3: **ENTREPRENEURSHIP INDEX (%) OVER TIME**

Year	Total	Male	Female	Manufacturing	Trade	Services
1998	0.29	0.33	0.25	0.07	0.35	0.33
1999	0.27	0.32	0.22	0.06	0.29	0.32
2000	0.27	0.34	0.21	0.06	0.36	0.34
2001	0.26	0.31	0.23	0.08	0.27	0.31
2002	0.29	0.36	0.22	0.08	0.32	0.36
2003	0.30	0.38	0.22	0.09	0.31	0.38
2004	0.30	0.37	0.24	0.10	0.27	0.37
2005	0.29	0.35	0.24	0.10	0.28	0.35
2006	0.29	0.35	0.23	0.09	0.26	0.35
2007	0.30	0.41	0.20	0.08	0.24	0.41
2008	0.32	0.42	0.24	0.11	0.33	0.42
2009	0.34	0.43	0.25	0.13	0.34	0.43
2010	0.34	0.44	0.24	0.08	0.28	0.44
2011	0.32	0.42	0.23	0.11	0.30	0.42

Note: The Kauffman Index of Entrepreneurial Activity is the percent of individuals (ages twenty to sixty-four) who do not own a business in the first survey month that start a new firm in the following month with fifteen or more hours worked for 1998-2011.

Finally, table 4 summarizes the region characteristics for entrepreneurs and non-entrepreneurs. Entrepreneurs appear to be located in different regions than non entrepreneurs. Entrepreneurs are more likely to be located in less concentrated and lower MES industry regions than non-entrepreneurs, consistent with lower barriers to entry or lower competition. Entrepreneurs are also more likely to be located in regions with higher overall concentrations of new and small firms. The average entrepreneur's region is about 13% more concentrated with other entrepreneurs, and has about 13% greater share of small firms. Additionally, entrepreneurs are located in denser regions with higher wages.

Table 4: **KIEA REGION INDICATORS**

	Mean	Lin. Std. Err.	95% Conf. Interval	
MES				
	0.752	0.001	0.751	0.753
	0.434	0.004	0.430	0.448
Location Quotient				
	1.394	0.002	1.391	1.397
	1.139	0.015	1.109	1.169
New Firms LQ				
	1.070	0.000	1.069	1.070
	1.211	0.007	1.197	1.225
Small Business Share				
	0.438	0.000	0.438	0.439
	0.565	0.002	0.562	0.568
Average Wage				
	30.932	0.016	30.901	30.963
	31.255	0.296	30.675	31.835
Employment Density				
	290.472	0.206	290.069	290.876
	325.561	4.091	317.544	333.579
Jacobs				
	0.366	0.000	0.366	0.367
	0.369	0.001	0.367	0.371

Note: Statistics are derived from Kauffman Index of Entrepreneurial Activity and County Business Patterns 1998-2011. Formulas for measures are provided in the text. The upper statistic is for non-entrepreneurs and lower statistic is for entrepreneurs, adjusted for Current Population Survey weights. Standard errors are estimated using Taylor linearization.

4 Empirical Estimations

4.1 Model

We present our empirical framework used to estimate the probability of an individual starting a new firm. We begin by considering a general model and then analyzing the determinants by industry sector.

A logit binary outcome model with cumulative density function (logistic distribution) F is given by:

$$p_{ijrt} = F(\beta_1 + \beta_2 Individual_j + \beta_3 Industry_{ri(t-1)} + \beta_4 Region_{ri(t-1)}) \ ,$$

wherep_{jr} is the probability that individual j in region r becomes an entrepreneur in industry i and time period t.

The results are reported as logit coefficients using the weights of the CPS with standard errors calculated using a Taylor linearization. Industry, and region fixed effects are added to control for unobserved time-invariant heterogeneity, such as the natural advantage of New York City's location and historical importance as a port. Removing variation common to all entrepreneurs within a city or industry yields estimates based on the variation of individuals within region-industries. We also add year fixed effects to control for any macroeconomic changes that affect all individuals in a particular time period.

One concern is the possibility that current income is endogenous if entrepreneurs are likely to be those laid off from a well-paying job. Older workers that earn a higher income may be unlikely to start a new firm and earn less. In this case, lower income is a consequence of being laid off and the entrepreneur may attempt to make up the difference in income from a prior job through entrepreneurship. To resolve this issue, the model is also run while excluding income and the results are presented in the appendix. The results are similar to our main findings and do not present any concerns.

Another concern is endogeneity arising from simultaneity between the region characteristics and the probability of becoming an entrepreneur. Startups may be more likely in regions with a greater concentration of new firms. However, the concentration of new firms may be driven by the probability of becoming an entrepreneur in that same year. Hence, lagged region and industry characteristics are used throughout the estimations.

4.2 Results

Table 5 displays the results from survey-weight-adjusted logit estimations where the dependent variable is an indicator for whether or not the individual starts a new firm after controlling for industry and region characteristics. An F-test of joint significance and the individual coefficients' significance suggest that region and industry characteristics should be included when modeling the propensity of individuals to open new firms. Model I accounts for year fixed effects, model II accounts for year and industry fixed effects, and model III includes year, industry, and region fixed effects. The main findings are quite robust to the fixed effect treatments.

Local industrial, social, and institutional conditions are significant determinants of startups; given the significance of the majority of industry and region regressors, there is strong evidence that characteristics of the region are important when starting a new firm. The Chinitz hypothesis is the only significant agglomeration theory. A higher concentration of entrepreneurs in a region increases the likelihood of starting a new firm and is highly significant for all of the models. A 10% increase in the new firm location quotient increases the likelihood of starting a new firm by over 6%. The share of small businesses also positively affects the probability of starting a new firm. A 10% increase in the share of small businesses increases the likelihood of starting a new firm by 15%. A higher than average concentration of new and small firms indicates a more entrepreneurial region with business churn, supplier networks, and entrepreneur training and assistance programs. This is consistent with social and institutional structures of a dense ecosystem of other small businesses further encourages individuals to open their own firms, perhaps in part through absorbing the tacit managerial skills of running a firm. The benefits of regions characterized by small and new firms enable potential entrepreneurs to make the choice to open a new firm.

The Chinitz hypothesis appears to be of greater importance to startup decisions than other agglomerations, consistent with Glaeser and Kerr (2009). Interestingly, when excluding Chinitz agglomeration, Jacob's industry diversity is statistically significant. While Jacobs and Marshallian agglomeration are insignificant in the full models, they may be statistically significant in denser locations. Model 4 includes interaction terms between density and these two agglomeration theories. Both interaction terms are statistically significant, suggesting that concentrated and diverse regions increase the likelihood of a new launch in denser regions.

The industry controls are highly significant and negatively associated with starting a new firm. A 10% increase in the MES will decrease the likelihood of starting a new firm by almost 3%. This suggests that individuals consider the scale of investment or their ability to compete with larger and more efficient incumbents when opening a new firm. The effect of the average wage of the region-industry is also highly significant, such that a 10% increase in the region-industry's average wage decreases the likelihood of starting a new firm by about 1.5%. Higher wages may deter individuals from starting a firm because of higher opportunity costs of the owner's time or because of the larger overhead cost and inability to attract quality workers that are employed by incumbents.

Individual characteristics associated with starting a new firm have been studied extensively, and the results are confirmed here. Individuals with a high school diploma or some college are less likely to start a new firm, relative to individuals with only some high school. These individuals have better employment options than individuals without a diploma, for whom acceptable employment options may be slim. Older, married, male, and home-owning individuals are also more likely to start a firm. Married individuals are able to draw on support from spouses, and homeowners can draw on the equity of their homes to finance startups. The CPS labor force codes reveal that previously unemployed and disabled or retired individuals are more likely to start a new firm, compared to currently employed individuals. Immigrants rather than native U.S. citizens are more likely to start a new firm; this is consistent with previous literature.

Minorities are less likely than white individuals to start a firm. The income categories reveal that the middle-income individuals are less apt than low-income individuals to start a new firm. Low-income individuals may expect higher net returns to self employment, while high-income individuals have greater opportunity costs in starting a new firm.

The determinants of emergent entrepreneurship and the nature of agglomeration effects may differ according to the industry an entrepreneur enters. Table 6 presents logit estimates of launching a new firm (alternative is being employed) in five large industry sectors: Manufacturing (MFG), Trade and Transportation (TT), Information, Finance, and Real Estate (IFR), Education and Health Care (EHC), and Entertainment, Recreation, and Food Services (ERF).

The coefficients for the local industrial conditions vary in significance and sign across industries. The Chinitz hypothesis for agglomeration is highly significant for all industries except EHC. The small business share affects the probability of starting a new firm more than the concentration of entrepreneurs. Hence, small suppliers may be more important when considering self employment, but the region's entrepreneurial culture still matters. A one standard deviation increase in the small business share in a region makes individuals 3% more likely to start a MFG firm.

The Chinitz effect again eliminates the effect of Marshallian agglomerations, except for EHC startups. Labor pooling may be particularly important in medical startups (e.g. physicians offices or laboratory testing centers), which need specialized workers. Furthermore, health care startups may agglomerate around hospitals to benefit from complementarities. Individuals in regions with a one standard deviation higher industry location quotient have 2.5% higher probability of starting a new EHC firm. The Jacobs hypothesis is only significant for the IFR industry. Industrial diversity increases the probability of launching a new IFR firm. Knowledge spillovers between industries may be more important for software and financial services; Urbanization encourages startups in these industries. Chinitz agglomeration also yields employment density insignificant for all industries. Employment density may not be a sufficient measure for customer and supplier linkages.

Table 5: **REGRESSION RESULTS - KIEA**

Individual Characteristics	**Model 1**	**Model 2**	**Model 3**	**Model 4**
HS Diploma	-0.177***	-0.213***	-0.174***	-0.174***
Some College	-0.136***	-0.196***	-0.170***	-0.170***
Bachelors	0.049	-0.052	-0.035	-0.036
Grad Degree	0.117**	-0.023	0.002	0.001
Medium-low Income	-0.002	-0.047	-0.062	-0.061
Medium-high Income	-0.093*	-0.151***	-0.175***	-0.174***
High Income	0.034	-0.021	0.055	0.056
Married	0.239***	0.242***	0.242***	0.243***
Previously Unemployed	0.939***	0.938***	0.941***	0.942***
Previously Disabled/Retired	1.244***	0.752***	0.752***	0.753***
Black	-0.247***	-0.213***	-0.241***	-0.240***
Asian	-0.175***	-0.139**	-0.156**	-0.159**
Other Race	-0.115	-0.086	-0.103	-0.103
Female	-0.407***	-0.342***	-0.341***	-0.341***
Native U.S.	-0.233***	-0.256***	-0.229***	-0.233***
Same Industry	-3.205***	-3.632***	-3.623***	-3.622***
Age	0.151***	0.156***	0.155***	0.155***
Age^2	-0.002***	-0.002***	-0.002***	-0.002***
Home Owner	0.112***	0.128***	0.136***	0.138***
Region and Industry Characteristics				
Employment Density	0.000	0.000	0.001	0.001
Location Quotient (LQ)	-0.008	-0.002	0.005	-0.006
Jacobs	-0.065	0.060	-0.165	0.324
Employment Density x LQ	-	-	-	0.001***
Employment Density x Jacobs	-	-	-	-0.001***
New Firms LQ	0.223***	0.233***	0.150***	0.148***
Small Business Share	3.717***	3.508***	3.701***	3.666***
Average Wage	-0.006***	-0.005***	-0.006***	-0.006***
MES	-0.521***	-0.401***	-0.434***	-0.447***
Fixed Effects				
Metro Area	No	No	Yes	Yes
Industry	No	Yes	Yes	Yes
Sample Size	2,404,524	2,352,841	2,341,779	2,341,779

Note: Statistics are derived from Kauffman Index of Entrepreneurial Activity and County Business Patterns 1998-2011. Formulas for measures are provided in the text. The coefficients are estimated using a logit binary outcome model adjusted for Current Population Survey weights and standard errors are estimated using Taylor linearization. Year fixed effects are included in each regression.

The Industry controls are statistically and economically meaningful and in the expected directions. Higher wage industry-regions deter entry for all industries except ERF. Larger MES industries deter entry in IFR and EHC, while encourage startups in ERF. IFR and EHC individuals may be less likely to launch firms because of difficulties attracting customers and labor away from larger incumbents or obtaining enough startup capital to compete with larger scale incumbents. The positive influence of MES in ERF startups is explained by Audretsch (1991), who argued that entry into capital-intensive industries is promoted by prices above minimum average cost. Restaurant launches may be encouraged despite the entry barriers.

Finally, the individual controls reveal a few interesting characteristics of startups in particular industries. Previously retired, previously disabled, older, or married individuals are more likely to start a new firm in all industries. However, the remaining individual characteristics affect startups differently. Having a graduate degree increases the probability that an individual will start a new firm in the MFG, IFR, and ERF industries. However, having a graduate degree decreases the odds of starting a EHC firm by 53%. Child care and community relief startups do not require specialized knowledge obtained through an advanced degree like lawyers (IFR) opening a new practice. Immigrants have a greater probability of starting a new firm than native citizens, but is not significant for MFG where fewer immigrant startups occur. Finally, home owners have a higher probability of starting a new firm in all industries but MFG and EHC.

5 Conclusions

We have estimated the effect of local industrial conditions on the probability of an individual launching a new firm. We have contributed to the expanding literature on entrepreneurship by using the KIEA dataset, considering individual startup decisions that control for individual motivations, and confirming the importance of the Chinitz hypothesis in new firm launches. The Chinitz hypothesis maintained that a network of smaller suppliers would create social and institutional

Table 6: **KIEA ESTIMATES BY SECTOR**

Individual Characteristics	**Manufacturing**	**Trade and Transportation**	**Information, Finance, and Real Estate**	**Education and Health Care**	**Entertainment and Food Services**
HS Diploma	0.096	-0.159	-0.236***	-0.550***	0.529***
Some College	0.761***	-0.065	-0.140	-0.964***	0.474**
Bachelors	0.987***	0.307**	0.070	-1.184***	0.965***
Grad Degree	1.151***	0.206	0.298***	-0.762***	1.367***
Medium-low Income	0.040	-0.015	0.054	-0.190**	0.254*
Medium-high Income	-0.398	-0.086	-0.096	-0.281**	0.212
High Income	-0.298	0.136	0.057	-0.238**	0.242***
Married	0.345**	0.569***	0.160***	0.162**	0.303***
Previously Unemployed	0.787***	0.763***	1.022***	0.780***	1.263***
Previously Disabled/Retired	1.247***	0.593***	0.728***	0.910***	0.943***
Black	-0.449	-0.031	-0.545***	-0.239**	-0.610***
Asian	-0.627	0.268*	-0.568***	-0.412**	0.450**
Other Race	0.353	0.077	-0.216	-0.164	-0.578*
Female	0.100	-0.135**	-0.612***	0.141	-0.385***
Native U.S.	0.396	-0.523***	-0.212***	-0.310***	-0.218
Same Industry	-4.044***	-3.826***	-3.569***	-3.973***	-3.125***
Age	0.124***	0.151***	0.152***	0.131***	0.172***
Age^2	-0.001**	-0.001***	-0.002***	-0.001***	-0.002***
Home Owner	0.191	0.155*	0.251***	-0.081	0.245**
Region and Industry Characteristics					
MES	-0.131	-0.016	-0.636***	-2.093***	0.420*
Location Quotient	-0.085	-0.054	0.014	0.974***	-0.087*
New Firms LQ	0.323**	0.190***	0.185***	0.089	0.053
Small Business Share	2.706***	5.043***	3.039***	0.287	6.471***
Average Wage	-0.017***	-0.007***	-0.006***	-0.050***	-0.000
Employment Density	-0.002	0.000	0.002	0.001	-0.001
Jacobs	-0.185	-0.062	-0.458**	0.034	-0.521
Sample Size	244,749	435,007	560,384	587,497	185,266

Note: Statistics are derived from Kauffman Index of Entrepreneurial Activity and County Business Patterns 1998-2011. Formulas for measures are provided in the text. The coefficients are estimated using a logit binary outcome model adjusted for Current Population Survey weights and standard errors are estimated using Taylor linearization. MSA and year fixed effects are included in each regression.

structures that promote entrepreneurship. We find strong evidence of the Chinitz hypothesis, both small suppliers and an entrepreneurial culture, across several large industry sectors. The theories of Marshall and Jacobs were significant in denser regions, though startups in the Education and Health Care sector were more likely in industrially concentrated regions and startups in the Information, Finance, and Real Estate sector were more likely in diverse regions.

Policy makers interested in increasing startups in an effort to promote economic growth should foster an entrepreneurial environment characterized by small and new firms. Specifically, supporting small businesses has a large effect on individuals who may gain advice from role models, managerial skills, or benefit from open supplier networks. A greater concentration of new firms can also encourage social structures that support startup failures and encourage new startups. Policies directed at particular industries that are agglomerated may not promote new firms. Such a policy might be to incentivize a large firm to relocate, increasing the industry concentration; This may lead to individuals remaining employed and does not signal a culture supportive of entrepreneurs. Rather, broad policies that emphasize new and small firms in any industry will support new firm formation across the region. Of course, not all regions can become entrepreneurial “hotbeds”, but investments in incubators, equity/debt pools, and small business support services may encourage startups.

Future work might consider more specific measures for the Chinitz hypothesis. Specific supplier linkages and cultural attitudes may provide additional insights. Additional research may apply spatial econometric models to examine the distance at which the Chinitz hypothesis affects startups. While Marshall’s agglomeration economies are highly local, social and institutional structures that support entrepreneurship may have a more distant effect.

Chapter II

Do New Firm Shutdowns Occur in a Vacuum or Does the Region Matter?

6 Introduction

Boston, MA and Silicon Valley, CA are two of the most entrepreneurial regions, and also produce some of the best performing startups (i.e. "gazelles") in the U.S. (Kenney and Patton, 2013). Why do some regions enhance startup survival and growth more than others? Focusing on survival, we add to the growing literature on entrepreneurship by considering the effect of local industrial and social conditions on a startup's probability of shutdown, using the Kauffman Firm Survey (KFS).

Understanding how new firm survival is enhanced by regions is particularly relevant for policy makers interested in entrepreneurship-focused growth plans. Through increased competition and innovation pressures, surviving startups encourage existing firm improvements and future regional growth (Fritsch and Mueller, 2004; van Stel et al., 2010). Despite an extensive literature considering various types of agglomeration, only cluster agglomeration has been studied in the context of new firm closures. The industrial organization literature considering firm survival has mainly focused on internal economies of scale (De Silva and McComb, 2011), while the literature on the effects of the region can be classified into two main streams: organizational ecology and evolutionary economics (Geroski et al., 2007; Henderson, 1999; Agarwal and Audretsch, 2001). The organizational ecology perspective (Hannan and Freemand, 1977) suggests that there is a greater probability of closure in competitively denser locations and a lower probability in locations with organizational legitimacy. The evolutionary economics perspective (Nelson and Winter, 1982) suggests that over the industry life cycle, varying market conditions (e.g. organizational structure, technology, and market growth) affect firm closure (Audretsch, 1991; Winter, 1984; Bradburd and Caves, 1982).

An implication, or at least an implicit assumption in the modeling, of the existing literature is that all types of closures have the same determinants. However, conditions leading up to a positive exit are fundamentally different than leading up to a shutdown. Mergers and Acquisitions (M&A) may occur to: improve efficiency through economies of scale, increase market power, and improve diversification in internal capital and management. Andrade et al. (2001) found M&A in the 1990's was caused by vast deregulation, which created investment opportunities and eliminated previously existing barriers to M&A. Similarly, agglomeration effects may differ significantly for preventing shutdowns compared to encouraging positive exits. We contribute to the expanding literature on entrepreneurship by considering shutdowns and positive-exits separately, using a comprehensive model including firm and local agglomeration conditions, and separately exploring how they may differ for different types of firms.

Section 7 develops hypotheses for how shutdowns are affected by local industrial conditions. Previous studies have considered the effects of clusters on new firm survival, but have not considered other theories of agglomeration. Shaver and Flyer (2000) found that firms were more likely to shutdown as a firm's cluster increased in size. Folta et al. (2006) confirm this result and examine a broad base of performance metrics. Biotech firms benefitted from clusters through patenting, partnerships, and attraction of equity funding. We distinguish and explore the relative importance of four sources of agglomeration benefits for new firms: density, clusters, Jacobs diversity, and the Chinitz entrepreneurial culture hypothesis. Jacobs proposed that industry diversity enhanced knowledge spillovers and innovation in startups, which may reduce the probability of shutdown. Finally, Chinitz (1961) suggested that the presence of small and independent firms leads to social and institutional structures that may promote new firm survival.

Section 8 describes the extensive KFS data, which provides detailed geographic information for each of the almost five thousand new firms in the U.S. as well as numerous detailed owner and firm characteristics. We then present summary statistics and our main variables measuring local industry conditions and control variables for owner, firm, and industry characteristics. Section 9 discusses a competing-risk discrete-time survival model we use, that accounts for the different types of closure (i.e. "competing risks"): M&A and shutdowns. Finally, section 10 discusses future literature pathways and policy implications.

7 Entrepreneur Closures

7.1 Theoretical Framework

Falck (2007) presents a simple theoretical framework, based on Evans and Jovanovic (1989), on how entrepreneur's start and continue new firms. The individual considers the difference between accounting profits from a new firm and the alternative wage that could be obtained if employed. Accounting profits will be dependent on owner, firm, industry, and region characteristics. Survival then requires a positive difference, or economic profit, to initially open and continue operating the new firm. This straightforward model has been widely supported by empirical studies and the following hypotheses explain several ways in which survival may be affected.

7.2 Agglomeration

There are four types of potential agglomeration benefits for new firms that we consider in this study: density, clusters, Jacobs diversity, and the Chinitz hypothesis. One of the basic benefits to agglomerating is that firm productivity can improve through lower transportation costs if customers and suppliers are colocated. Individuals may launch a new firm near other firms to partake in these external cost savings. The key agglomerating mechanism in New Economic Geography is the savings from cheaper shipping costs (Fujita et al., 1999). Sugar, for example, was refined in New York City in the nineteenth century rather than the tropics because of the large costs in transporting refined sugar (Glaeser and Kerr, 2009).

These cost savings may discourage shutdowns, but density may also indicate competitive pressures on the new firm (Hannan and Freeman, 1987). Geroski et al. (2007) describe two reasons for why denser regions increases the probability of shutdown. New firms in dense regions may suffer from the “liability of scarcity,” where competition for critical resources may prevent new firms, not yet with the optimal structural configuration, from making appropriate investments or implementing correct routines. New firms may also suffer from “tight niche packing,” where crowded markets irreversibly push new firms into unpromising market niches.

7.2.1 Cluster Agglomeration

In addition to the effects of density, clusters of related and supporting industries may further affect performance. Clusters like Silicon Valley, Route 128, the Research Triangle, Austin, Seattle, Bangalore, Tel Aviv, and Lund exhibit benefits for inhabiting firms such as: increased productivity, specialized labor pooling, and knowledge spillovers (Porter, 1998). While research on clusters has largely focused on the effect of clusters on regional performance (Kolko, 2007; Porter, 2003), a few studies have found that clusters enhance new firm performance (Baptista and Swann, 1998; Wennberg and Lindqvist, 2010; Delgado, et al., 2010).

The labor hired in the first few years, vital to any new firm’s success, may be constrained by the quality of the labor force in the surrounding region (Dahl and Klepper, 2007). Specialized workers may be required in certain industry startups and are more likely to pool around agglomerated firms. Labor pooling amongst clustered firms can smooth the effect of firm-specific shocks on individual workers (Marshall, 1890). Workers can easily change jobs when their employer is affected by a negative shock, making workers more productive under such insurance (Krugman, 1991). Large labor pools in a city may also facilitate matching between startups and employees (Helsley and Strange, 1990). Hence, new and existing firms needing similar specialized labor are likely to colocate and benefit from a greater availability of workers or lower wages in thick labor markets (Glaeser and Kerr, 2009).

Additionally, industry clusters may promote new firm survival through the dissemination of existing and new knowledge. In Silicon Valley, the transfer and flow of ideas was an essential mechanism for entrepreneur success (Saxenian, 1994). Acs et al. (1994) suggested that clusters benefit entrepreneurs more so than incumbents via enhanced knowledge spillovers, where customers and suppliers can share issues with existing products or describe needs and wants for new products (Porter, 1990). Rosenthal and Strange (2003) found these knowledge spillovers to be highly localized, similar to studies on patent citations (Jaffe et al., 2000; Carlino et al., 2007). Audretsch and Feldman (1996) found that innovations are also clustered around research and development (R&D) and university research.

Contrary to clustering of related industries, Jacobs (1970) proposed that vital knowledge flows to firms from outside their own industry. Under this view, variety and diversity will lead to greater knowledge transfer and promote innovation. Several studies have attempted to test whether concentration or diversity is better for regional growth, with mixed findings (Glaeser et al., 1992; Henderson et al., 1995).

7.2.2 Chinitz Hypothesis

Another source of agglomeration may be in the characteristics of suppliers, which Chinitz (1961) used to explained entrepreneurial differences between Pittsburgh and New York. Chinitz described the supplier needs of entrepreneurs as highly localized, compared to those of large incumbent firms that could internalize these needs. The vertically integrated steel firms in Pittsburgh were not concerned with the input needs nor output capabilities of entrepreneurs. On the other hand, New York City's small supplier network to the garment industry provided entrepreneurs with specialized inputs. Small firms further exhibit a lack of division of labor, enabling employees to learn a breadth of managerial knowledge that may be particularly important in operating a new firm (Reynolds et al., 1994). The Chinitz hypothesis suggests that the presence of small and independent firms leads to social and institutional structures that promote a culture of entrepreneurship (Glaeser and Kerr, 2009).

Some regions exhibit an entrepreneurial culture that is not limited to specialized input suppliers (Hofstede, 2001). Glaeser and Kerr (2009) describe agglomerations in entrepreneurship that lead to a social structure that reduces the stigma of failure and increases the likelihood that others take risks (Landier, 2004). The Silicon Valley for example, encourages entrepreneur trials and emphasizes cooperation between young startups (Saxenian, 1994). Early semiconductors led the way for future entrepreneurs through open inter-firm communication and a vertically disintegrated industry structure.

The importance of local new firm services can also provide guidance and legitimacy for new firms (e.g. Porter, 1998; Muller and Zenker, 2001; Scott, 2002). Entrepreneurial support institutions may cluster around concentrations of entrepreneurs and aid in solving new firm struggles (e.g. angel investors, small business incubators, and specialized legal or accounting services).

7.3 Owner Characteristics

While analysis at the region level may consider local industrial, social, and institutional conditions, analysis at the firm level allows for the inclusion of owner and firm determinants of new firm shutdowns. Several studies have found that male-owned firms outperform female-owned firms (Loscocco et al., 1991; Fischer et al., 1993). Female-owned firms may be less successful because they lack start-up capital and have less previous business experience (Fairlie and Robb, 2008). Other studies have found that there is no difference in success or performance between female-led and male-led firms after accounting for organizational structure and owner attributes (Kalleberg and Leicht, 1991). However, female-led firms were smaller and had lower earnings than male-led firms.

Age may also be an important factor in the firm's performance. Older executives may have a stronger commitment to their organization than younger executives (Becker, 1973). Firm performance is also found to be greater in firms with older managers (Brockmann and Simmonds, 1997). The success may be driven by experience of older individuals, while younger individuals are less experienced. However, younger individuals may be more willing to change and recognize opportunities than older individuals (Carlsson and Karlsson, 1970). Experience with previous startups may make new firms less likely to shutdown, if the owner has learned from his previous ventures. However, serial entrepreneurs may be more willing to close in favor of some other new venture that they believe offers higher rewards.

Finally, human capital has been found to positively affect firm performance. Innovative firms are most often started by highly educated individuals, but after working for a period of time (Fritsch, 2010). Human capital has been found to improve survival chances because imitation and trade cannot be executed on human capital, but can on physical capital (Geroski et al., 2007).

7.4 Firm Characteristics

Owner characteristics are important for the direction and adaptability of the firm to changing market conditions, but there are also firm characteristics that play a role in the success of the firm over the first few years. Many studies have found that initial size of the startup is positively related to new firm survival (Geroski, 1995). Small firms may be more vulnerable than larger startups that are operating closer to minimum efficient scale (MES). Larger initial size may also indicate access to capital, putting smaller firms at a disadvantage regarding economies of scale (Geroski et al., 2007). With better funding, larger startups may be in a better position to overcome economic shocks. Finally, higher ability operators may ensure lower operating costs and positively affect the size of the firm (Geroski et al., 2007). An exception may be in the form of home-based firms, which may be smaller and less susceptible to shutdown if cash flow falters than firms that must lease space and cover higher overhead.

The firm's intellectual property may further enhance survival probability. Though most firms in the KFS do not have a patent in their first years, many have a copyright. A copyright signifies effective knowledge and information management and is further evidence of proprietary knowledge that the firm can gain a competitive advantage with. Patents may not be appropriate in some industries or for some firms that do not realize gains from the potentially long and expensive patent process.

Finally, new firms are greatly affected by injections of capital, which can decrease the probability of shutdown. In order for a new firm to receive a loan or other debt instrument, a financial intermediary carries out a vetting process. Asymmetric information about the creditability and lack of credit history can make financing a new firm risky. Receiving a loan is an indicator of the firm's strong business plan, finances, and collateral. Landier (2003) suggests that debt financing is more likely for low risk firms where owners face high costs to exit.

Equity financing may come to a firm in the form of an angel investor or venture capitalist, and may be sought by a new firm who cannot obtain debt financing because of a high risk business plan or lack of collateral. Giving up ownership and future growth income may discourage some entrepreneurs, but equity investments are generally accompanied by managerial assistance and guidance. Landier (2003) finds that equity will be the primary financing mode of high risk firms located in regions where entrepreneurs face many outside options. Hence, while equity offers a cash infusion and possible advice, firms that receive equity financing may be more likely to shutdown because of their higher risk and set of outside options.

7.5 Industry Factors

Finally, new firm shutdowns may be determined by industry characteristics. In order for firms in competitive industries to become profitable, new firms must reach minimum efficient scale (MES) (Audretsch, 1995). Survival is expected to be higher if this scale is smaller, as firms do not need as many resources to compete (Audretsch et al., 2000). Entrepreneurs that enter with a size closer to the MES in an industry are more likely to survive, while smaller entrepreneurs will have difficulty reaching profitability. Larger MES industries also require larger upfront capital and may raise the cost of capital above existing firms' (Lyons, 1980). Finally, entrants may have difficulty attracting quality workers from larger existing firms.

Small firms may not be deterred from entering industries where scale economies are important (Audretsch, 1991). Industries in which the price level is above the minimum average cost may promote the existence of suboptimal capacity firms, i.e. startups. The further above minimum average cost the price is (i.e. high net-margin markets), the greater the probability of survival is (Weis, 1976). Industries with large-scale firms may also promote selection of a few high-quality startups while encouraging exits of low-quality startups (Fritsch et al., 2006).

8 Data

8.1 The KFS

The KFS is a longitudinal panel survey of 4,928 businesses founded in 2004 and surveyed annually through 2010. The limited-access KFS dataset provides detailed information on each firm and the owners. The KFS includes businesses that were founded by individuals and teams, existing firms purchased by new owners, or purchases of franchises. The survey does not include not-for-profits, wholly owned subsidiaries, or inherited businesses. In order to ensure representation of women and high-tech firms, the sample was stratified according to industry, technology, and gender of the owner . Ballou et al. (2008) describe the survey methodology and design in greater detail.

Figure 5 compares the industry distribution of the KFS to the Census employer firm births and the Panel Study of Entrepreneurial Dynamics (PSED). The top three industries are oversampled by the KFS as these industries have a larger proportion of female owners. Manufacturing is also oversampled to get a larger sample of high-tech firms. The oversampling in these industries result in a smaller representation of other industries such as accommodation and food services. However, the KFS provides stratification and sampling weights to correct for the complex survey design.

We map the KFS dataset to the U.S. Census Bureau's County Business Pattern (CBP) dataset by industry-region-year to obtain information on employment, annual payroll, the size distribution of firms, and number of establishments. We create the primary local industry conditions of a particular metropolitan area from the CBP dataset. Because the information is taken from administrative firm records, the CBP provides very accurate information on employment, annual payroll, number of establishments by size, and number of establishments. Hence, there are no sampling errors to bias these measures. We aggregate the county-based CBP variables by core-based statistical areas

Figure 3: **INDUSTRY DISTRIBUTION COMPARISON OF KFS**

Industry Name and NAICS	KFS	Census Employer Births	PSED New Businesses
Professional (54), Management, and Educational Services (61)	16.1	14.1	16.8
Retail trade (44)	15.6	12.0	18.6
Administrative and Support, and Waste Management and Remediation Services (56)	11.4	6.0	2.1
Construction (23)	9.8	15.7	10.0
Other Services excl. Public Services (81)	8.0	8.5	0.3
Manufacturing (31)	7.2	3.2	3.5
Wholesale Trade (42)	6.0	4.5	1.5
Real Estate, Rental and Leasing (53)	3.7	5.1	5.3
Finance and Insurance (52)	4.7	2.2	3.1
Health Care and Social Assistance (62)	4.2	7.7	2.9
Information (51)	2.6	1.4	4.2
Transportation and Warehousing (48)	2.9	3.3	2.4
Arts, Entertainment, and Recreation (71)	3.1	2.1	3.2
Accommodation and Food Services (72)	3.9	9.1	10.9
Agriculture, Forestry, Fishing, and Hunting (11)	1.4	0.4	2.0
Mining (21)	0.0	0.3	0.5
Utilities (22)	0.0	0.1	0.5
Management of Companies and Enterprises (55)	0.0	0.1	6.7
Unclassified (99)	0.0	2.2	5.6

Source: *Nassereddine (2012)*

(CBSA).

8.2 Variables

Figure 4 presents the owner and firm control variables provided by the KFS. Figure 5 presents local industry measures calculated at the 3-digit industry NAICS and at the CBSA level using the County Business Patterns (CBP) dataset. We measure the colocation of firms using the employment density of a region. Density is calculated as the number of employees per square mile of land area. Unfortunately, this measure does not separate the importance of customers or suppliers in a particular industry. We construct cluster concentration measures using cluster definitions developed by Porter (2003) and promoted by the Cluster Mapping Project. Regional knowledge is measured by the research expenditures of colleges and universities in the region (Integrated Post-secondary Education Data System). Jacobs spillovers are measured using the ratio of employment in the largest five industries to employment in the entire region (Glaeser et al., 1992). We include the share of small businesses to estimate the Chinitz effect and the concentration of entrepreneurs to estimate entrepreneur agglomerations.

We use the national median firm size for a particular industry to measure MES. Finally, in order to control for outside options of individuals considering employment or starting a new firm, the logged average payroll per employee in a industry-region is included.

8.3 Summary Statistics

Table 7 summarizes owner characteristics of the baseline KFS correcting for survey design. Approximately 70% of owners are male. 47% of owners are over the age of 45, while only 19% are under 35. 53% of owners do not have a four-year degree, but 30% of these owners have some college education. 24% of owners have a bachelor's and 23% have an advanced degree. Only 10% of owners have no experience in the same industry, while 51% of owners have more than 10 years of experience. 41% of KFS owners have already started a new firm, but 58% are first-time entrepreneurs. Finally, the majority of owners work full-time, while about 49% of owners work more than 46 hours per week.

Table 8 summarizes the characteristics of KFS firms. 59% of KFS firms begin with no employees and 27% have more than two employees. The ownership of firms is mostly by a single individual (65%), compared to the 35% of firms with multiple owners. Intellectual property is rare, with only 2% of firms possessing a patent and approximately 9% possessing a copyright. Approx-

Owner/Firm	Measurement
Work Exp. Same Ind.	Years of experience in same industry.
Entrepreneur Exp.	Number of previous startups.
Male	Gender of the primary owner is male.
Age	Primary owner's age and age squared.
College Grad	Primary owner is a college graduate.
Owner Hours	Number of hours the primary owner works per week.
Non Employer	Firm has no employees.
Competitive Advantage	Owner believes firm has competitive advantage. (Confidence)
Sole Owner	Firm only has one owner-operator.
Patent	Firm has a patent.
Copyright	Firm has a copyright.
Home-based	Firm is based in a home, not commercial space.
Debt Financed	Firm has obtained debt-financing.
Equity Financed	Firm has obtained equity-financing.

Figure 4: **DEFINITION OF FIRM AND OWNER VARIABLES WITH EXPECTED SIGNS**

Region/Industry	Measurement
Employment Density	Employment density or employment in region r per square mile of land area. $EmpDensity = \frac{E_r}{LandArea_r}$
Cluster LQ (Porter)	Ratio of a region's share of employment in cluster c relative to the nation's share of employment in that same cluster. $lq^c = \frac{E_{cr}/E_r}{E_c/E}$ E_{cr} = number employees in cluster c and region r
Diversity (Jacobs)	Ratio of the region's employment in the five largest industries. (Smaller values indicate greater urbanization) $Jacobs = \frac{E_r^5}{E_r}$
New Firms LQ (Chinitz)	Ratio of a region's share of entrepreneurial firms relative to the nation's share of entrepreneurial firms. $lq_E = \frac{F_r^E/F_r}{F^E/F}$
Small Business Share (Chinitz)	Share of a region's employment in firms with fewer than 5 employees $SmlBizSh = \frac{E_r^{1-5}}{E_r}$
Region/Industry Controls	
Log Research Expenditures	Logged expenditures on research from colleges within CBSA.
Average Wage	Region's logged annual payroll per employee.
MES	National median firm size for industry i. $MES = median_i(\frac{E_{ir}}{F_{ir}})$

Figure 5: **DEFINITION OF REGION AND INDUSTRY VARIABLES WITH EXPECTED SIGNS**

Table 7: **KFS OWNERS**

	Survey Proportion (%)	Sample Count
Work Experience Same Industry		
Zero	9.6	398
1–9	39.2	1,781
10–24	35.0	1,835
25 +	16.1	896
Previous Startups		
Zero	58.5	2,820
1	21.3	1,046
2 +	20.3	1,030
Hours per Week		
Less than 35	36	1,782
35–45	15	717
46 +	49	2,334
Male	69.2	3,649
Age		
Less than 35	19	868
35–44	33.8	1,629
45 +	47.2	2,406
Education		
Less than Bachelor's	52.9	2,392
Bachelor's	24.2	1,215
More than Bachelor's	22.9	1,290

Note: Summary statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004. (Robb and Reedy, 2012)

Table 8: **KFS FIRM CHARACTERISTICS**

	Survey Proportion (%)	Sample Count
Initial Size (Employment)		
Zero	59.2	2,838
1	14	690
2 +	27	1,295
Initial Owners		
1	65.2	3,163
2 +	34.9	1,765
Patent	2.2	187
Copyright	8.7	485
Home-based	49.2	2,483
Debt Financed	56.2	2,697
Equity Financed	9.6	488

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004. (Robb and Reedy, 2012)

imately 51% of firms have a commercial leased or rented property, while the other 49% work in the owner's home. Finally, 56% of firms have obtained debt financing, compared to only 10% of firms that obtained external equity investments.

Summary statistics for region and industry characteristics are provided in table 9. The average startup is located in regions that are more concentrated than the nation in cluster employment and new firms. 57% of employment is accounted for by small firms in the region surrounding new firms. The average firm is located in an industry where the median scale is approximately 10 employees. 336 employees are located in each square mile of the startup's region. Finally, 42% of employment is accounted for by the largest 5 industries in a startup's region.

8.4 KFS Closures

Table 10 describes closures over the six year period, after adjusting for survey weights. The hazard of closure is the probability that firms entering the time interval will close during the inter-

Table 9: **KFS REGION AND INDUSTRY CHARACTERISTICS**

	Survey Mean	**Std. Error**
Logged Research Expenditures	17.85	0.087
Cluster LQ	1.08	0.012
New Firm LQ	1.03	0.013
Small Business Share	0.57	0.003
Logged Pay Per Employee	2.99	0.023
MES	10.33	0.150
Employment Density	335.86	6.446
Relative Top Industry Employment (Jacobs)	0.42	0.003

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey and calculated using County Business Patterns.

Table 10: **KFS CLOSURE**

	Closures	**Cumulative Closure**	**Hazard**
2004–2005	297	0.060	0.062
2005–2006	334	0.128	0.075
2006–2007	425	0.214	0.104
2007–2008	355	0.287	0.096
2008–2009	297	0.347	0.088
2009–2010	248	0.424	0.082

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004-2010.

val. Hazard of firm closure has an inverse-U relationship over time with a peak in the third year, consistent with Falck (2007). Table 11 describes hazard rates for positive exits and shutdowns. Approximately 249 (13%) of closures are positive exits, compared to 1,707 (87%) shutdowns. The shutdown hazard has an inverse-U shape, while the hazard of positive exit is flat, only increasing in the second and last time interval.

Table 11: **KFS SHUTDOWN AND POSITIVE EXITS**

	Shutdowns		Positive Exits	
	Number	Hazard	Number	Hazard
2004–2005	254	0.053	43	0.009
2005–2006	287	0.064	47	0.011
2006–2007	380	0.093	45	0.011
2007–2008	315	0.085	40	0.011
2008–2009	261	0.078	36	0.011
2009–2010	210	0.070	38	0.012

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004-2010.

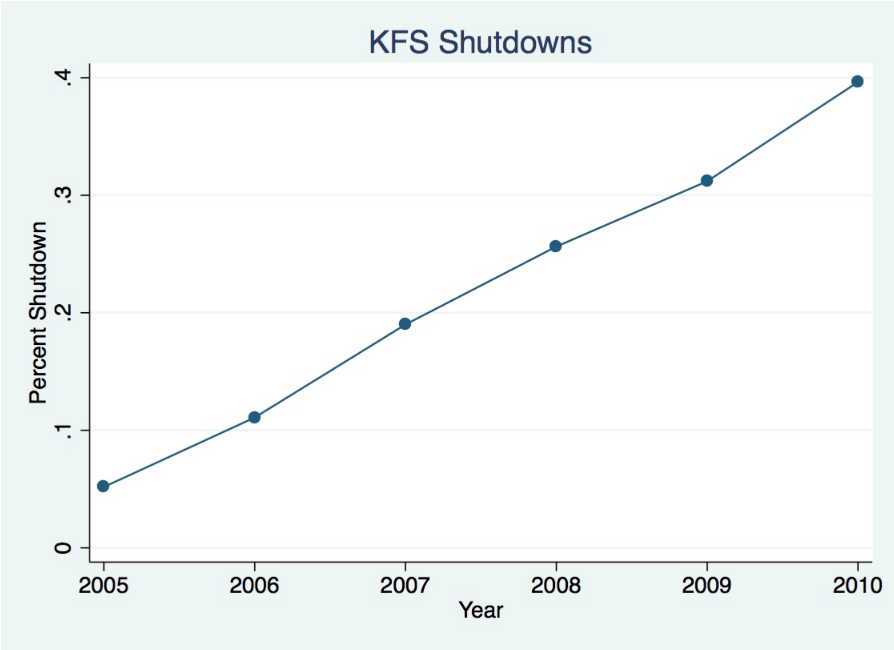

Figure 6: **KFS CUMULATIVE SHUTDOWNS**

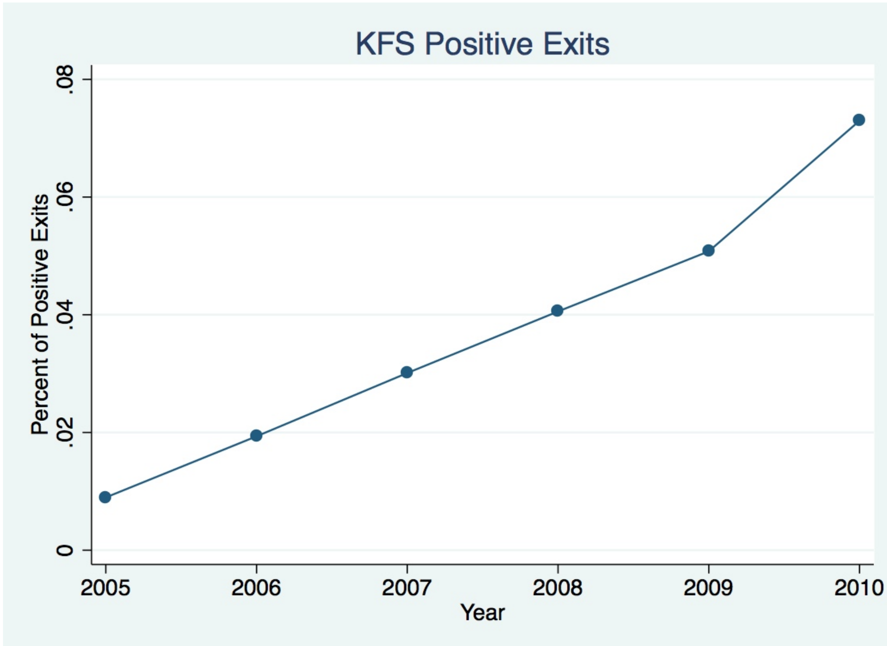

Figure 7: **KFS CUMULATIVE POSITIVE EXITS**

9 Empirical Estimation

9.1 Model

While other studies have used regional models (Acs et al., 2007; Audretsch, 1991; Fritsch et al., 2006), we use survival, or event-history, modeling to estimate the probability of business shutdown, conditional on the firm surviving to the beginning of time interval. Falck (2007) uses a continuous-time specifications (e.g. semi-parametric Cox proportional hazard model or parametric exponential model), but may be biased in the context of interval-censored data. We estimate a discrete-time failure model, after taking into account the sampling and stratification of the KFS.

Discrete survival models overcome the bias resulting from using a continuous time model to estimate grouped data survival. Firm survival is observed annually, despite the underlying continuous risk of a firm closing at any time within year-interval. Firm closure and continuance are determined for each year the data are collected and recorded in the KFS. However, the Cox model assumes that durations are recorded as values that can take on any continuous non-negative value. The likelihood estimation then orders these durations, but annually-grouped "coarse" data will have many "ties" (i.e. identical values) in years where there are multiple firm closure. In the case of the KFS, there are only six follow-ups, at the time of writing, and between 250 and 425 exits in a particular year. Ties will bias the coefficients and the covariance in the Cox or other parametric models (Kalbfleisch and Prentice, 1980). The discrete-time survival model will not suffer from bias due to closure ties, and can easily accommodate non-proportional and non-parametric hazard specifications.

Let T_j be the continuous and non-negative measure for survival time (i.e. event time) for firm j. The survival model will estimate the probability that the business exits in the time interval t, conditional on the firm surviving up to at least the beginning of the interval and given the other regressors $\mathbf{x}_{jt}$. The conditional hazard h_{jt} is then defined as,

$$h_{jt} = Pr(T_j = t | T_j \geq t, \mathbf{x}_{jt}),$$

where $\mathbf{x}_{jt}$ is a vector of time-varying covariates. We use the logit model out of familiarity, but other models (e.g. cloglog) did not change coefficient signs or significance tests. The logit hazard specification for firm j in region r and industry i is then,

$$logit(h_{jrit}) = log\left(\frac{h_{jrit}}{1-h_{jrit}}\right) = \alpha_t + \beta_1 owner_{jt} + \beta_2 firm_{jt} + \beta_3 industry_{ri(t-1)} + \beta_4 region_{ri(t-1)} \ ,$$

where α_t is a logit of the baseline hazard function and is a potential source of parameterization beyond the logit relationship. In continuous-time models, the Cox model does not specify the baseline hazard, while others are named for this parameterization (e.g. exponential or Weibull). The discrete-time logit model is quite flexible in this regard, and several models were tested. The non-parametric specification is to allow each year's baseline hazard to vary, or to estimate dummy variables for each year t . Logged time, linear, or splines are alternative choices, sometimes chosen to reduce the number of coefficients that need to be estimated. We chose the most flexible unspecified baseline hazard, while other models make assumptions about the shape of the baseline hazard that are inappropriate for new firm survival. A linear specification would assume that the hazard of failure at any time t decreased or increase constantly over the first few years of the firm's life. However, table 10 shows that the hazard is bell-shaped, with a peak around year three. Falck (2007) found the baseline hazard to also have a bell shape with a peak in the hazard around year five; Other studies have found the peak to occur between years three and five.

This simple model suffers from an aggregation bias, grouping all possible exits together. We wish to estimate the probability of shutdown, controlling for positive exits (i.e. M&A). A single risk duration model assumes that the baseline hazard and the effects of each covariate have the same effect, regardless of shutdown or M&A.

Individual firms have three possible outcomes: continue operations (censored), shutdown, or positive exit. To allow these "competing risks," a type-specific and separate hazard function is specified for event m. Allison (1984) shows that the overall hazard is simply the sum of each type-specific hazard function where the other events are considered censored. Allison (1984) shows that the hazard of exiting type m in time t is,

$$logit(h^{m}_{jrit}) = log\left(\frac{h^{m}_{jrit}}{1-h^{m}_{jrit}}\right) = \alpha_t + \beta_1 owner_{jt} + \beta_2 firm_{jt} + \beta_3 industry_{ri(t-1)} + \beta_4 region_{ri(t-1)}\ .$$

In this way, an observation is created for every individual and year interval until they experience one of the events, drop out of the survey, or are censored. There are 4,928 firms in the KFS and six followup surveys, generating 29,568 observations. However, once a firm closes, they are no longer at risk of closing in the future. Other firms may exit the KFS because of nonresponse and future firm-year observations are dropped. Two exit variables are created for each exit type. If a firm exits through a M&A, the positive exit variable is coded as a one in the particular year of occurrence while all other firm-year observations receive a zero. Firms that shutdown or do not close are censored. Similarly, an exit variable is created for firms that shutdown. Figure 8 displays this dataset for two individuals. The first firm experienced a merger in the fourth followup, while the second firm remained open for all six followups and was then censored. Separate models are then estimated for each event type.

The use of survey weights and stratification from the KFS makes the model more complicated, but this is accounted for in the coefficient and standard error estimates; The majority of model "fit"

Firm	Year	Closure	Positive Exit	Shutdown
1	1	0	0	0
1	2	0	0	0
1	3	0	0	0
1	4	1	1	0
2	1	0	0	0
2	2	0	0	0
2	3	0	0	0
2	4	0	0	0
2	5	0	0	0
2	6	0	0	0

Figure 8: **COMPETING RISK DATA STRUCTURE**

statistics are incalculable under a complex survey design. To formally test for the baseline hazard specification, we use a goodness-of-fit test for survey-weighted logit models, following Archer et al. (2007). The results indicate that the unspecified or non-parametric baseline does not reject goodness-of-fit.

Finally, to address potential endogeneity through simultaneity of the region and industry variables, each covariate is lagged one year (Wennberg and Lindqvist, 2010). Omitted industry and region variables are also a concern if firm closures or performance are inherently different across regions and industries. For example, restaurants have a notoriously high failure rate, while some states have very favorable tax conditions for startups. State and 1-digit NAICS industry fixed effects will control for these time-invariant natural (dis)advantages.

9.2 Estimates

9.2.1 Closure Estimates

We begin by estimating a discrete-time logit model of closure based on 23,109 firm-year observations and 4,148 firms summarized in table 12. The table contains logit coefficients that, when exponentiated, give the percent change in the risk of closure for a one unit increase in the covariate. We include models of owner and firm characteristics, local industry conditions, and a comprehensive model as earlier studies without individual or firm variables may suffer from omitted variable bias. While the effects of owner and firm characteristics are largely stable, the effects of local industry conditions change in the comprehensive model.

Several owner and firm characteristics remain statistically significant, but change in magnitude after including local industry conditions: work experience, age, sole-owner, copyright, debt-financed. However, entrepreneur experience, owner hours, and non-employers become statistically insignificant in the full model. When only local industry conditions are considered, research expenditures and the small business share are statistically significant. However, MES is the only statistically significant industrial or regional determinant of firm closure in the comprehensive model.

9.2.2 Competing Risk Estimates

Table 13 presents the competing risk estimates for shutdowns and positive exits. Similar to the preceding results, estimating the comprehensive model changes the statistical significance and magnitude of firm and local industry effects for both types of closure. Considering only one level (i.e. owner, firm, industry, or region) of variables results in omitted variable bias.

The most striking result is that modeling multiple levels of variables yields individually and jointly insignificant effects of local industry conditions on shutdowns. While this indicates that the region may not determine new firm shutdowns, the region appears to be important for positive exits. The Chinitz effect suggests that firms are at a lower risk of positive exit the higher the small business share is. This finding indicates that the benefits of a region defined by small firms may lower costs enough to decrease the benefits a positive exit or reduces the likelihood that a larger firm acquires new firms. The environment perpetuates by encouraging new firms to remain independent and autonomous. MES is also statistically significant, such that a 10% increase in the MES increases the likelihood of a positive exit by approximately 5%. Firms may attempt to combine with other firms to be more competitive as the MES increases.

Table 12: **KFS CLOSURE ESTIMATES**

Owner/Firm	**Owner/Firm**	**Region**	**Full**
Work Experience	-0.013***	—	-0.015***
Startup Experience	0.017*	—	0.012
Male	-0.007	—	0.039
Age	-0.146***	—	-0.114***
Age^2	0.001***	—	0.001***
College Grad	-0.045	—	-0.053
Owner Hours	-0.003*	—	-0.003
Non-Employer	-0.140*	—	-0.141
Competitive Adv.	-0.064	—	-0.093
Sole Owner	-0.290***	—	-0.255**
Patent	-0.178	—	-0.239
Copyright	-0.599***	—	-0.598***
Home-based	-0.112	—	-0.151
Debt-Financed	-1.020***	—	-1.089***
Equity-Financed	0.126	—	0.168
Region/Industry			
Research Expenditures	—	-0.021**	-0.008
Cluster LQ	—	-0.039	-0.010
New Firms LQ	—	0.061	0.058
Small Business Share	—	-0.952**	-0.449
Average Wage	—	-0.033	0.006
MES	—	-0.005	0.004**
Employment Density	—	0.136	-0.005
Jacobs	—	0.167	0.215
Firms	4,928	4,928	4,928

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include industry and state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * $p < .10$; ** $p < .05$; *** $p < .01$

We also find evidence that owner determinants of positive exits and shutdowns differ. Previous entrepreneur experience, rather than industry-specific experience, increases the chance of positive-exit. Firms with older owners are also less likely to positive-exit, but the positive sign on the square term indicates a slightly convex relationship. Owners with a college degree have a 77% higher likelihood of positive exit, yet do not affect the risk of shutdown. This finding suggests that formal college education may not be the only provider of managerial skills to run a business. Alternatively, unobserved managerial skill and ingenuity may better measure the owner's quality than a college degree. Approximately half of the owners in the KFS have a college degree and approximately half of the firms that shutdown had college-educated owners. Owners believing their firm to have a competitive advantage are more likely to positively exit and less likely to shutdown, indicating how well owners know their firms. Similar to Robb and Watson (2012), gender of the primary owner does not have a significant effect on firm exit.

Firm characteristics also reveal different effects on positive-exits and shutdowns. Sole-owner firms have a lower probability of both positive-exit and shutdown. Having other owner operators can decrease the burden of managerial work for the primary owner and bring complementary skills to the ownership team. However, solo entrepreneurs may have a clear vision and direction for the firm that may be easier to follow in the absence of other owners. Home-based firms have a 65% lower likelihood of positive-exit, while the risk of shutdown is unaffected. Though home-based firms are smaller, they have fewer liabilities and no observed quality differences. Therefore, home-based firms may be less attractive takeover targets or owners may prefer working at home to commuting. Firms with copyrights have a 46% lower risk of shutdown, indicating the importance of information management and ownership of intellectual property in the small number of firms who possess copyrights. However, neither type of intellectual property affected positive-exits. Finally, debt-financed firms are at a lower risk of both shutdown and positive-exit. Debt-financing occurs after due diligence is conducted and the lender judges the quality of the firm; This may then indicate quality and financial stability, while overcoming the obstacle of low cash flow. However, firms with existing debt have a lower net present value and reduced ability to raise future financing for a positive-exit.

9.2.3 High-tech Shutdown

The absence of an effect of local industry conditions on shutdowns may seem unsettling, given the theoretical and empirical findings of previous studies. However, the KFS provides a breadth of firms, which may be heterogeneous in how local industry conditions affect their risk of shutdown. In this section, we consider these differences for high-tech startups.

Previous studies have used the proportion of inputs or value added that is devoted to R&D as a defining characteristic of high-tech firms. Industries with greater than 3.5% of inputs devoted to R&D are classified as innovative, and as high-tech if the share is greater than 8.5% (Fritsch, 2010; for Economic Co-Operation and , OECD). The OECD listing classifies industries based on knowledge and R&D investments and on innovativeness of products. However, this approach suffers from a number of issues. First, the classification is meant for inter-country analyses, yet U.S. innovative industries may look quite different from innovative industries in other countries. Second, the definitions are based on industry data from 1973–1995 and are quite different, given the vast number of new technologies that have been introduced in the past two decades. Third, identifying products based on their innovativeness has some level of arbitrary assignment. The National Science Foundation (NSF) also produces estimates of industry R&D workers, but use a modified listing of industries that is inconsistent with North American Industry Classification System (NAICS) codes available for KFS firms. The NSF also only includes scientists and engineers, but excludes other R&D employees such as technicians.

We choose the high-tech industry classification of Hecker (2005). High-tech industries are identified based on their proportion of technology-oriented workers who are engaged in R&D, use knowledge to develop new products or services, and apply technology in other activities (Hecker, 2005). We use the Occupation Employment Statistics (OES) data to associate occupations with four-digit NAICS industries. High-tech industries are classified as those whose technology-

Table 13: **KFS COMPETING RISK ESTIMATES**

Owner/Firm	**Shutdowns**			**Positive Exits**		
	Owner/Firm	**Region**	**Full**	**Owner/Firm**	**Region**	**Full**
Work Experience	-0.012***	—	-0.014***	-0.013***	—	-0.010
Startup Experience	0.003	—	0.007	0.033***	—	0.028***
Male	-0.029	—	0.028	0.029	—	0.072
Age	-0.141***	—	-0.109***	-0.239***	—	-0.216***
Age^2	0.001***	—	0.001***	0.002***	—	0.002***
College Grad	-0.107	—	-0.129	0.429**	—	0.571***
Owner Hours	-0.004**	—	-0.004*	0.001	—	-0.001
Non-Employer	-0.130	—	-0.161*	-0.257	—	-0.061
Competitive Adv.	-0.101	—	-0.168*	0.285	—	0.444*
Sole Owner	-0.277***	—	-0.222**	-0.454**	—	-0.450*
Patent	-0.144	—	-0.185	-0.333	—	-0.619
Copyright	-0.594***	—	-0.610***	-0.467*	—	-0.349
Home-based	-0.035	—	-0.027	-1.241***	—	-1.058***
Debt-Financed	-1.024***	—	-1.095***	-0.919***	—	-0.940***
Equity-Financed	0.200*	—	0.222*	-0.230	—	-0.216
Region/Industry						
Research Expenditures	—	-0.026**	-0.014	—	-0.038**	0.010
Cluster LQ	—	-0.031	-0.002	—	-0.633**	-0.170
New Firms LQ	—	0.048	0.047	—	0.035	0.167
Small Business Share	—	-0.773*	-0.953	—	-4.877***	-1.723*
Average Wage	—	-0.018	0.028	—	-0.259**	-0.167
MES	—	-0.008	0.003	—	-0.037**	0.005**
Employment Density	—	0.236	0.103	—	0.500	-0.605
Jacobs	—	0.094	0.233	—	-1.719*	-0.160
Firms	4,679	4,679	4,679	3,220	3,220	3,220

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include industry and state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification.

* $p < .10$; ** $p < .05$; *** $p < .01$

oriented employment accounted for at least the average industry proportion of 4.9%. This classification provides a US-specific listing, uses 2002 and 2012 (projected) data, and uses NAICS codes.

The estimates for high-tech shutdowns is presented in table 14, while estimates of high-tech positive exits are included in the Appendix. The importance of knowledge for high-tech firms is validated by the significance of research expenditures in preventing closure. A 10% increase in the research expenditures decreases the risk of high-tech shutdown by 35%. High-tech firms may benefit from highly-skilled workers, specialized equipment and facilities, and commercialization opportunities (Abel and Deitz, 2011). MES is also statistically significant for high-tech firms and negatively related to shutdown. A 10% increase in the industry's MES decreases the risk of shutdown by approximately 3%. While a large MES is a barrier to entry for smaller, new firms that face cost disadvantages, high-tech firms may be more likely to survive the market shakeout because of their higher quality or longer product development timeline.

Low-tech shutdowns are affected by the Chinitz hypothesis, while the other local industry conditions are statistically insignificant. A one percentage point increase in the share of small businesses in a region decreases the likelihood of closure by 49%. Low-tech startups may be more dependent on local supplier networks than high-tech startups.

Interestingly, entrepreneurs that have started new firms previously are at a greater risk of shutdown, but only for high-tech firms. Serial entrepreneurs may be more likely to start high-tech ventures. Additionally, high-tech entrepreneurs with a college degree and working more hours decrease the risk of shutdown. High-tech ventures may require knowledge accumulated in higher education and more work hours to be successful. Alternately, owner hours and education may simply reflect the ability and devotion of the entrepreneur to make the firm successful. Finally, the positive effect of equity on firm shutdown only remains for low-tech firms, while high-tech firms are unaffected by the receipt of equity-financing.

Table 14: **KFS HIGH-TECH SHUTDOWN ESTIMATES**

Owner/Firm	**High-tech Shutdowns**			**Low-tech Shutdowns**		
	Owner/Firm	**Region**	**Full**	**Owner/Firm**	**Region**	**Full**
Work Experience	-0.009	—	-0.013**	-0.013***	—	-0.014***
Startup Experience	0.022**	—	0.034***	-0.009	—	-0.011
Male	-0.270**	—	-0.202	0.002	—	0.044
Age	-0.132***	—	-0.099***	-0.155***	—	-0.145***
Age^2	0.001***	—	0.001***	0.002***	—	0.002***
College Grad	-0.281*	—	-0.276*	-0.094	—	-0.072
Owner Hours	-0.009***	—	-0.001***	-0.003	—	-0.003
Non-Employer	-0.166	—	-0.241**	-0.160*	—	-0.179*
Competitive Adv.	-0.133	—	-0.227	-0.073	—	-0.122
Sole Owner	-0.533***	—	-0.566***	-0.254**	—	-0.239*
Patent	-0.529	—	-0.482	-0.164	—	-0.235
Copyright	-0.893***	—	-0.859***	-0.566***	—	-0.558***
Home-based	0.261	—	-0.330	0.062	—	-0.000
Debt-Financed	-1.266***	—	-1.269***	-0.987***	—	-1.069***
Equity-Financed	0.133	—	0.250	0.222*	—	0.255*
Region/Industry						
Research Expenditures	—	-0.069***	-0.036**	—	-0.039***	-0.012
Cluster LQ	—	-0.138	-0.019	—	-0.103	-0.024
New Firms LQ	—	0.045	0.123	—	-0.015	0.024
Small Business Share	—	-1.926***	0.751	—	-2.000***	-0.671*
Average Wage	—	-0.166***	-0.060	—	-0.061	0.028
MES	—	0.059***	-0.030**	—	-0.031***	0.023
Employment Density	—	0.434	0.049	—	0.294	-0.034
Jacobs	—	-0.258	0.583	—	-0.435	0.263
Firms	1,599	1,599	1,599	3,329	3,329	3,329

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

9.2.4 Manufacturing Shutdown

Finally, we consider the differences in determinants of shutdowns for manufacturing startups in table 14, while manufacturing firms are the source of several studies considering closures Folta et al. (2006); Shaver and Flyer (2000).

Manufacturing firms are less likely to shutdown in regions with more concentrated clusters and higher employment density. Specifically, a 10% increase in the cluster concentration decreases the likelihood of new firm shutdown by approximately 3%. Our results contrast Folta et al. (2006); Shaver and Flyer (2000), who explain that higher quality firms do not benefit as much as low-quality firms from locating in a cluster. However, the benefits of clusters have been widely theorized and corroborated by Porter and others (Delgado et al., 2010; Wennberg and Lindqvist, 2010). Firms located in clusters benefit from customer and supplier linkages and are able to internalize agglomeration economies to lower costs. Moreover, knowledge spillovers occur more frequently in clusters and may provide managerial, market, and supplier insights that benefit a new firm. Employment density is also statistically significant, such that a 10% increase in the employment density of a region decreases the risk of shutdown by 8%. Manufacturing startups in dense regions may benefit from increased productivity, reduced transportation costs, and labor pooling.

These findings suggest that previous findings may be driven by an emphasis on manufacturing sectors in these studies. Clusters may not be as important outside manufacturing startups or high-tech firms.

By contrast, non-manufacturer shutdowns are only affected by the Chinitz hypothesis. A one percentage point increase in the share of small businesses in a region decreases the risk of shutdown by 58%. Non-manufacturers, traded and service industries, may benefit from institutional and cultural structures that support small and new firms.

The statistically significant owner and firm determinants of shutdowns do not differ for manufacturing and non-manufacturing firms. However, the determinants of manufacturing shutdowns are greater in magnitude than non-manufacturing firms. Non-employer and competitive advantage are statistically significant and reduce the risk of shutdown for non-manufacturers.

10 Conclusion and Discussion

In this paper, we have explored how local industry conditions affect the probability of new firm shutdown using the KFS. We contribute to the expanding literature on entrepreneurship by considering shutdowns and positive-exits separately, using a comprehensive model including firm and local industry conditions, and estimating shutdown determinants for high-tech and manufacturing startups. We find strong evidence that the determinants of shutdown are significantly affected along these three dimensions.

We test the effect of cluster, Jacobs, and Chinitz agglomerations on new firm shutdowns, but find that new firm shutdowns on the whole are not consistently prevented by any source of agglomeration. Instead, the various sources of agglomeration appear relevant in different contexts. While concentrated clusters and dense regions promote survival for manufacturing firms, a regional structure with a large share of small firms (i.e. Chinitz hypothesis) promotes survival for non-manufacturing startups. A Chinitzian small business environment also decreases the risk of shutdown for low-tech startups, while higher industry MES and research expenditures decrease the risk of high-tech shutdown.

Policies concerned with startup survival should emphasize improving owner and firm conditions, unless policies are targeted at particular types of startups. In this way, policy makers should distinguish high-tech and manufacturing firms from their counterparts. Policies aimed at high-tech firms should emphasize strong higher education relationships, while manufacturers will benefit from stronger industry clusters. However, policy makers interested in improving survival for low-tech or non-manufacturing firms should develop programs to support small businesses.

Future work in this area might consider the determinants of positive-exits in more detail and the conditions leading up to shutdown. Another extension might consider the effects of local industry conditions on additional performance measures other than survival.

TABLE 15: KFS MANUFACTURING SHUTDOWN ESTIMATES

Owner/Firm	**Manufacturing**			**Non-Manufacturing**		
	Owner/Firm	**Region**	**Full**	**Owner/Firm**	**Region**	**Full**
Work Experience	-0.005	—	-0.027	-0.013***	—	-0.015***
Startup Experience	-0.067	—	-0.019	0.006	—	0.010
Male	-0.346	—	0.066	-0.025	—	0.008
Age	-0.137***	—	-0.189**	-0.125***	—	-0.138***
Age^2	0.001***	—	0.002**	0.002***	—	0.001***
College Grad	0.007	—	0.450	-0.140*	—	-0.147
Owner Hours	-0.009	—	-0.005	-0.003*	—	-0.003
Non-Employer	0.161	—	0.644	-0.179**	—	-0.193**
Competitive Adv.	0.112	—	-0.386	-0.122	—	-0.176*
Sole Owner	-0.626	—	-1.090**	-0.284***	—	-0.257**
Patent	-0.197	—	-1.157	-0.112	—	-0.122
Copyright	-0.400	—	-1.588***	-0.626***	—	-0.601***
Home-based	-0.275	—	-0.413	0.017	—	-0.026
Debt-Financed	-1.014***	—	-2.246***	-1.043***	—	-1.085***
Equity-Financed	-0.184	—	0.275	0.236**	—	0.235*
Region/Industry						
Research Expenditures	—	0.005	0.022	—	-0.047***	-0.017
Cluster LQ	—	-0.281*	-0.294**	—	-0.080	0.043
New Firms LQ	—	-0.571	-0.621	—	0.010	0.045
Small Business Share	—	-1.038	0.895	—	-2.146***	-0.857**
Average Wage	—	0.148	0.361	—	-0.089**	0.009
MES	—	-0.023	0.002	—	0.031***	0.002
Employment Density	—	-1.770**	-2.369**	—	0.439*	0.138
Jacobs	—	-3.415***	-0.120	—	-0.260	0.298
Firms	720	720	720	3,428	3,428	3,428

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * $p < .10$; ** $p < .05$; *** $p < .01$

Chapter III

Does the City Affect Capital Acquisition in New Firms?

11 Introduction

Entrepreneurship is a driver of regional and national competitive advantage and is the source of significant research attention. The performance of innovative young firms has been of particular interest in this expanding academic literature. While survival has been the predominant measure of performance, Gompers and Lerner (2001) emphasize that access to external finance is necessary for entrepreneurs to establish a competitive advantage. In this way, the acquisition of capital is a great milestone for startups and is indicative of performance and ability of the new firm to continue to innovate and grow. We add to this understudied area of research by considering the effects of local industry conditions on external capital acquisition of new firms using the Kauffman Firm Survey (KFS).

Startups suffer in their ability to obtain financing through traditional means due to information asymmetries. The markets that new firms may access are largely private equity or debt that offer highly structured and complex contracts to new firms because of the greater degree of uncertainty (Berger and Udell, 1998). However, large and established firms are able to access public debt and equity markets where they enter into homogeneous and transparent financial contracts. Financial intermediaries provide the essential function of evaluating new firms and represent a vital asset in any region. Berger and Udell (1998) explain that firms deemed high-risk–high-growth can not supply intangible assets as collateral and often choose equity markets. Low-risk–low-growth entrepreneurs often have tangible assets to supply as collateral for private debt contracts.

The different strategies and interconnectedness for each mode of finance further complicates entrepreneurial finance. Equity finance may be the only option for high-tech firms, but at the cost of relinquishing ownership. Private debt offers firms capital without giving up ownership, but may require past equity from internal or angel investments. Relationship banking provides new firms with greater access and more attractive financing costs. Audretsch et al. (2006) point out that external and internal sources of capital are substitutes if credit markets are perfect.

We make several contributions to the existing entrepreneurial finance literature. First, we account for heterogeneity in financing methods and repeated transactions using a competing risk empirical model. Second, we explore how specific local industry agglomerations and the Landier model affect new firm financing. Third, we consider how the determinants of financing differ for high-tech firms.

Section 12 distinguishes between four sources of agglomeration benefits for new firms: density, clusters, Jacobs diversity, and the Chinitz hypothesis. Agglomeration of related firms and industries in close proximity create knowledge spillovers, labor pooling, and supplier linkages. Additionally, agglomeration encourages support services and institutional structures (e.g. financial intermediaries) in regions. Chen et al. (2009) find that venture capital firms and venture deals are concentrated in only a few cities across the U.S.. Landier (2003) develops a theoretical model in which regional culture and acceptance of failure may determine funding source. While trial and error is encouraged in Silicon Valley, the pool of entrepreneurs that have previously failed is comprised of talented and high-quality individuals. In this case, equity investors are more likely to take on such risk while monitoring and providing smaller initial levels of funding. Conversely, high stigma regions (Saxenian (1994) identified route 128 around Boston, MA) give financial intermediaries the upper hand, as entrepreneurs have an incentive to succeed and are more likely to be high quality. In this case, firms have a higher probability of debt-financing. Despite the theoretical implications, studies have not empirically tested the Landier model.

Section 15 reviews the KFS dataset and presents summary statistics of the variables we use in this study. Section 16 describes the competing risk framework we estimate to account for different motivations and constraints of external finance. The event history model estimates the determinants of external debt and equity infusions over the first six years of existence. Repeated infusions are controlled for to account for the relationship between entrepreneurs and financiers over time. Specialization of a region in a subset of industries and lower wages in a region are associated with a higher likelihood of both equity and debt acquisition. Startups in strong regional clusters are at a greater risk of debt infusion, while regions with greater university research expenditures decrease the risk of debt financing.

Finally, section 18 discusses conclusions, presents considerations for policy makers, and suggests a direction for future research on new firm financing.

12 Hypotheses and Theoretical Framework

Obtaining financing is critical to an entrepreneur in order to secure a competitive advantage and surviving the “liability of newness” that results in the closure of many small firms (Gompers and Lerner, 2001). Financial capital alleviates binding financial constraints for new firms (Evans and Jovanovic, 1989; Blanchflower and Oswald, 1998), while obtaining financing supports a new firm’s credibility amongst suppliers and customers. Receipt of financing is then a proxy for the quality of the business or confidence in the strength of the new firm’s prospects. However, information asymmetries prevent intermediaries from assessing new firm risk and drive up the cost of capital. Higher-quality firms may then seek forms of financing where financing structures offer better terms than commercial banking (Stiglitz and Weiss, 1981).

12.1 New Firm Financing

Entrepreneur financing integrates several disparate fields through complex theoretical models and empirical findings. Modigliani and Miller (1958) suggested that under symmetric information, the financing decision has no effect on the future value of the firm. Moreover, internal and external financing may be considered perfect substitutes in such a perfect world (Audretsch et al., 2006). However, actual financing decisions involve information that may not be verifiable, creating moral hazard concerns and making the method of financing important (Aghion and Bolton, 1992).

The type of financing especially depends on risk and credit rationing in the financial market. The price of credit (i.e. the interest rate) does not equilibrate the market, but rather limits the supply of credit at different levels of the interest rate (Stiglitz and Weiss, 1981). Financial intermediaries ration in this way because the riskiness of the borrower increases with the interest rate charged, and because of asymmetric information, quality or risk of the new firm are indiscernible by the lenders. Hence, a typical price discrimination solution does not work since asymmetric information prevents such a strategy from being carried out. Over the course of the financing relationship, borrowing firms may be able to generate a reputation and credit history to receive more favorable contract terms in the future.

Bolton and Freixas (2000) argued that debt is preferred for any entrepreneur and that only high risk startups enter into equity as a last resort. Owner-operators may prefer debt financing because no ownership or future profits are relinquished (as in equity contracts). Collateral can serve to reduce risk and overcome credit rationing in financial markets, but high risk firms often lack such marketable collateral. Banks are less likely to lend to high-risk borrowers where payback is more uncertain and collateral is unavailable.

Each method of financing is also interlocked. Angel investors may precede venture capitalists, making these forms of financing complements. Avery et al. (1998) found that commitment of owner's wealth increases the chances of obtaining external debt. The Pecking Order Theory suggests that internal finance sources will be used prior to external financing (Myers and Majluf, 1984). High-growth–high-risk ventures will access external equity prior to external debt because of the acute information asymmetries of these firms (Berger and Udell, 1998).

Despite the theoretical base, the determinants of debt and equity financing in startups in an under-researched area of entrepreneur literature. The few studies that analyze entrepreneur financing do not consider the effects of local social and industrial conditions. Considering high-tech firms, Carpenter and Petersen (2002) found that high-risk firms are only able to access debt markets after receiving public equity and establishing a reputation. Audretsch et al. (2006) found, with a sample of German firms, that venture capital and debt are substitutes for German firms. Schafer et al. (2004) found that high-risk small and medium enterprises (SMEs) are more likely to select equity financing than debt financing.

12.2 Landier Model

In addition to the intricacies of entrepreneurial finance, the environment surrounding an entrepreneur is particularly important. This section discusses a model in which the owner's outside options affect financing decisions. Landier (2003) presented a theoretical model of the "hold-up" problem encountered by entrepreneurs seeking financial capital. Entrepreneurs can withdraw from the firm, while financiers can deny future funding; The entrepreneur's shutdown option forms the basis for financial method chosen. In environments where shutdown is undesirable, the entrepreneur requires protection from the financier, who may exhibit rent-seeking behavior. Lending institutions offer large initial investments to reduce the need for future funding and the potential of hold-up. Entrepreneurs are also committed to the venture because shutdown is undesirable.

Other environments may present entrepreneurs with attractive alternative venture opportunities, leading investors to require protection (e.g. monitoring and control rights). Small periodic cash infusions further decrease the incentive of entrepreneurs to shirk responsibility, while investors must take on additional monitoring costs to ensure entrepreneur effort. Better outside venture opportunities lead to more involved investors, which may be determined by the "stigma of failure" in the surrounding environment. If high-quality ventures fail more in a region, the stigma may be lower for a firm to fail and the entrepreneur's bargaining power is enhanced. Conversely, when failures are associated with low-ability, stigma is high for entrepreneurs who shutdown.

Two equilibria are possible in the Landier model. The low-risk equilibrium is characterized by an environment where high-ability entrepreneurs remain in business and low-quality entrepreneurs exit. This high-stigma environment encourages the entrepreneur who is afraid of failure and reduces the need of monitoring on the part of the investor. Entrepreneurs pursue safe and low-risk strategies to avoid the high costs of stigma and are serviced by debt contracts. In the high-risk equilibrium, entrepreneurs choose risky and high-growth strategies, regardless of ability. Hence, high-ability entrepreneurs fail more and reduce the stigma of failure. In this case, entrepreneurs have the advantage and equity investors will be the most likely financiers.

12.3 Region Characteristics

This study is among the first to determine how regions affect new firm financing, though the region may affect financing choice and availability. Chen et al. (2009) found that venture capital firms and deals are concentrated in just three U.S. cities. Agglomerations may encourage specialized financial intermediaries (e.g. venture capitalists), and support other potential financing sources. Additionally, the extensive literature on new firm survival provides a guide for the effects of local industry conditions on financing events, another performance metric for many startups.

12.3.1 Agglomeration

The potential benefits of agglomeration may affect financing decisions in a few ways. First, agglomeration may increase the likelihood of investment, given the expected performance gains for individual firms. Second, regions rich with knowledge may present entrepreneurs with high-value alternatives and shutdown options. Third, if particular industries are concentrated in a region, or if a region specializes in certain industries, financiers may similarly specialize in financing certain industries or clusters where information asymmetries are lower.

There are four sources of agglomeration benefits for new firms that we consider in this study: density, clusters, specialization, and the Chinitz hypothesis. One of the basic benefits to agglomerating is that firm productivity can improve through lower transportation costs if customers and suppliers are colocated. Individuals may launch a new firm near other firms to partake in these external cost savings. The key agglomerating mechanism in New Economic Geography is the savings from cheaper shipping costs (Fujita et al., 1999). Sugar, for example, was refined in New

York City in the nineteenth century rather than the tropics because of the large costs in transporting refined sugar (Glaeser and Kerr, 2009).

These cost savings may make new firm investment appealing for financiers, but density may also indicate competitive pressures on the new firm (Hannan and Freeman, 1987). Geroski et al. (2007) describe two reasons for why denser regions increase the probability of shutdown. New firms in dense regions may suffer from the "liability of scarcity," where competition for critical resources (e.g. financing) may prevent new firms, not yet with the optimal structural configuration, from making appropriate investments or implementing correct routines. New firms may also suffer from "tight niche packing," where crowded markets irreversibly push new firms into unpromising market niches.

12.3.2 Cluster Agglomeration

In addition to the effects of density, clusters of related and supporting industries may further affect financing. Clusters like Silicon Valley or Route 128 Corridor in Boston, MA exhibit benefits for inhabiting firms such as: increased productivity, specialized labor pooling, and knowledge spillovers (Porter, 1998). While research on clusters has largely focused on the effect of clusters on regional performance (Kolko, 2007; Porter, 2003), a few studies have found that clusters enhance new firm performance (Baptista and Swann, 1998; Wennberg and Lindqvist, 2010; Delgado, et al., 2010). We are aware of no studies that investigate clusters' effects on startup financing.

The labor hired in the first few years, vital to any new firm's success, may be constrained by the quality of the labor force in the surrounding region (Dahl and Klepper, 2007). Specialized workers may be required in certain industry startups and are more likely to pool around agglomerated firms. Labor pooling amongst clustered firms can smooth the effect of firm-specific shocks on individual workers (Marshall, 1890). Workers can easily change jobs when their employer is affected by a negative shock, making workers more productive under such insurance (Krugman, 1991). Large labor pools in a city may also facilitate matching between startups and employees (Helsley and Strange, 1990). Hence, new and existing firms needing similar specialized labor are likely to colocate and benefit from a greater availability of workers or lower wages in thick labor markets (Glaeser and Kerr, 2009).

Additionally, industry clusters may affect performance, and in turn financing, through the dissemination of existing and new knowledge. In the Silicon Valley, the transfer and flow of ideas was an essential mechanism for entrepreneur success (Saxenian, 1994). Acs et al. (1994) suggested that clusters benefit entrepreneurs more so than incumbents via enhanced knowledge spillovers, where customers and suppliers can share issues with existing products or describe needs and wants for new products (Porter, 1990). Rosenthal and Strange (2003) found these knowledge spillovers to be highly localized, similar to studies on patent citations (Jaffe et al., 2000; Carlino et al., 2007). Audretsch and Feldman (1996) found that innovations are also clustered around research and development (R&D) and university research.

Finally, a clustering of related industries may encourage financial intermediaries, familiar with the cluster, to colocate. Repeated dealings with similar firms and individuals along with industry-specific knowledge may reduce the information asymmetries of startups. Contrary to Jacobs diversity, regions may specialize in a limited number of industries that creates financial intermediaries familiar with specific industries.

12.3.3 Chinitz Hypothesis

An agglomeration of small and new firms may enhance entrepreneurial finance access and reduce the stigma of failure. Chinitz (1961) described the supplier needs of entrepreneurs as highly localized, compared to those of large incumbent firms that could internalize these needs. The vertically integrated steel firms in Pittsburgh were not concerned with the input needs nor output capabilities of entrepreneurs. However, New York City's small supplier network to the garment industry provided entrepreneurs with specialized inputs. The Chinitz hypothesis suggests that the presence of small and independent firms leads to social and institutional structures that promote a culture of entrepreneurship (Glaeser and Kerr, 2009).

Some regions exhibit an entrepreneurial culture that is not limited to specialized input suppliers

(Hofstede, 2001). Glaeser and Kerr (2009) describe agglomerations in entrepreneurship that lead to a social structure that reduces the stigma of failure and increases the likelihood that others take risks (Landier, 2004). The Silicon Valley for example, encourages entrepreneur trials and emphasizes cooperation between young startups (Saxenian, 1994). Early semiconductors led the way for future entrepreneurs through open inter-firm communication and a vertically disintegrated industry structure. The Landier model suggests that such regions, with a low stigma of failure, will exhibit higher rates of equity financing.

The importance of local new firm services can also provide guidance and legitimacy for new firms (e.g. Porter, 1998; Muller and Zenker, 2001; Scott, 2002). Entrepreneurial support and finance institutions may cluster around concentrations of entrepreneurs and aid in solving new firm struggles (e.g. angel investors, entrepreneur-specific lenders, small business incubators, and specialized legal or accounting services). This is the first paper that tests the Chinitz hypothesis in the context of startup financing.

12.4 Owner Characteristics

We include several owner and firm characteristics to control for the perceived investment opportunity of the new firm. Several studies found that male-owned firms outperform female-owned firms (Loscocco et al., 1991; Fischer et al., 1993). Female-owned firms may be less successful because they lack start-up capital and have less previous business experience (Fairlie and Robb, 2008). Other studies have found that there is no difference in success or performance between female-led and male-led firms while looking at organizational structure and owner attributes (Kalleberg and Leicht, 1991). However, female-led firms were smaller and had lower earnings than male-led firms.

Age may also be an important factor in the firm's financing options. Older executives may have a stronger commitment to their organization than younger executives (Becker, 1973). Firm performance is also found to be greater in firms with older managers (Brockmann and Simmonds, 1997). The success may be driven by reputation or networks of older individuals, while younger individuals have thinner track records. However, younger individuals may be more willing to change and recognize opportunities than older individuals (Carlsson and Karlsson, 1970). Experience with previous startups may make new firms more able to navigate or attract funding opportunities, if the owner has learned from his previous ventures. However, serial entrepreneurs may be more willing to close in favor of some other new venture that they believe offers higher rewards and take advantage of the hold-up problem.

Finally, human capital has been found to positively affect firm performance. Innovative firms are most often started by highly educated individuals, usually after working for a period of time (Fritsch, 2010). Human capital has been found to improve performance because imitation and trade cannot be executed on human capital, but can on physical capital (Geroski et al., 2007).

12.5 Firm Characteristics

Owner characteristics are important for the direction and adaptability of the firm to changing market conditions but, there are also firm characteristics that play a role in the success of the firm over the first few years. Many studies have found that initial size of the startup is positively related to new firm performance (Geroski, 1995). Small firms may be more vulnerable than larger startups that are operating closer to minimum efficient scale (MES). Larger initial size may also indicate access to capital, putting smaller firms at a disadvantage regarding economies of scale (Geroski et al., 2007). With better funding, larger startups may be in a better position to overcome economic shocks. Finally, higher ability operators may ensure lower operating costs and positively affect the size of the firm (Geroski et al., 2007). An exception may be in the form of home-based firms, which may be smaller and less financially-committed than firms that must lease space and cover higher overhead.

The firm's intellectual property may further enhance attractiveness to investors. Though most firms in the KFS do not have a patent in their first years, many have a copyright. A copyright signifies effective knowledge management and is further evidence of proprietary knowledge that the firm can gain a competitive advantage with. Patents may not be appropriate in some industries or for some firms that do not realize gains from the potentially long and expensive patent process.

12.6 Industry Factors

Finally, we control for industry characteristics that may affect the funding of new firms. In order for firms to become profitable, new firms must reach minimum efficient scale (MES) (Audretsch, 1995). Performance is expected to be higher if this scale is smaller, as firms do not need as many resources to compete (Audretsch et al., 2000). Entrepreneurs that enter an industry with a size closer to the MES are more likely to persist, while smaller entrepreneurs will have difficulty reaching profitability. Larger MES industries also require larger upfront capital and may raise the cost of capital above existing firms' (Lyons, 1980). Finally, entrants may have difficulty attracting quality workers from larger existing firms.

Small firms may not be deterred from entering industries where scale economies are important (Audretsch, 1991). Industries in which the price level is above the minimum average cost may promote the existence of suboptimal capacity firms, i.e. startups. The further above minimum average cost the price is, the greater the probability of performance and financing are (Weis, 1976). Large scale industries may also promote selection of a few high-quality startups while encouraging shutdowns of low-quality startups (Fritsch et al., 2006).

13 Data

13.1 The KFS

The KFS is a longitudinal panel survey of 4,928 businesses founded in 2004 and surveyed annually through 2010. The limited-access KFS dataset provides detailed information on each firm and the owners. The KFS includes businesses that were founded by individuals and teams, existing firms purchased by new owners, or purchases of franchises. The survey does not include not-for-profits, wholly owned subsidiaries, or inherited businesses. In order to ensure representation of women and high-tech firms, the sample was stratified according to industry, technology, and gender of the owner . Ballou et al. (2008) describe the survey methodology and design in greater detail.

Figure 5 compares the industry distribution of the KFS to the Census employer firm births and the Panel Study of Entrepreneurial Dynamics (PSED). The top three industries are oversampled by the KFS as these industries have a larger proportion of female owners. Manufacturing is also oversampled to get a larger sample of high-tech firms. The oversampling in these industries result in a smaller representation of other industries such as accommodation and food services. However, the KFS provides stratification and sampling weights to correct for the complex survey design.

We map the KFS dataset to the U.S. Census Bureau's County Business Pattern (CBP) dataset by industry-region-year to obtain information on employment, annual payroll, the size distribution of firms, and number of establishments. We create the primary local industry conditions of a particular metropolitan area from the CBP dataset. Because the information is taken from administrative firm records, the CBP provides very accurate information on employment, annual payroll, number of establishments by size, and number of establishments. Hence, there are no sampling errors to bias these measures. We aggregate the county-based CBP variables by core-based statistical areas (CBSA).

13.2 Variables

Figure 10 presents the owner and firm control variables provided by the KFS. Figure 11 presents local industry measures calculated at the 3-digit NAICS and at the CBSA level using the County Business Patterns (CBP) dataset. We measure the colocation of firms using the employment density of a region. Density is calculated as the number of employees per square mile of land area. Unfortunately, this measure does not separate the importance of customers or suppliers in a particular industry. We construct cluster concentration measures using cluster definitions developed by Porter (2003) and promoted by the Cluster Mapping Project. Regional knowledge is measured

Figure 9: **INDUSTRY DISTRIBUTION COMPARISON OF KFS**

Industry Name and NAICS	**KFS**	**Census Employer Births**	**PSED New Businesses**
Professional (54), Management, and Educational Services (61)	16.1	14.1	16.8
Retail trade (44)	15.6	12.0	18.6
Administrative and Support, and Waste Management and Remediation Services (56)	11.4	6.0	2.1
Construction (23)	9.8	15.7	10.0
Other Services excl. Public Services (81)	8.0	8.5	0.3
Manufacturing (31)	7.2	3.2	3.5
Wholesale Trade (42)	6.0	4.5	1.5
Real Estate, Rental and Leasing (53)	3.7	5.1	5.3
Finance and Insurance (52)	4.7	2.2	3.1
Health Care and Social Assistance (62)	4.2	7.7	2.9
Information (51)	2.6	1.4	4.2
Transportation and Warehousing (48)	2.9	3.3	2.4
Arts, Entertainment, and Recreation (71)	3.1	2.1	3.2
Accommodation and Food Services (72)	3.9	9.1	10.9
Agriculture, Forestry, Fishing, and Hunting (11)	1.4	0.4	2.0
Mining (21)	0.0	0.3	0.5
Utilities (22)	0.0	0.1	0.5
Management of Companies and Enterprises (55)	0.0	0.1	6.7
Unclassified (99)	0.0	2.2	5.6

Source: *Nassereddine (2012)*

by the research expenditures of colleges and universities in the region (Integrated Postsecondary Education Data System). Jacobs spillovers are controlled for using the ratio of employment in the largest five industries to employment in the entire region (Glaeser et al., 1992). We include the share of small businesses and the concentration of entrepreneurs to estimate entrepreneur agglomerations to estimate the Chinitz effect .

We use the national median of average firm size for a particular industry to measure MES. Finally, in order to control for outside options of individuals considering employment or starting a new firm, the logged average payroll per employee in a industry-region is included.

13.3 Summary Statistics

Table 16 summarizes owner characteristics of the baseline KFS correcting for survey design. Approximately 70% of owners are male. 47% of owners are over the age of 45, while only 19% are under 35. 53% of owners do not have a four-year degree, but 30% of these owners have some college education. 24% of owners have a bachelor's and 23% have an advanced degree. Only 10% of owners have no experience in the same industry, while 51% of owners have more than 10 years of experience. 41% of KFS owners have already started a new firm, but 58% are first-time entrepreneurs. Finally, the majority of owners work full-time, while about 49% of owners work more than 46 hours per week.

Table 17 summarizes the characteristics of KFS firms. 59% of KFS firms begin with no employees and 27% have more than two employees. The ownership of firms is mostly by a single individual (65%), compared to the 35% of firms with multiple owners. Intellectual property is rare, with only 2% of firms possessing a patent and approximately 9% possessing a copyright. Approximately 51% of firms have a commercial leased or rented property, while the other 49% work in the owner's home. Finally, 56% of firms have obtained debt financing, compared to only 10% of firms that obtained external equity investments.

Owner/Firm	Measurement
Work Experience	Years of experience in same industry.
Startup Experience	Number of previous startups.
Male	Gender of the primary owner is male.
Age	Primary owner's age and age squared.
College Grad	Primary owner is a college graduate.
Owner Hours	Number of hours the primary owner works per week.
Non Employer	Firm has no employees.
Competitive Advantage	Owner believes firm has competitive advantage. (Confidence)
Sole Owner	Firm only has one owner-operator.
Patent	Firm has a patent.
Copyright	Firm has a copyright.
Home-based	Firm is based in a home, not commercial space.

Figure 10: **DEFINITION OF FIRM AND OWNER VARIABLES WITH EXPECTED SIGNS**

Region/Industry	Measurement
Employment Density	Employment density or employment in region r per square mile of land area. $EmpDensity = \frac{E_r}{LandArea_r}$
Cluster LQ (Porter)	Ratio of a region's share of employment in cluster c relative to the nation's share of employment in that same cluster. $lq^c = \frac{E_{cr}/E_r}{E_c/E}$ E_{cr} = number employees in cluster c and region r
Specialization (Jacobs)	Ratio of the region's employment in the five largest industries. (Smaller values indicate greater urbanization) $Jacobs = \frac{E_r^5}{E_r}$
New Firms LQ (Chinitz)	Ratio of a region's share of entrepreneurial firms relative to the nation's share of entrepreneurial firms. $lq_E = \frac{F_r^E/F_r}{F^E/F}$
Small Business Share (Chinitz)	Share of a region's employment in firms with fewer than 5 employees $SmlBizSh = \frac{E_r^{1-5}}{E_r}$
Region/Industry Controls	
Log Research Expenditures	Logged expenditures on research from colleges within CBSA.
Average Wage	Region's logged annual payroll per employee.
MES	National median firm size for industry i. $MES = median_i(\frac{E_{ir}}{F_{ir}})$

Figure 11: **Definition of Region and Industry Variables with Expected Signs**

Table 16: **KFS OWNERS**

	Survey Proportion (%)	Sample Count
Work Experience Same Industry		
Zero	9.6	398
1–9	39.2	1,781
10–24	35.0	1,835
25 +	16.1	896
Previous Startups		
Zero	58.5	2,820
1	21.3	1,046
2 +	20.3	1,030
Hours per Week		
Less than 35	36	1,782
35–45	15	717
46 +	49	2,334
Male	69.2	3,649
Age		
Less than 35	19	868
35–44	33.8	1,629
45 +	47.2	2,406
Education		
Less than Bachelor's	52.9	2,392
Bachelor's	24.2	1,215
More than Bachelor's	22.9	1,290

Note: Summary statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004. (Robb and Reedy, 2012)

Table 17: **KFS FIRM CHARACTERISTICS**

	Survey Proportion (%)	**Sample Count**
Initial Size (Employment)		
Zero	59.2	2,838
1	14	690
2 +	27	1,295
Initial Owners		
1	65.2	3,163
2 +	34.9	1,765
Patent	2.2	187
Copyright	8.7	485
Home-based	49.2	2,483
Debt Financed	56.2	2,697
Equity Financed	9.6	488

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004. (Robb and Reedy, 2012)

Summary statistics for region and industry characteristics are provided in table 18. The average startup is located in regions that are more concentrated than the nation in cluster employment and new firms. 57% of employment is accounted for by small firms in the region surrounding new firms. The average firm is located in an industry where the median scale is approximately 10 employees. An average of 336 employees are located in each square mile of a startup's region. Finally, regions are fairly specialized with 42% of employment accounted for by the largest 5 industries in a startup's region.

13.4 Capital Acquisition

Table 19 displays financing events and the hazard rate over time for external sources. The hazard rate calculates a non-parametric probability of financing event in a particular year, such that the firm may receive financing at the beginning of the time interval. These estimates use a gap time methodology where time is reset after an infusion occurs. Debt is much more common than equity,

Table 18: **KFS REGION CHARACTERISTICS**

	Survey Mean	**Std. Error**
Logged Research Expenditures	17.85	0.087
Cluster LQ	1.08	0.012
New Firm LQ	1.03	0.013
Small Business Share	0.57	0.003
Logged Pay Per Employee	2.99	0.023
MES	10.33	0.150
Employment Density	335.86	6.446
Specialization	0.42	0.003

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004.

Table 19: **KFS FINANCING EVENTS**

	Outside Debt			**Outside Equity**		
Years Since Last Infusion	Infusions	Cumulative	Hazard	Infusions	Cumulative	Hazard
0–1	225	5%	5%	47	1%	1%
1–2	474	15%	11%	82	3%	2%
2–3	433	25%	13%	83	5%	2%
3–4	249	32%	10%	68	6%	2%
4–5	162	37%	8%	41	7%	1%
5–6	92	41%	6%	27	8%	1%

Note: Statistics are derived from 4,928 firms from the Kauffman Firm Survey 2004-2010.

consistent with new firm preference for ownership. The hazard rate appears to have an inverse-U shape for both financing sources, with a peak around the third year following the start of the firm or since the previous financing event.

14 Empirical Model and Results

14.1 Event History Model

We estimate capital acquisition using the very flexible discrete-time event history model, sometimes referred to as survival model. We begin by presenting the basic model before extending the model to include the different sources of financing and repeated nature of financing rounds. Let T_i

be the continuous and non-negative measure for survival time or event time for firm i. The survival model estimates the probability that the business acquires financing in the time interval t conditional on the firm not receiving any financing up to at least the beginning of the interval, and given the other regressors. The conditional hazard h_{it} is then defined as,

$$h_{it} = Pr(T_i = t | T_i \geq t, \mathbf{x}_{it}),$$

where $\mathbf{x}_{it}$ is a vector of time-varying covariates. We use the logit model out of familiarity, but other models (e.g. cloglog) did not change coefficient signs or significance tests. The logit hazard specification is then,

$$logit(h_{it}) = log\left(\frac{h_{it}}{1-h_{it}}\right) = \alpha_t + \beta_1 individual_{it} + \beta_2 firm_{it} + \beta_3 industry_{i(t-1)} + \beta_4 region_{i(t-1)} \ ,$$

where α_t is a logit of the baseline hazard function and is a potential source of parameterization beyond the logit relationship. In continuous-time models, the Cox model does not specify the baseline hazard, while others are named for this parameterization. (e.g. exponential or Weibull) The discrete-time logit model is quite flexible in this regard, and several models were tested. The non-parametric specification is to allow each year's baseline hazard to vary by estimating dummy variables for each year t . Logged, linear, or splined time are alternative choices that are sometimes chosen to reduce the number of coefficients that need to be estimated. We use the most flexible unspecified baseline hazard, while other models make assumptions about the shape of the baseline hazard that may be inappropriate for new firm financing.

Startups seek additional financing to fulfill growth strategies and choose between equity and debt financing. However, the preceding model assumes that a single type of event may occur only once. Relationships with financial intermediaries serve as mitigating factors to information asymmetries for young firms. Young firms rarely provide extensive financial documentation to external financiers because of the large cost of such disclosures or lack of disclosure rules (Audretsch et al., 2006). If a new firm were to only enter into a single financial contract, the financial intermediary may find the cost of acquiring such information to be too high. An existing relationship that generates a credit history and reputation reduces such costs and may be passed on to the startup (Neuberger, 1998).

The determinants of future funding rounds will differ from initial funding as financier's build relationships with entrepreneurs. Repeated events may be handled in various ways. Prentice, Williams, and Peterson (1981) define a conditional model, which we adopt, where observations are only at risk after prior events have occurred. The kth occurrence of an event has a corresponding risk set that only includes firms that have experienced $k-1$ events. Estimates are stratified by financing round to allow the baseline hazard of each round to vary. Duration is modeled using the concept of gap time or inter-event time, where time is the number of years since last funding event.

Beck, Katz, and Tucker (1998) incorporate an event counter to allow inter-event dependence and several of our models apply this approach as a comparison to the gap time models. However, this assumes that the hazard for subsequent events is simply proportional to the baseline hazard. Later funding events may have different determinants, and Box-Steffenseier and Jones (2004) provide an alternative modeling approach. Each funding round is estimated separately, which allows different baseline hazards for each round and covariates to vary across rounds of funding.

In addition to repeated funding events, the process underlying equity and debt financing is different. To allow these "competing risks," we specify a type-specific and separate hazard function for event m. Allison (1984) shows that the overall hazard is simply the sum of each type-specific hazard function. Models involving both repeated and different events are estimated using Markov renewal models. Allison (1984) translates these modeling techniques to the event-history framework and shows that the hazard of obtaining a type of financing m for the kth time in time t' since last funding event is

$$logit(h_{it'}^{mk}) = log\left(\frac{h_{it'}^{mk}}{1-h_{it'}^{mk}}\right) =$$
$$\alpha_{t'}^{mk} + \beta_1^{mk} individual_{it'} + \beta_2^{mk} firm_{it'} + \beta_3^{mk} industry_{i(t'-1)} + \beta_4^{mk} region_{i(t'-1)}.$$

The use of survey weights and stratification from the KFS makes the model more complicated, but this is accounted for in the coefficient and standard error estimates; The majority of model "fit" statistics are incalculable under a complex survey design. To formally test for the baseline hazard specification, we use a goodness-of-fit test for survey-weighted logit models, following Archer et al. (2007). The results indicate that the unspecified or non-parametric baseline does not reject goodness-of-fit.

Finally, to address potential endogeneity through simultaneity of the region and industry variables, each of those covariates is lagged one year (Wennberg and Lindqvist, 2010). Omitted industry and region variables are also a concern if financing is inherently different across regions and industries. Metro areas (i.e. CBSAs) and 1-digit NAICS industry sector fixed effects will control for these time-invariant natural (dis)advantages.

We estimate separate models for each spell and event type, and compare these estimates to the event counter approach (Box-Steffenseier and Jones, 2004). This allows the hazard of equity and debt financing, and subsequent financing events, to change. Figure 12 displays the dataset for two firms identified by the variable “Firm”. The event of debt acquisition requires the construction of three variables identifying gap time, event indicator, and the round of financing. Firm 1 is observed for four years and experienced debt financing in years two and four. Debt spell indicates which round of financing the firm is at risk of experiencing. Finally, gap time resets the observation after a financing event, but now the firm is at risk of a second financing event, or spell. Firm 1 did not receive equity financing and is at risk for a first equity financing event each year observed and gap time never resets.

14.2 General Capital Acquisition

Table 20 considers repeated external capital acquisitions using the event counter approach and separate event regression approach, but does not distinguish between debt and equity. The previous event counter is highly significant, suggesting that with each additional capital acquisition, the firm is 3 times as likely to receive a subsequent capital infusion. This interpretation is obtained by exponentiating the logit coefficients, but may be the result of unexplained heterogeneity rather than causality (Allison, 1984). Firms with an additional owner investment are 18% less likely to

Firm	Year	Debt Gap Time	Debt	Debt Spell	Equity Gap Time	Equity	Equity Spell
1	1	1	0	1	1	0	1
1	2	2	1	1	2	0	1
1	3	1	0	2	3	0	1
1	4	2	1	2	4	0	1
2	1	1	0	1	1	0	1
2	2	2	0	1	2	1	1
2	3	3	0	1	1	1	2
2	4	4	0	1	1	0	3
2	5	5	1	1	2	0	3
2	6	1	0	2	3	0	3

Figure 12: **EVENT HISTORY DATA STRUCTURE**

obtain capital, suggesting that internal and external financing may be substitutes.

Region and industry characteristics affect capital acquisition in several ways. Firms located in regions with greater research expenditures and concentrated clusters are less likely to obtain financing, such that a one standard deviation increase in research expenditures decreases the risk of receiving external capital by 2%. Concentrated clusters increases the chance of capital acquisition, consistent with the presence of specialized financial intermediaries. Additionally, a one standard deviation increase in the average payroll per employee in an industry-region decreases the risk of financing by 0.4%. This may reflect lower valuations due to more productive competitors and higher labor costs for the startup. Finally, the specialization effect reveals that firms in regions that specialize in certain industries have a higher probability of new firm financing, such that a one standard deviation increase in the share of employment in the top five industries makes firms almost 2.3% more likely to receive a capital infusion.

The owner and firm characteristics are consistent with our hypotheses. Firms with owners experienced in the industry are more likely to receive capital, while startup experience in this general model is insignificant. Owners with a college education, and who work more hours, are also more likely to obtain financing. Finally, firms with employees and a copyright are more likely to obtain financing.

As expected, the results change over acquisition occurrence. Owner and firm characteristics have a larger magnitude effects for initial rather than later rounds of financing. The wage and specialization effects are consistent over financing events, but research expenditures and clustering seem to only affect later financing events. Interestingly, new firm concentration is significant for later financing rounds and in the expected direction.

14.3 Competing Risks of Debt and Equity

The preceding results naively combine funding sources and do not differentiate between equity and debt financing. The event counter in table 21 suggests that subsequent debt infusions are almost 4 times as likely to occur for each additional financing event. If a new firm has obtained external equity in the past, it is 26% less likely to receive an external debt investment. The negative effect is also significant for internal investment, contrary to the hypothesis that external debt and internal equity are complements. Both internal and external equity appear to be substitutes for external debt. Across rounds of financing, the effects attenuate or lose significance. The negative effect of previous equity investments becomes more pronounced, supporting the substitutability of equity and debt. After several rounds of debt financing, a firm that has also received equity investments is unlikely to need further debt financing.

The region characteristics that affect external debt financing are very similar to the pooled estimates. A one standard deviation increase in research expenditures decreases the risk of external debt financing by 2.5% percent. Universities may attract new firms and encourage innovation in existing firms making capital acquisition more competitive (Abel and Deitz, 2011). However, greater research intensity is associated with greater human capital in the region because of the demand for specialized skills. Firms may have difficulty obtaining debt financing in a competitive environment with higher labor costs. A one standard deviation increase in the average payroll per employee decreases the probability of external debt by 0.4%. Higher wages increase the overhead costs of new firms and decrease their ability to attract the best employees. New firms located in regions specializing in a few industries are more likely to obtain debt financing. Commercial banks have intimate industry knowledge, lowers information asymmetries and increases the chances that

Table 20: **External Capital Acquisition**

Owner/Firm	**Counter**	**First**	**> First**
Event Counter	1.227***	—	—
Internal Equity	-0.331***	-0.731***	-0.263***
Work Experience	0.005***	0.009***	0.015***
Startup Experience	0.008	0.026	-0.015
Male	0.049	0.103	0.058
Age	-0.017	0.003	0.040
Age^2	0.000	-0.000	-0.001
College Grad	0.164***	0.432***	0.164***
Owner Hours	0.013***	0.012***	0.016***
Non-Employer	-0.106**	-0.106**	0.061
Competitive Advantage	-0.060	-0.182*	-0.326***
Sole Owner	-0.039	0.141	0.026
Patent	0.056	-0.088	-0.160
Copyright	0.122**	-0.061	0.244
Home-based	-0.038	0.154	0.153
Region/Industry			
Research Expenditures	-0.250***	-0.240	-0.273***
Cluster LQ	0.098**	-0.019	0.218*
New Firms LQ	0.067	0.128	0.370**
Small Business Share	0.075	-0.279	0.431
Average Wage	-0.197***	-0.316***	-0.184***
MES	-0.002	-0.006*	0.005
Employment Density	0.323	0.720	1.621*
Specialization	2.050***	2.346***	2.604***
Firms	4,760	2,914	1,846

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include cbsa and industry sector fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

new firms can get financing.

Owners with previous work experience are more likely to get initial debt financing, perhaps due to the lower perception of risk by financiers. After financing is established, however, this experience is unlikely to matter more than experience with the new firm. Though not significant in the event counter model, a firm's competitive advantage decreases the likelihood of external debt financing in the first two rounds of funding. This effect is surprising, given that owner confidence is expected to encourage debt negotiations. However, confident owners may be more likely to engage in other forms of financing besides external debt. These owners may also require monitoring and represent greater risk, making equity a more likely source of financing.

Later rounds of external debt exhibit larger region effects, as firm and owner characteristics attenuate. Hence, banks seem to eliminate information asymmetries through relationship lending and accessing the new firm's credit history. In later rounds of funding, the region plays a bigger role in determination of startup funding. Employment density and cluster concentration become significant, and positively affect funding. This result deserves greater attention in future studies, as the sample becomes quite small in later rounds of funding.

The external equity funding results in table 22 confirm that equity and debt have different determinants. Firms that have received previous equity funding are more likely to receive equity financing. This effect is considerably larger than for debt financing and may indicate more unexplained heterogeneity in the equity model. However, the Landier model suggests that equity financiers are more likely to invest smaller amounts more often. Banks are expected to make fewer, but larger investments. Previous external debt decreases the likelihood of equity investment, confirming that the two sources are substitutes. Internal equity again appears to be a substitute, rather than a complement, for external equity.

Region characteristics reveal a great divergence between equity and debt funding. The wage and specialization effects remain significant and in the same direction. However, new firm concentration significantly increases the likelihood of equity investment, such that a one standard deviation increase in a region's new firm location quotient increases the likelihood of equity financing

Table 21: **External Debt Acquisition**

Owner/Firm	**Counter**	**First**	**Second**	**Third**	**Fourth**	**> Fourth**
Event Counter	1.367***	—	—	—	—	—
Previous Equity	-0.301***	-0.402***	-0.038	-0.523***	-1.075***	-1.798***
Internal Equity	-0.321***	-0.752***	-0.222***	-0.267***	-0.067	-0.363
Work Experience	0.006***	0.013***	0.007	0.006	0.010	0.022
Startup Experience	0.012	0.015	0.034*	0.021	0.012	0.137
Male	0.090*	0.057	0.086	0.290**	0.076	-0.249
Age	-0.011	-0.012	0.061	0.093	-0.045	-0.100
Age^2	-0.000	-0.000	-0.001	-0.001	-0.000	0.001
College Grad	0.153***	0.431***	0.057	0.204***	-0.130	0.024
Owner Hours	0.014***	0.012***	0.021***	0.019***	0.013	0.006
Non-Employer	-0.100	-0.071	-0.023	0.545**	0.164	0.617
Competitive Advantage	-0.052	-0.354***	-0.374***	-0.200	0.111	1.101
Sole Owner	-0.079	0.078	-0.114	0.139	0.520	0.583
Patent	0.066	-0.267	0.163	0.515	1.494**	-0.315
Copyright	0.098	0.169	0.128	0.253	1.061**	-1.728**
Home-based	-0.035	0.261**	0.088	-0.227**	0.250	-1.135
Region/Industry						
Research Expenditures	-0.336***	-0.204	-0.406	-0.592***	-12.730***	-3.617
Cluster LQ	0.113**	0.145**	0.120	0.334**	0.855**	0.410
New Firms LQ	0.014	0.129	0.244	-0.433	-1.002*	-1.239
Small Business Share	0.018	-0.464	0.706	1.327	1.994	3.321
Average Wage	-0.204***	-0.334***	-0.252***	-0.580***	-0.571*	0.735
MES	-0.002	-0.005*	0.002	0.024	-0.016	-0.106*
Employment Density	0.901	1.249	2.690***	-2.144	2.766***	7.221***
Specialization	2.164***	2.725***	2.805***	3.680***	14.703***	-20.003
Firms	4,760	2,677	1,655	1,014	640	387

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include cbsa and industry sector fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

by 0.4%. This is consistent with the Landier model and Chinitz hypothesis, where a lower stigma of failure encourages equity investment. Firms in denser regions are less likely to receive external equity, while density is positively related to debt financing. Hence, equity and debt may be viewed as substitutes in employment density.

Initial rounds of equity financing share the same regional determinants as in the event counter model. However, the small business share is significant and increases the likelihood of equity financing. A one standard deviation increase in the share of small businesses makes a firm 0.7% more likely to receive an initial round of equity financing. This finding again supports the Landier model and Chinitz hypothesis where lower-stigma entrepreneurial regions make equity financing more attractive and provides more small business financiers.

Owners with a college degree are 40% more likely to receive equity financing, while working an additional hour per week increases the chance of equity financing by 2%. Home-based firms are less likely to receive external equity, whereas the effect is unstable for debt financing. Unlike debt funding, non-employers and sole-owned firms are less likely to receive equity financing, perhaps because they like to maintain sole control while equity investors prefer a team of owners.

Initial and later funding round estimates contrast with the event counter estimates. Work experience is marginally significant for initial funding and highly statistically significant for later rounds. Owners with a college degree and non-employer firms are no more (or less) likely to receive funding across funding rounds. The effect of competitive advantage also becomes marginally significant and positive. In comparison to debt funding, this effect suggests that equity serves as a substitute for debt when firms are more risky. Finally, the effect of home-based firms is insignificant for initial equity investment, but becomes highly significant for later rounds, and in the expected negative direction.

14.4 High-Tech Financing

There may be significant differences between high-tech and low-tech firms from a more pronounced information asymmetry in high-tech firms. High-tech startups are inherently risky, as

Table 22: **External Equity Acquisition**

Owner/Firm	**Counter**	**First**	**> First**
Event Counter	3.443***	—	—
Previous Debt	-0.433***	-0.621***	-0.482***
Internal Equity	-0.375***	-0.616***	-0.143
Work Experience	0.002	0.009*	0.027***
Startup Experience	0.005	0.013	-0.033
Male	-0.126	0.020	-0.519**
Age	-0.027	0.055	0.079
Age^2	-0.000	-0.001	-0.001
College Grad	0.337***	0.244	0.468
Owner Hours	0.015***	0.014***	0.009
Non-Employer	-0.289**	-0.017	-0.488
Competitive Advantage	0.048	0.294*	0.681*
Sole Owner	-0.284**	0.106	-0.632
Patent	0.021	0.046	0.298
Copyright	0.231	0.253	0.569*
Home-based	-0.271*	-0.120	-1.021***
Region/Industry			
Research Expenditures	-0.152	-0.097	-0.269**
Cluster LQ	-0.005	-0.066	-0.164
New Firms LQ	0.244**	0.436**	0.001
Small Business Share	0.644	0.909**	1.131
Average Wage	-0.210***	-0.189***	-0.066
MES	0.002	-0.007	0.029
Employment Density	-2.129**	-2.652	-1.245
Specialization	1.690***	1.811***	2.741**
Firms	4,760	888	283

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include cbsa and industry sector fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * $p < .10$; ** $p < .05$; *** $p < .01$

they often lack capital and collateral (Kortum and Lerner, 2000). Aghion and Bolton (1992) emphasized the double moral hazard that arises when the entrepreneur and the financier choose second-best actions, especially in high-tech firms. The entrepreneur scales back effort after funding, while the equity investor is incentivized to find a replacement. Some equity investors may contribute technical knowledge and managerial assistance, while monitoring the entrepreneur and firm.

Previous studies have used the proportion of inputs or value added that is devoted to R&D as a defining characteristic of high-tech firms. Industries with greater than 3.5% of inputs devoted to R&D are classified as innovative, and as high-tech if the share is greater than 8.5% (Fritsch, 2010; OECD, 2005). The OECD listing classifies industries based on knowledge and R&D investments and on innovativeness of products. However, this approach suffers from a number of issues. First, the classification is meant for inter-country analyses, yet U.S. innovative industries may look quite different from innovative industries in other countries. Second, the definitions are based on industry data from 1973–1995 and are quite different, given the vast number of new technologies that have been introduced in the past two decades. Third, identifying products based on their innovativeness has some level of arbitrary assignment. The National Science Foundation (NSF) also produces estimates of industry R&D workers, but use a modified listing of industries that is inconsistent with North American Industry Classification System (NAICS) codes available for KFS firms. The NSF also only includes scientists and engineers, but excludes other R&D employees such as technicians.

We choose the high-tech industry classification of Hecker (2005). High-tech industries are identified based on their proportion of technology-oriented workers who are engaged in R&D, use knowledge to develop new products or services, and apply technology in other activities (Hecker, 2005). We use the Occupation Employment Statistics (OES) data to associate occupations with four-digit NAICS industries. High-tech industries are classified as those whose technology-oriented employment accounted for at least the average industry proportion of 4.9%. This classification provides a US-specific listing, uses 2002 and 2012 (projected) data, and uses NAICS codes.

Table 23 compares equity and debt acquisition for high- and low-tech firms using the event counter approach. Local industry conditions affect high and low-tech debt financing differently. A one standard deviation increase in the average payroll per employee decreases the likelihood of external debt by 0.5% for low-tech firms and 0.7% for high-tech firms. The specialization effect is also more pronounced for high-tech firms. A one standard deviation increase in the share of employment in the top five industries makes a high-tech firm 4% more likely to receive debt financing compared to 3% more likely for low-tech firms. Research expenditures and cluster concentration are only significant for low-tech debt acquisition. Low-tech firms may have difficulty obtaining debt financing in a competitive environment perpetuated by university research.

Equity acquisition shows greater differences between high- and low-tech firms than debt acquisition. Industry wages is the only statistically significant local industry variable for high-tech firms, such that a one standard deviation increase in the average payroll per employee decreases the chance of external equity by 0.7%. Low-tech firms only have a 0.4% lower risk of equity financing for the same increase in wages. Additionally, the preceding Chinitz and specialization effects are only statistically significant for low-tech firms.

15 Conclusion and Discussion

We have considered the effects of local industry conditions on external capital acquisition of new firms using the Kauffman Firm Survey (KFS). We estimate models of external debt and equity funding using a discrete-time event history (survival) competing risk model allowing for repeated events. We contribute to the entrepreneurial financing literature by accounting for heterogeneity in financing methods and repeated transactions, exploring how local industry conditions affect new firm financing, and considering how the determinants of financing differ for high-tech firms.

We find that the region in which a firm operates significantly affects the funding chances of new firms. New firms are more likely to receive external equity and debt infusions in regions that specialize in certain industries and in industries with lower wages. While the chance of equity

Table 23: **HIGH-TECH CAPITAL ACQUISITION**

Owner/Firm	**Low-Tech**		**High-tech**	
	Debt	**Equity**	**Debt**	**Equity**
Event Counter	1.345***	3.561***	1.593***	4.027***
Previous Equity	-0.272***	—	-0.268*	—
Previous Debt	—	-0.518***	—	-0.353***
Internal Equity	-0.343***	-0.429***	-0.303***	-0.352***
Work Experience	0.006**	-0.002	0.009**	0.014**
Startup Experience	0.021**	-0.008	-0.017	0.023***
Male	0.204**	0.128	-0.017	-0.168
Age	0.017	-0.037	-0.069**	-0.107
Age^2	-0.000*	0.000	-0.001*	0.001
College Grad	0.109*	0.390***	0.373***	0.355
Owner Hours	0.013***	0.015***	0.020***	0.019***
Non-Employer	-0.099	-0.398***	0.068	-0.112
Competitive Advantage	-0.041	0.070	-0.168	-0.174
Sole Owner	-0.155	-0.383**	-0.071	0.394
Patent	0.027	-0.123	0.005	-0.181
Copyright	0.128	0.120	0.026	0.096
Home-based	-0.039	-0.088	-0.126	-0.290
Region/Industry				
Research Expenditures	-0.264***	-0.180	-0.963	-0.025
Cluster LQ	0.145**	0.006	-0.029	-0.275
New Firms LQ	-0.007	0.319**	0.127	-0.018
Small Business Share	-0.072	0.226	0.697	0.677
Average Wage	-0.213***	-0.194***	-0.331***	-0.372***
MES	-0.002	0.002	0.009	-0.001
Employment Density	1.212	-2.704	-0.144	-0.076
Specialization	2.210***	1.947**	2.682***	0.883
Firms	3,329	3,329	1,599	1,599

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include cbsa and industry sector fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

financing is greater in regions with an entrepreneurial culture and a higher proportion of small firms (Landier model and Chinitz hypothesis), the likelihood of debt financing is greater in regions with concentrated clusters and lower university research expenditures. Interestingly, these effects are mirrored for low-tech startups, while high-tech startups are only affected by the industry's wage and region's specialization.

Policy makers interested in promoting high-tech entrepreneur financing should encourage specialization rather than diversity within their region. This strategy will allow financiers to similarly specialize in industries and decrease the risk of information asymmetries. Promoting an entrepreneurial culture may also enhance equity financing in low-tech startups. Finally, while regions with large research universities have a lower rate of debt financing, policy makers may wish to expand alternative funding sources.

Future research on this subject should include a comparison sample of new firms, in order to corroborate these findings. The difference in determinants of financing source across multiple rounds suggests the importance of a detailed dataset. Other studies should consider the specific regional financial markets by using venture capital and banking data. Additional firm risk measures may provide a better stratification variable than high-tech industry classifications. Finally, other funding sources, such as trade credit, may be particularly important for entrepreneurs and has not been considered in the context of this paper.

Chapter IV

Conclusion

While an extensive literature has established the importance of agglomeration for urban growth, we have established how various agglomeration theories affect three stages of entrepreneurship: emergence, capital acquisition, and shutdown. Cities play an important role in both the launching of a new firm and the infusion of capital, while shutdowns appear to occur in a vacuum and are only influenced indirectly through capital availability. Obtaining financing decreases the risk of shutdown for a new firm and is more likely to occur in conducive urban environments.

We have explored the relative importance of several theories of agglomeration, but find the recurring significance of the hypotheses of Chinitz in each study. The Chinitz hypothesis suggests that the presence of small and new firms leads to social and institutional structures that promote a culture of entrepreneurship. Developing such a culture within a city not only encourages new firm launches, but supports capital access and reduces the risk of shutdown. While other studies have linked clusters of related industries to urban growth and entrepreneurial success, we find that clusters only significantly affect low-tech financing and manufacturing shutdowns. The breadth of firms in the Kauffman Index of Entrepreneurial Activity and the Kauffman Firm Survey allows for these insights and the ability to control for owner and firm characteristics unavailable in most datasets.

We make several contributions to the vast literature on entrepreneurship in addition to using novel data sources. Looking at new firm launches, we find that controlling for individual motivations decreases the importance of agglomeration influences and that an entrepreneurial culture has a greater effect on startup decisions than previously studied agglomeration theories. Considering new firm closures, we are among the first to distinguish shutdowns from positive exits, which have different determinants. In so doing, we find shutdowns to be affected by owner and firm characteristics rather than the urban environment. Previous findings concerning the effects of agglomeration on shutdowns appear to be mainly the result of samples limited to manufacturing firms. Finally, we are among the first to explore how the city influences startup financing.

This dissertation emphasizes the importance of the city, especially in the emergence rather than the shutdown of new firms. Policymakers may use these findings to support entrepreneurship in their cities, while researchers have opportunities to extend the new questions posed by these findings.

Chapter V

Appendix

Table 24: **EX-INCOME KIEA ESTIMATES**

Individual Characteristics	Income Check
HS Diploma	-0.155***
Some College	-0.149***
Bachelors	0.000
Grad Degree	0.071
Medium-low Income	-
Medium-high Income	-
High Income	-
Married	0.234***
Previously Unemployed	0.995***
Previously Disabled/Retired	0.820***
Black	-0.255***
Asian	-0.152***
Other Race	-0.107
Female	-0.352***
Native U.S.	-0.224***
Same Industry	-3.512***
Age	0.147***
Age^2	-0.002***
Home Owner	0.127***
Region and Industry Characteristics	
MES	-0.413***
Location Quotient	-0.010
New Firms LQ	0.145***
Small Business Share	3.670***
Average Wage	-0.006***
Employment Density	0.000
Jacobs	-0.251**
Fixed Effects	
Metro Area Fixed Effects	Yes
Industry Fixed Effects	Yes
Year Fixed Effects	Yes

Note: Statistics are derived from Kauffman Index of Entrepreneurial Activity and County Business Patterns 1998-2011. Formulas for measures are provided in the text. The coefficients are estimated using a logit binary outcome model adjusted for Current Population Survey weights and standard errors are estimated using Taylor linearization.

Table 25: **KFS DISCRETE SURVIVAL ESTIMATES**

Owner/Firm	Base	Industry FE	State and Industry FE
Work Experience	-0.014***	-0.014***	-0.015***
Startup Experience	0.017	0.017	0.012
Male	0.021	0.032	0.039
Age	-0.152***	-0.125***	-0.114***
Age Squared	0.002***	0.001***	0.001***
College Grad	-0.044	-0.053	-0.053
Owner Hours	-0.003*	-0.003	-0.003
Non-Employer	-0.164*	-0.142	-0.141
Competitive Adv.	-0.095	-0.106	-0.093
SoleOwner	-0.302***	-0.256***	-0.255**
Patent	-0.271	-0.223	-0.239
Copyright	-0.574***	-0.582***	-0.598***
Home-based	-0.126	-0.133	-0.151
Debt-Financed	-1.047***	-1.058***	-1.089***
Equity-Financed	0.167	0.148	0.168
Region/Industry			
Research Expenditures	-0.002	0.002	-0.008
Cluster LQ	-0.052	-0.017	-0.010
New Firms LQ	0.050	0.062	0.058
Small Business Share	-0.967***	-0.578	-0.449
Average Wage	-0.033	-0.007	0.006
MES	-0.004	0.003	0.004**
Employment Density	0.033	0.008	-0.005
Jacobs	0.072	0.161	0.215
Firms	4,148	4,148	4,148

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

Table 26: **MANUFACTURING POSITIVE-EXITS**

Owner/Firm	**Manufacturing**	**Non-Manufacturing**
Work Experience	0.026**	-0.016*
Startup Experience	0.023**	0.026*
Male	-0.450	0.128
Age	-0.192***	-0.221***
Age Squared	0.002**	0.002***
College Grad	-0.416	0.646***
Owner Hours	-0.022	0.000
Non-Employer	1.381**	-0.194
Competitive Adv.	-0.323	0.495**
SoleOwner	-0.237**	-0.464*
Patent	0.346	-0.718
Copyright	-1.490**	-0.256
Home-based	-4.163***	-0.953***
Debt-Financed	-0.241	-0.996***
Equity-Financed	1.014**	-0.399
Region/Industry		
Research Expenditures	-0.032	0.028
Cluster LQ	-0.053	-0.368
New Firms LQ	0.034	0.168
Small Business Share	1.236	-1.893***
Average Wage	-0.145	-0.172
MES	0.000	0.005**
Employment Density	0.245	0.033
Jacobs	-1.327	-0.085
Firms	720	3,428

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

Table 27: **HIGH-TECH POSITIVE-EXITS**

Owner/Firm	**High-tech**	**Low-tech**
Work Exp. Same Ind.	-0.008	-0.010
Entrepreneur Exp.	0.039***	0.026*
Male	0.058	0.066
Age	-0.209***	-0.218***
Age Squared	0.002***	0.002***
College Grad	-0.203	0.660**
Owner Hours	0.000	-0.001
No Employees	-0.814**	0.045
Competitive Advantage	-0.063	0.504*
Sole Owner	-0.536	-0.465
Patent	-0.517	-0.617
Copyright	0.069	-0.410
Home-based	-0.765*	-1.082***
Debt Financed	-0.843**	-0.968***
Equity Financed	-0.544	-0.159
Region/Industry		
Log Research Expenditures	0.080*	0.005
Cluster LQ	0.275**	-0.426
New Firms LQ	0.140	0.179
Small Business Share	-1.178	-1.807**
Average Wage	-0.161	-0.170
MES	0.004	0.005**
Employment Density	-1.636*	0.237
Jacobs	0.011	-0.203
Firms	720	3,428

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include state fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

Table 28: **MANUFACTURING CAPITAL ACQUISITION**

Owner/Firm	**Non-manufacturing**		**Manufacturing**
	Debt	**Equity**	**Equity**
Event Counter	1.390***	3.511***	5.007***
Previous Equity	-0.324***	—	—
Previous Debt	—	-0.445***	-0.286
Internal Equity	-0.324***	-0.374***	-0.473**
Work Experience	0.006**	0.000	-0.001
Startup Experience	0.019**	-0.009	0.012*
Male	0.198***	0.119	-0.597
Age	-0.013	-0.002	-0.365***
Age^2	-0.000	-0.000	0.003***
College Grad	0.167***	0.320**	-0.003
Owner Hours	0.014***	0.015***	0.012
Non-Employer	-0.098*	-0.303**	0.182
Competitive Advantage	-0.029	0.002	0.635*
Sole Owner	-0.117*	-0.182	-0.788**
Patent	0.119	-0.134	0.960**
Copyright	0.091	0.198	0.211
Home-based	-0.032	-0.408***	-0.108
Region/Industry			
Research Expenditures	-0.336***	-0.144	-11.210***
Cluster LQ	0.168**	0.093	-0.032
New Firms LQ	0.018	0.289**	0.564*
Small Business Share	-0.018	1.023*	-0.134
Average Wage	-0.228***	-0.207***	-0.329***
MES	-0.004	0.002	-0.002
Employment Density	0.815	-3.382***	3.820*
Jacobs	2.259***	1.521**	2.173
Firms	4,358	4,358	940

Coefficients are estimated using a discrete-time survival model with a Logit-link function and non-parametric baseline hazard specification. Estimates include cbsa and industry sector fixed effects. Estimates and standard errors are corrected for KFS longitudinal weights and stratification. * p < .10 ; ** p < .05 ; *** p < .01

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Curriculum Vitae

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Education

2013 PhD Economics **Lehigh University**, Bethlehem, PA
Fields: Urban, Innovation, and Entrepreneurship Economics; Applied Microeconomics; Applied Microeconometrics

2008 B.A. Economics **Moravian College**, Bethlehem, PA
Mathematics secondary major, *summa cum laude*

Research Papers

Dissertation

Essays on Entrepreneurship across Space: How Cities Support the Emergence, Survival, and Capital Acquisition of Entrepreneurs

The Influence of Local Social and Industrial Characteristics on Emergent Entrepreneurship

Do New Firm Shutdowns Occur in a Vacuum or Does the Region Matter

Does the City Affect Capital Acquisition of New Firms?

Working Papers

Identifying the Matriculation Matching Effect: How Student Preferences Favor Fit Over Selectivity. with James Dearden and Chad Meyerhoefer

An Economic Analysis of Campus Crime: A Love-Hate Relationship Between Communities and Campuses

Awards and Honors

2012	Kauffman Firm Survey Followup Research Assistant
2011	Teacher Development Program Completion, Lehigh University
2010	Warren-York Fellow, Lehigh University
2004-2008	President's Scholarship, Moravian College

Conference Activity/Participation

2012	The Impacts of Urban Market Characteristics on Entrepreneurial Start-up Rates Eastern Economic Association Annual Conference - March
2012	Doctoral Consortium - Dissertation Proposal US Association Small Business and Entrepreneurship Annual Conference - January
2011	Kauffman Firm Survey 101 - October
2011	Identifying the Matriculation Matching Effect: How Student Preferences are Influenced by Relative College Quality Lehigh University Scholars - April
2011	Identifying the Matriculation Matching Effect: How Student Preferences are Influenced by Relative College Quality Eastern Economic Association Annual Conference - February

Teaching Experience

Instructor

			Sections	Students
2013	Statistical Methods	Lehigh University	3	90
2012	Applied Microeconomic Analysis	Lehigh University	4	98
2012	Principles of Economics	Lehigh University	2	44
2011	Principles of Economics	Lehigh University	2	31
2011	Principles of Economics	Moravian College	1	7

Teaching Assistant

			Sections	Students
2008-2011	Principles of Economics	Lehigh University	20	~450
2010	Money, Banking, and Financial Markets	Lehigh University	4	~90

Research Experience

Research Assistance

2012	Assisted Bill Forster in collecting original qualitative information about nascent entrepreneurs as a followup to the Kauffman Firm Survey
2011	Assisted Chad Meyerhoeffer in collecting, codifying, and cleaning out-patient doctor surveys to analyze the efficiency of a large hospital's electronic medical records system.
2010	Assisted James Dearden in collecting and analyzing matriculant data on a large Northeastern university.
2010	Collected crime and university data for Thomas Hyclak. (2011) "Casinos and Campus Crime." *Economic Letters, 112*

Professional

2012	Conducted an analysis of available resources and performance of entrepreneurs in the Lehigh Valley for a local economic development organization.
2009-2011	Conducted a competitive industry analysis of the Lehigh Valley in addition to various economic reports for businesses looking to relocate in the Lehigh Valley for a local economic development organization.

Professional Affiliations

The American Economic Association

Eastern Economic Association

Regional Studies Association

Journal of Urban Economics

US Association for Small Business and Entrepreneurship

References

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