Entrepreneurial Financing, Serial Venturing, and Experiential Learning

Abstract

We attempt to assess the impact of founders' experiential learning from serial venturing on entrepreneurial success. Our empirical analysis focuses first on Weibull regressions on duration of new ventures, second on parameter estimation of a Bayesian model on diffusion of entrepreneurial finance, and third on the alternative entrepreneurial finance. This paper intends to clarify entrepreneurial capital acquisition alternatives based on social ties or community attention. If succeeding in the first venture, then the entrepreneur's follow-on ventures may signal reputation effect to capital providers. Our findings show the relative roles of basic information transmission, and distinguish capital acquisition information passing by serial entrepreneurs and first-time startup founders. The probability of exits falls with past experience at starting new ventures. Finally, angel funding by these three angel groups is associated with improved venture performance.

Keywords: Experiential Learning, Social Ties, Community Attention, Serial Venturing

Introduction

Entrepreneurial start-ups suffer high rates of business failure, or under-entry (Artinger & Powell, 2016). Nevertheless, is serial entrepreneurship which shows high re-entry rates an exemption? This inquiry calls for attention to the linkage between social innovation of capital acquisition, serial entrepreneurship, and venture success. Raising capital for capturing business opportunities and then supporting new venture developments are central to entrepreneurial finance.

The more reputable founders are, the more likely they could access social tie- and community attention-based financing alternatives, such as angel funds, micro-finance, and crowd-funding. For instance, Huang et al.(2015) employed kickstart.com's archival data to study the reputation effect of entrepreneurs on fund-raising. The cognitive learning-based reputation effect played an important role in attracting the supporters of crowd-funding in successive rounds at early stages of venturing activities.

To survive the "death-valley" stage of venturing activities (Cumming & Johan, 2014), startup founders need to leverage their social ties and to draw on community attention. First, founders could benefit from such financing alternatives based on social ties -- i.e., micro-finance, angel funds. Mitteness et al.'s (2016) results showed that although individuals frequently established relations with similar others, conditions existed when angels exerted the extra effort required to form relations with dissimilar others. Community members could be an important source of such dissimilar investors.

Due to insufficient funding vehicles available for new ventures in such traditional industries, survival rates for retail startups are arguably low. Thus, an acceptable yardstick for measuring venturing success is the duration of ownership controlled by the founder. Lacking of professional reputation could disable entrepreneurs to secure favorable terms in fund-raising. Two questions emerge from the above social innovation of entrepreneurial finance. First, to what extent, social tie-

based financing alternatives spill over among the entrepreneur community in retail? Second, what is the duration of serial ventures conditioned on the reputation effect of entrepreneurship? To address these two questions, this study proposes a Bayesian model that draws on a bootstrap algorithm. We attempt to find out the diffusion patterns of social tie-based entrepreneurial finance alternatives.

An entrepreneur of serial ventures starts more than one venture due partly to inherent superior opportunity discovery capability (Amaral, Baptista & Lima, 2011). Serial entrepreneurs could proactively pursue new skill combinations that disrupt the existing economic equilibrium and capture business opportunities (Keyhani, Levesque & Madhok, 2015).

The business success of entrepreneurship has been measured by the duration of new ventures (Gompers, et al., 2010), wealth creation and managerial control (Wasserman, 2012), and entrepreneurial rents in general (Keyhani et al., 2015). Once an entrepreneur has a second startup in such low entry-barrier industries as retail, the probability of starting a follow-on venture tends to increase. This may be due to the (over)confidence of founders in their own skills relative to others' (Cain, Moore, & Haran, 2015), which has two-side effect on venturing success.

The likelihood of serial entrepreneurship also depends on the founder's capacity of cognitive learning — i.e., being more likely to adapt self-behavior after success than after failure. Drawing on literature on the role of values in judgment and decision-making, Matusik et al. (2008) found that the founder's process value (i.e., values governing the types of means to an end that an individual values) influenced the perceived worth of the founder's human capital. Such "value homophily" arising from venturing activities could affect how evaluators view objective criteria for venture performance and fund-raising (Hsu, 2007). Startup experiences based on cognitive learning in specific, on learning-by-doing in general, are central to the venturing activities in the "brick-and-mortar" industry contexts such as retailing.

Entrepreneurs with a track record of success were more likely to succeed in follow-on ventures than first-time entrepreneurs (Gompers, et al., 2010). An inquiry into the duration of serial

venturing in retail is appealing. The retail and small-scale services businesses have high churning rates, i.e., a proxy for serial venturing activities pursued by entrepreneurs. Once one becomes an entrepreneur for a second time, the probability of starting a follow-on venture keeps rising, which could be driven further by the cognitive learning-based reputation effect.

The structure of this paper is organized as follows. We review relevant literature and industry context of US retailing is discussed in Section Two. Research method is presented in Section Three. In next section, this paper demonstrates empirical findings from econometric analysis on the sample of US retail startups. We conclude this paper in Section Five.

Literature Review and Industry Context

Cognitive learning is important for the success of an entrepreneur's serial ventures (Lazear, 2005). Conditioned on the capacity of cognitive learning, serial venturing actions involved varied degrees of social interactions with multiple stakeholders. Capital acquisition alternatives based on social ties and community attention are more viable options for startup founders. Thus, entrepreneur communities and founder's social contacts emerge as crucial stakeholders for the success of serial entrepreneurship.

Moreover, do entrepreneurial start-ups suffer high rates of business failure, or under-entry? Artinger & Powell (2016) found that statistical model with random errors explained 60 percent of excess entry. However, it did not fully explain observed patterns of over-entry and under-entry, especially the extreme excess entry found in the smallest and most volatile markets. In addition, confidence added significantly to the explanatory power of the model. They concluded that entrepreneurial entry stemmed from a combination of statistical, psychological, and market factors.

Due to cognitive biases, the entrepreneur's interests may misalign with stakeholders' (Wassermanm, 2012). Lacking of cognitive awareness to new service know-how, a startup founder might fail to build customer bases efficiently. Without reaching a critical mass of service operations

timely, capital providers are likely to withdraw from a startup's next-round fund raising.

An entrepreneur is a generalist who need not possess just one skill, but could be competent in many domains (Lazear, 2005). In the venturing process, an entrepreneur strives to leverage and deploy fungible resources, in order to get the value that corresponds to the minimum of return on assets underlying the generalist's skills. Generalists could be simply endowed with the multi-functional skill set that makes them better entrepreneurs. Prior experiences acquired from a generalist's role results in the skills that make an entrepreneur perform better.

On the other hand, an entrepreneur' prior startup success could lead to overconfidence in follow-on ventures. Overconfidence may further misguide overly risky product innovation (Simon & Houghton, 2003), ill-fated market entries (Koellinger, Minniti & Schade, 2007), competitive blind spots (Ng, Westgren, & Sonka, 2009), and overvaluation of businesses (Hayward & Hambrick, 1997). Hubris may complicate the assessment of an entrepreneur's professional quality.

From the standpoint of capital providers, how do they perceive and evaluate the value of a founder's entrepreneurship? Drawing on literature on the role of values in judgment and decision-making, Matusik et al. (2008) found that the founder's process value influenced the perceived worth of the founder's human capital. Such "value homophily" may affect how evaluators view objective criteria for venture performance and fund raising (Hsu, 2007). Specifically, Startup experience based on cognitive learning in specific, on learning by doing in general, positively affects capital providers' evaluations of a founder's venturing quality; on the other hand, value homophily positively moderates the relationship between the founder's startup experience and evaluation of his/her self-direction value (Matusik et al., 2008).

Table One shows the number of existing retail businesses between 1900 and 2011 in the State of New York, USA. The population of retail ventures grew by more than 50% over the time period of sampling. Regarding the level of entry and exit each year, 2,452,311 businesses were opened, while 2,214,460 of them were closed. Relatively monotonic growth in the number of retail

businesses in Column 1 shows a high churning rate: About 20% of retailers exiting each year indicate relatively short life of survival; 95% of retail ventures have fewer than 20 stores opened.

Insert Table 1 about here

Due to data limitation, we are not able to analyze the differences between each financing alternatives for entrepreneurs. Instead, we attempt to find out the factors that affect the duration of serial ventures, whose reputation effect could signal to capital providers. In turn, the more reputable founders are, the more likely they could access social tie- and community attention-based financing alternatives, such as angel funds, micro-finance, and crowd-funding. Huang et al.(2015) employed kickstart.com's archival data to study the reputation effect of entrepreneurs on fund-raising. They found that the cognitive learning-based reputation effect played an important role in attracting the supporters of crowd-funding in successive rounds at early stages of venturing activities.

Entrepreneurship reflects an individual's conjecture that a first-person opportunity exists and is attractive. If realized, such an opportunity promises a favorable net profit margin (Eckhardt & Ciuchta, 2008). Thus, it is important to consider how potential entrepreneurs evaluate third-person opportunities and overcome uncertainty. McMullen and Shepherd (2006) posited that the opportunity recognition process consists of "attention" and "evaluation" stages. In the attention stage, individuals observe third-person opportunities by virtue of having been sensitized to a given set of problems and exposed to information describing potential solutions. Once an individual recognizes a third-person opportunity, a first-person evaluation ensues, during which the individual identifies a defined course of action and determines whether the identified course of action is feasible and desirable.

Within the context of small business owners with no more than 20 ventures, only 25.6% of

those owners who had opened another venture since 1990. Moreover, only 9% of such entrepreneurs had opened two or more businesses by the time they opened new ones. Our sample of retail ventures covers the majority of small business owners' serial venturing activities. In fact, most of these entrepreneurs operate their ventures sequentially.

Social Tie-Based Entrepreneurial Finance

The service domain of entrepreneurial action consists of lead-entrepreneur attributes and knowledge probing. Venturing opportunities evolving in the service domain could spread among socially-networked entrepreneurs. Service-oriented knowledge spillover is driven by creation of transferable know-how that can be harnessed to meet demand for services such as retail. In service ventures, lead entrepreneurs experience knowledge constraints so acutely that they start developing workable solutions by themselves. A lead local retailer serves as the role of lead entrepreneur for new retail venture models in this paper.

Although lead locals experience bottlenecks and performance constraints more clearly than ordinary peers, the former's estimations regarding the potential economic value of service solutions may be short of external validation. Therefore, although early discovery of third-person opportunities is likely to prompt speculation whether or not lead local-developed solutions might be prevalent (Jeppesen & Laursen, 2009), solution discovery alone may not be sufficient to trigger entrepreneurial action, such as entrepreneurial finance for serial venturing:

Hypothesis 1: The entrepreneur with a high degree of lead-local attributes is more likely to engage in entrepreneurial finance for serial venturing.

Knowledge probing provides informational advantages that facilitate the recognition of service opportunities. By opening new discussions, knowledge probers can receive early feedback about the viability of service domain knowledge for them. This information advantage enhances a prober's ability to recognize which developments are possible for service ventures and which developments

an entrepreneur community supports. For the retail startup, because knowledge probing only explores emergent venturing paths, it does not necessarily yield information advantages regarding the founder's need.

Here, knowledge probers for retail ventures help steer the allocation of transferable know-how in the entrepreneur community. The agenda-setting effect of such probing facilitates the emergence of venturing solutions. The emergence of such solutions should trigger opportunity evaluation:

Hypothesis 2: The entrepreneur engaged in a high degree of service-oriented knowledge probing is more likely to engage in entrepreneurial finance for serial venturing.

Community Attention-Based Entrepreneurial Finance

Another striking feature of serial ventures is that the probability of opening an additional store rises with the number of prior ventures. This could be due to two social domains of entrepreneurial action -- i.e., community attention and community spanning. When one store opened in our data period, the probability of opening a second one or more within the next 15 years of the first is 29% in our sample. Given two stores opened, the probability of opening a third is 35%; given three, the probability of opening a fourth is 40%. This increasing likelihood of serial ventures could benefit from more legitimacy and accountability acknowledged by the society.

Community attention could lower market uncertainty. Attention signals that the individual's actions resonate with others in the entrepreneur community and shows emotional commitment to the eventual outcome. This may increase an individual's confidence that others will commit to a solution (Franke, Schreier & Kaiser, 2010).

A high level of community attention to a focal individual's expressed service interests informs the individual that a widespread need exists for the solution. Community's intense attention is also evident that peers could likely experience psychological ownership of the resulting solution. In addition, close attention paid by the entrepreneur community also shows that the community is

likely to accept a solution supplied by a startup founder. All this lowers market uncertainty and therefore, the threshold for entrepreneurial action:

Hypothesis 3: The entrepreneur who receives a high degree of community attention is more likely to engage in entrepreneurial finance for serial venturing.

Community spanning refers to participation in multiple communities, which enhance awareness of credibility and thus lowers the threshold for entrepreneurial finance. First, community spanners gain informational advantages from participation in social activities (Vaghely & Julien, 2010). Second, community spanning helps entrepreneurs judge the economic viability of service options and anticipating demand patterns (Gaglio & Katz, 2001). Third, an entrepreneur with diverse community membership could nurture his cognitive capabilities, which may lower perception of market uncertainty in retail ventures.

Multi-community membership also enables entrepreneurs to draw on reasoning analogies and group belief when evaluating venturing opportunities. Analogous reasoning provides a useful device for predicting the path of "value homophily" (Matusik et al., 2008), which helps make venturing decisions. Community belief also serves the reference point that enables entrepreneurs to accurately estimate availability of entrepreneurial finance. Demand patterns often unfold in similar ways in related communities; hence, the ability to draw on analogous examples from other communities could help lower demand uncertainty.

By virtue of their ability to better reframe the problem to which a given venturing development is applied, community spanners are able to circumvent seemingly difficult obstacles, thereby sidestepping aspects of market uncertainty. When market uncertainty is lowered, entrepreneurial finance is more likely to come up with:

Hypothesis 4: The entrepreneur who engages in a high degree of community spanning is more likely to engage in entrepreneurial finance for serial venturing.

In addition to the duration of serial ventures, this study also attempts to develop a structural model for estimating the spillover effect of entrepreneurial finance in the retail founder community. Following Banerjee et al.'s (2012) modeling approach, this paper employs a Bayesian bootstrap estimation in next section (1) to determine the relative roles of basic information transmission versus other forms of peer influence, and (2) to distinguish financing information passing by serial entrepreneurs and first-time startup founders. We hypothesize that serial entrepreneurs are more likely to pass social tie- and community attention-based financing opportunities on to their peers than new comers to retail businesses in our sample.

Bayesian Estimation

We use the method of simulated moments (MSM) to first estimate β using fund-raising decisions among the set of leaders (who are known to be informed of the entrepreneurial finance opportunities). To estimate q^N, q^P, and λ (or any subset of these in the restricted models), we proceed as follows. The parameter space Θ is discretized (henceforth we use Θ to denote the discretized parameter space) and we search over the entire set of parameters. For each possible choice of $\theta \in \Theta$, we simulate the model 80 times, each time letting the diffusion process run for the number of trimesters that a given entrepreneur was exposed to entrepreneurial finance (i.e., 6 to 9). For each simulation, the moments are calculated.

Next, we take the average over the 80 runs, which gives us the vector of average simulated moments, which we denote $m_{sim,r}$ for entrepreneur r. We let $m_{emp,r}$ denote the vector of empirical moments for entrepreneur r. Then we choose the set of parameters that minimizes the criterion function, namely:

$$\widehat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmin}} \left(\frac{1}{R} \sum_{1}^{R} m_{sim,r}(\theta) - m_{emp,r} \right)' \left(\frac{1}{R} \sum_{1}^{R} m_{sim,r}(\theta) - m_{emp,r} \right),$$

To estimate the distribution of $\hat{\theta}$, we use a simple Bayesian bootstrap algorithm. The bootstrap exploits the independence across entrepreneurs. Specifically, for each grid point $\theta \in \Theta$, we

compute the divergence for the r^{th} entrepreneur, $d_r(\theta) = m_{sim;r}(\theta) - m_{emp;r}$ and interpolate values between grid points. We bootstrap the criterion function by re-sampling, with replacement, from the set of 52 entrepreneurs.

For each bootstrap sample b = 1, …, 1200, we estimate a weighted average, $D_b(\theta) = \frac{1}{R}\sum_{r=1}^{R} \omega_r^b \cdot d_r(\theta)$. Note that our objective function uses a weight of 1 for every entrepreneur. Here, the weights are drawn randomly to simulate re-sampling with replacement. Then $\widehat{\theta^b} = \text{argmin}_{\theta\in\Theta}\, D_b(\theta)' D_b(\theta)$. This method allows us to estimate standard errors in a computationally simple manner for a GMM model that requires numerous runs of a complicated of a diffusion process.

Overall, the Bayesian bootstrap estimation procedures discussed above help (1) to determine the relative roles of basic information transmission versus other forms of peer influence, and (2) to distinguish financing information passing by serial entrepreneurs (i.e., the founders proactive for creating new ventures serially) and first-time startup founders. Thus, we come up with the following hypothesis for the duration of serial venturing that signal reputation effects to capital providers as follows:

Hypothesis 5: Serial entrepreneurs with community centrality are more likely to pass information about financing alternatives on to peers than first-time founders.

Thus, the diffusion of entrepreneurial finance stated in the above model should further indicate importance of social tie- and community attention-based financing choices, such as the angel fund, microfinance, and crowd-funding. In line with Banerjee et al.'s (2012) network modeling, we propose that communication centrality underlying the nodal position of the entrepreneur who is proactive for seeking financing alternatives imply an informational brokerage advantage over the first-time entrepreneur.

The Research Method

Data of Retail Ventures

The research method that this paper employed is stated in this section. Table 1 presents a large sample of retail businesses in existence in a given year, which we calculate by identifying all those in existence on July 4th of that year, whether they were started before or after our data period. The population of retail businesses opened in the State of New York of USA from 1990 to 2011 is huge, with 544,377 retail businesses still in existence in 2011. These retail businesses in our sample grew by more than 50% over the time period of our data.

Insert Table 2 about here

Table Two shows descriptive statistics for our dataset of 2,331,988 retail businesses of small business owners, who have fewer than 20 ventures in the initial data, opened from 1990 to 2011. The businesses in our data have an average duration of 42 months, while the median duration is 24 months. These average and median figures underestimate distribution of venture duration, because the data are censored from the right. That is, there are some businesses are still opened after 2011. In calculating the average and median, the duration of these establishments is counted as if they closed at the end of 2011.

To test face validity of our sample, we drew on Cain et al. (2015) to collect data on market entry from Dun & Bradstreet's records of firm starts. These records break firms into 118 different industries based on Standard Industrial Classification (SIC) codes. Start rates (number of firm founding per 10,000 existing firms) for years from which we were able to obtain data of 4-year time duration (up to 1995) are moderately stable. The correlation across industries between different years' start rates averages around 0.32. The industries that see persistent high rates of entry are the same ones that see persistent high rates of exit (Schwalbach, 1991).

To collect data of perceived ease, this paper adopted Cain et al.'s (2015) survey method in an

EMBA community located in a major B-School in East Asia. Each participant was asked to rate the ease of succeeding in each of the 118 major industry categories. Due to concerns about the monotony of this task and the risk of routinized responses from participants, each participant rated a subset of the industries. Then, each participant was given one of seven different subsets covering a different combination of the 118 industries. For each industry, we asked each participant to indicate the degree to which his/her understands what it takes to run a successful venture, by providing a 7-point Likert scale running from 1 (no idea) to 7 (confident).

This experiment merely corroborates the notion that there is excess entry into easy industries such as retail. Also, we sought to distinguish perceived ease of performance from ease of entering the market. Therefore, we also asked participants to rate the barriers to entry for each industry on a 7-point Likert scale, ranging from 1 (none) to 7 (maximal barriers to entry).

To test convergent validity of our sample, we computed the entry rates for each industry for each year in which data was available. The way that entry rates are computed (entrants per 10,000 existing firms) allows one to account for industry size. Then, rates of entry are averaged across all years. This distribution was highly skewed, so a log transformation on the data was employed.

Insert Table 3 about here

Moreover, this study did an OLS regression analysis with the rate of entry as dependent variable and perceived ease as the independent, controlling for barriers to entry. The result showed that the explanatory power of perceived ease for market entry rates was statistically significant, where β =0.355, t (115) = 3.44, p =0.001. Table 3 shows the 10 easiest sectors based on their rated ease, among which six sectors are retail-based.

Data of Angel-Fund Financing

To further verify the role of alternative financing vehicles for retail entrepreneurs, we drew on the data from three angel-fund providers (i.e., angel groups) X, Y, Z for financing retail ventures. These three angel groups have invested in diverse industries but have strong interests in retail subsectors. We collected data of 130 retail ventures covered in our dataset from these angel groups' internal documents.

We developed three categories of ventures' results: venture survival and success, venture operations and growth, and venture financing. Our simplest measure is a binary indicator variable for firm survival as of December 2010. This survival date is a minimum of four years after the potential funding event with the angel group. We develop this measure through several data sources. We first directly contacted as many ventures as possible to learn their current status. Second, we looked for evidence of the ventures' operations in industry databases or news wires. Finally, we examine every venture's web site, if one exists. Existence of a web site is not sufficient for being alive, as some ventures leave a web site running after closing operations. We thus based our measurement on how recent various items like press releases were.

Our second measure is a binary indicator variable for whether the venture had undergone a successful exit by December 2010. A successful exit can either be an initial public offering (IPO) or a successful acquisition. In total, 3 and 8 of our 130 venture sample had a successful IPO or acquisition by December 2010, respectively. Given the short time horizon, some successful entrepreneurs may have passed on exit opportunities to continue growing their businesses, or started a follow-on venture (i.e., serial venture). Thus, our third measure augments the successful exit measure to also include if the venture has 75 or more employees in 2010, which we will also adjust below to thresholds of 50 and 100 employees. 22 of our 130 ventures are successful according to this combined measure. By contrast, 45 of the 130 ventures have closed or had an unsuccessful exit.

Our second set of metrics quantifies venture operations and growth after the potential financing event. While we would ideally consider a broad range of performance variables such as

sales and product introductions, obtaining data on private ventures is extremely challenging. This is especially true for unfunded ventures. We are able to employ three outcome variables: employment, patents, and web site traffic. These three measures also allow for more differentiation between firms than the binary indicators used for venture success.

We first consider the employment level of the venture in 2010. Employment measures are collected using the sources described above for venture survival. While we identified exact employment levels for many ventures, in other cases we had to transform reported employment ranges into point estimates. We applied a consistent rule in these cases to all ventures with the specified range. The chosen point estimates reflect the typical firm size distribution through the range (e.g., an employment level of 20 was assigned when the reported range was 10-50 employees). We further coded the employment levels of closed ventures with a zero value.

Finally, we faced the question of how to code employment levels for successful retail ventures. These outliers with several hundred employees can have large effects on the outcomes. Other very successful cases have been acquired by large companies and thus are no longer reported separately. To address these issues, we cap the maximum employment level at 100 employees. We also code very successful exits as having 100 employees. The results are robust to instead using caps of 50 employees or 250 employees. Using a maximum of 100 employees, our average venture had 26 employees in 2010 (36 among operating businesses) versus 12 employees at the time of the pitch.

The second measure is an indicator variable for having been granted a patent by the United States Patent and Trademark Office (USPTO) by December 2010. About a quarter of the ventures received a patent. Many retail ventures in our sample are not seeking patent/trademark protection. We partially control for this in the regressions with our industry controls, but we acknowledge that patenting is an imperfect measure of innovation levels more generally.

Web traffic data in the summer of 2008 and January 2010 are also reported by these three angel groups. These data are separated into these two time points: 91 of the 130 retail ventures in one of

the two periods, and 58 ventures in both periods. The absolute level of web traffic and its rank are very dependent upon the specific traits and business models of ventures. This is true even within broad industry groups as degrees of customer interaction vary. We consider the changes in performance for the venture between the two periods. These improvements or declines are more generally comparable across ventures.

One variable simply compares the log ratio of the web rank in 2010 to that in 2008. This variable is attractive in that it measures the magnitudes of improvements and declines in traffic. A limitation, however, is that it is only defined for ventures whose web sites are active in both periods. We thus also define a second outcome measure as a binary indicator for improved venture performance on the web. This technique allows us to consider all 91 ventures for which we observe web traffic at some point, while sacrificing the granularity of the other measure.

Econometric Findings and Discussions

Proportional Hazard Rate Tests

Our empirical analysis focuses mainly on the duration model, which treats an exit as the function of the founder's prior experience measured as the number of retail businesses opened before. In Column 2 of Table 2, the founding owners of the ventures have opened only 0.45 business s by the time they start a new business; 68.8% of prior businesses are closed by the time the new venture is opened (.313/.455 = 68.8%). Finally, owners start as many businesses after the focal one as they do before (.460/.455).

The inquiry about whether or not serial entrepreneurs have higher success rates than first-time founders or not is the key issue of this study. Experienced entrepreneurs who have started businesses before will be more likely to succeed. We hence intend to examine the extent to which ambidextrous learning matters for venturing success. An entrepreneur is said to be more successful when his venture stays in business longer.

Small business owners receive lower expected value of the future profits when they exit from their startups (Fraser, 1999). Thus, we treat changes in ownership as equivalent to exit, because a startup is considered to a viable on-going concern only still under initial ownership. The following analyses are to measure the impact of the number of past businesses opened on the duration of retail ventures under the founder's initial ownership.

We examine the factors affecting duration of serial ventures by two econometric models -- i.e., the Cox model and Weibull model, respectively. The Cox proportional hazards model has the advantage of not relying on any distributional assumption, and as such provides a useful robustness check. The main drawback of the Cox model is that it assumes a constant hazard whereas the literature on firm survival suggests that negative duration dependence is to be expected in the data.

To capture negative duration data, this paper also employed the Weibull model: Given that the business has survived to time t, the hazard – i.e., instantaneous transition from origin (start of business) to destination (business exit) – can be stated as follows:

$h(t) = h_o(t)g(X)$, where $h_o(t) = p_t^{p-1}$, and p is the shape parameter.

In this hazard function, $p < 1$ refers to negative duration dependence where older businesses have lower exit rates. In contrast, $p > 1$ indicates positive duration dependence. Overall, when $p = 1$, the Weibull model reduces to the Cox model.

Both the Cox- and Weibull-models exhibit the "proportional hazard rate" property, at which a retail venture exits given it has survived until time t. Changes in independent variables shift the baseline hazard, and the coefficients capture the effect of a one-unit increase in a particular variable on the hazard ratio. Specifically, if the coefficient b is greater (smaller) than one, the difference (b - 1)*100 indicates the percentage by which a one unit increase in the explanatory variable would increase (decrease) the hazard of exit. Thus, while an independent variable with a coefficient greater than one increases the exit hazard rate, that with an coefficient small than one reduces hazard rate.

Two data truncation issues matter in this paper. First, for non-existing businesses, the duration spells are incomplete and their observations are right censored. Second, if a business started prior to 1990 did not survive to that time, we would not know it ever existed. For founding owners of retail ventures started prior to 1990, there would be a survivorship bias. Thus, we focused on those businesses that owners started since 1990.

Results for Social Tie-based Financing

Due to the sampling criterion that only selects small business owners with fewer than 20 startups, our models consist of 19 dummy variables for the number of previous stores. These dummies range from "1 business before" to "19 businesses before." Table 4 shows that prior venturing experience has a strong negative effect on the likelihood of exiting from the incumbent business. In Column 1 of Table 4, the coefficients of the Cox model bear out that the past startup experience lowers the exit rate, except when the "number of businesses before" becomes very large.

Column 2 of Table 4 shows the Weibull results. The probability of exit falls with venture longevity according to the estimated shape parameter, p. The pattern of coefficients of the "1 business before" to "19 businesses before" variables is the same as for the Cox model. For those owners with one previous business, the probability of exit for the current business falls by 7 percent (1 - .928).

Insert Table 4 about here

Nevertheless, as the number of prior businesses rises, the dummy variables become less populated. Only 25.6% of new businesses are started by owners who are experienced with one prior venture. Only 4 % of businesses are opened by owners who have opened three or more before the incumbent one. Dummy variables in Table 4 are less populated after three prior businesses.

Insert Table 5 about here

Table 5 shows the Weibull duration regressions, where "the number of previous businesses opened" enters the equations in columns 1 and 5, along with squared transformation of this variable in columns 2 and 6, respectively. Results demonstrate that the number of businesses opened prior to the focal one has a positive effect on its duration, though at a diminishing rate. Experiences matter for serial ventures: Current business duration increases as the number of prior businesses opened rises. This effect of past businesses on current success was not evident in the coefficients on the 19 dummy variables. However, the dummy variables representing more than three past stores are not very populated.

There are two paths to what we have referred to entrepreneurship for serial ventures known as "habitual entrepreneurship": An entrepreneur opens and then closes a series of businesses in sequence, typically operating only one at any given time. Alternatively, an entrepreneur opens and keeps running a number of businesses at the same time. The vast majority of founding owners operate only one venture at a time.

This paper then examine the issue about whether or not entrepreneurs with more than one venture currently open fare better than those with closed stores. To distinguish between open and closed stores, we replace the total number of businesses opened before by two variables, the "number opened before still open" for the number of stores that remain open, and the "number opened before but closed" for the number of past stores that are now closed.

As shown in columns 3 and 4 of Table 5, the "number opened before but closed" is the significant variable in the regression, decreasing the exit rate of the current venture. The "number opened before still open" variable has the reverse effect, but this effect is not statistically different

from zero, and is much smaller in magnitude: in column 3, each additional business opened but now closed reduces the hazard rate by 3.8 percent (1 – 0.962). An additional business opened still operating increases the hazard by only 0.3 percent.

In the model of Lazear (2005), entrepreneurs are those with general skills, not specific skills. The general skills he has in mind are from different management disciplines. An entrepreneur is said to be a generalist if he had multiple past roles from a track record in operations, and finance, and human resources.

Our retail data enables us to test whether the lead-local attributes of entrepreneurs are valuable. If multiple past roles lead to more entrepreneurship, do multiple past business types or sectors of activity lead to better entrepreneurship? In other words, the entrepreneur's past roles could include not just different managerial capabilities, but also the "reference points" for anchoring the peers' schematic value functions that define risk preferences over a range of wealth effects, from the perspective of prospect theory in Behavioral Economics.

In the hazard rate models of Tables 4 and 5, there are several control variables, and the one of greatest interest is "Opened in recession." This is a dummy variable equal to one if the current business was opened during a recession, for the three recessions that occurred between 1990 and 2011. Businesses opened during recessions are less likely to close. Apparently, these stores are more durable. Recall from Table 2 that only 10.4 percent of the stores are opened during a recession in these 22 years, within which 31 months (or 11.7 percent) are classified as recession months. It is therefore possible that the businesses opened during those periods are selected, i.e. that owners only pursue very promising business ideas during recessions. Businesses opened by small business owners in urban areas, defined in our data source as businesses located within city limits, are more likely to be of shorter duration.

Establishments of small business owners that are associated with a national brand are less likely to close. Nevertheless, the owner must have fewer than 20 businesses in total to be in our data

set. This restriction explains why only 2.0 percent of the businesses in our data are part of chains. The businesses in question are owned by franchisees. Each of these three variables is interacted with our measure of the extent of serial entrepreneurship in columns 5 and 6 of Tables 5. Serial entrepreneurship is more valuable to those stores opened in recessions, but less valuable to those stores in urban areas or those associated with national brands.

Overall, lead entrepreneurs' roles for setting reference points for schematic value functions of the peers serve a proxy for the degree of lead-local attributes. Column 1 ~ 4 of Table 5 provide a range of reference points on venturing timing and location choice. These findings suggested that the entrepreneur with a high degree of lead-local attributes be more likely to engage in entrepreneurial finance for serial venturing. Hence, hypothesis 1 is supported.

In addition, startup founders' managerial capabilities and venturing experiences serve as a proxy for technical know-how probing. Column 5 and 6 of Table 5 point out that ambidextrous learning over economic cycle by the entrepreneur with a high degree of service-oriented technical know-how probing could be more likely to engage in entrepreneurial finance for serial venturing. Thus, Hypothesis 2 is supported.

Speed of Diffusion: Structural Estimation

Table 6 presents the result of the estimation. Panel A.1 presents the parameters of the information model estimated using the first set of moments. q^N is 0.095, and q^P is 0.45, and both of these are significantly different from 0. This suggests that in every round, informed entrepreneurs who are themselves seeking financing alternatives based on social ties and community attention will inform a given contact about the alternative financing opportunities with probability .45. Nevertheless, those who just stick with traditional financing vehicles, such as small bank lending, inform a given contact with probability .095. We may reject the null hypothesis for the equality of diffusion paths with varying degrees of communication centrality (Renou & Tomala, 2012).

Insert Table 6 about here

Panel A.2 presents estimates of the endorsement effect, and there is no an extra endorsement effect above the information effect of our main model. Conditioned on being informed, an entrepreneur's decision to raise funds from alternatives of entrepreneurial finance is not affected by whether or not the founder's contacts seek new financing opportunities. The probability that an entrepreneur passes information to a contact is affected by the degree of being informed, but where there are no additional endorsement effects.

Results for Diffusion of Entrepreneurial Financing

We check to see how important a role the non-informed entrepreneurs play in passing information to their contacts. Even the non-informed pass information at a much lower rate than their informed peers, the former far out-numbers the later. In fact, our estimates indicate that information passing by the non-informed entrepreneurs is responsible for one-third of overall diffusion of information about social tie- and community attention-based entrepreneurial finance. We came with this finding by comparing the model as fit above to the results based on a model that allows only the informed entrepreneurs to spread information. That is, holding all else constant, we can then simulate the model when we set q^N to 0, and see how the fraction of informed entrepreneurs changes and how the pattern of information passing changes.

Moreover, we estimate that setting q^N equal to 0 would lead to a decline of roughly one-third in overall entrepreneurs of retail ventures, from more than 20.7 percent to 13.8 percent; and then a similar decline in the fraction of informed entrepreneurs, from over 86 percent to 59 percent. Thus, not only is the level of information passing by non-informed entrepreneurs statistically significant and different from that of the informed ones, but it also appears to substantially influence both the spread of information and the choice of fund-raising.

Overall, the above Bayesian bootstrap estimation procedures help (1) to determine the relative roles of basic information transmission versus other forms of peer influence, and (2) to distinguish financing information passing by serial entrepreneurs and first-time startup founders. Our simulation results confirmed serial entrepreneurs with community centrality are more likely to pass information about financing alternatives on to their peers than first-time founders. Thus, Hypothesis 5 is supported.

Robustness Checks for Bayesian Estimation

One potential concern with these results is that the structural estimation approach inherits the correlated effects and endogeneity problems that plague any effort to estimate peer effects from observational data. Given that the model makes a much more specific prediction about the diffusion of entrepreneurial finance than "people close to people who take up will take up themselves," it is encouraging that the structural model fits the data better than a mechanical model based on distance to the leaders who take up entrepreneurial finance. Nonetheless, there remains a concern that the patterns we identify may be spurious.

To address the concern about endogeneity of network position, we first control for the entrepreneur's characteristics. We also recognize that there could still be potential biases. However, because the source of variation is completely different than that which motivated the first set of moments, and the source of potential biases is also different, it will nevertheless be encouraging if the estimated effects are the same. This comparison will function as an over-identification test of sorts, since the differing biases have no reason to give us the same results. The results are presented in Panel B of Table 6. They are similar to the first set of results: we find $q^N = 0{:}08$ and $q^P = 0{:}65$, and the difference between the two remains significant.

Our second check is to control for a possible bias in our main estimate, which is that people's need for entrepreneurial finance could be related to their network position, and in particular correlated with their distance from the leaders. Hence, we add a control for an entrepreneur's social

distance to leaders who chose to seek entrepreneurial finance. We compare our structural estimates to those generated by the following modified "nested distance model":

$$P(Y \mid X_i; F_i; d_i) = \Lambda(\alpha + X_i' \beta + \lambda F_i + d(i; L^P)\rho)$$

Here $d(i; L^P)$ is the length of the shortest path between i and the nearest leader who participates in entrepreneurial finance. This nested specification ensures that our estimation relies on the specific functional form implied by the model, rather than being driven by correlated behaviors which just happen to correlate with network position in a way that would serve as a proxy for by information transmission from the lead entrepreneur. The results after controlling for shortest distance to the leader who also seeks entrepreneurial finance in the information model are presented in Panel C of Table 6. Both estimates are comparable to those from the original information model. Here, $(q^N; q^P) = (0{:}1; 0{:}45)$. The difference between the two parameters remains significant.

Results for Community Attention-based Financing

Furthermore, our large sample represents the businesses that indicate that they operate in the retail sector in New York State of USA, with sub-sector distribution in Table 7. We define retail broadly given that the presence of these businesses in the data already indicates that they collect sales taxes. We have 2,780,370 such businesses, owned by 1,890,321 owners, in our original sample of 3,200,824 businesses. Of these, 2,452,311 businesses, owned by 1,715,352 owners, are started from 1990 onward.

Insert Table 7 about here

Our interest in small business entrepreneurship leads us to focus most of our analyses on those owners with 20 or fewer businesses. Our sample of retail businesses started from 1990 onward and owned by small owners is 2,331,988 businesses for 1,713,112 owners. In other words, we have only

2240 large owners, and these are associated with only 120,323 retail establishments founded since January 1, 1990. Because these establishments have longer duration, they represent about 10 percent of the total number of retail businesses operating at a given point in time.

Insert Table 8 about here

In Table 8, we re-examined our standard measure of prior business experience, namely the number of businesses previously opened, to explore whether past domain experience matters in the largest retail sub-sectors in our data – those of restaurants (NAICS 722), clothing stores (NAICS 448), and repair businesses (NAICS 811). We also analyzed the general retail trade (NAICS 44-45) sector, where experience across types of retails may be useful.

Past experience was measured in two ways. The first was experience in the current domain, labeled "same sector," measuring the number of past businesses within the same industry. The second form of experience was that in other domains, "other sectors," measuring the number of past businesses outside the specific industry domain (defined at the 3-digit NAICS level, as described above, or at the relevant combination of 2-digit NAICS for the whole of retail trade). In each of these sectors, small business owners' experience is concentrated in the same sector: in clothing, the proportion of same industry experience, measured by the number of prior businesses in this sector as a proportion of the total number of prior businesses opened by the owner, is .358/.455, or 78.7 percent on average. In the restaurant and repair sectors, the corresponding proportions are 78.8 percent (.394/.500) and or 73.7 percent (.264/.358) respectively.

Column 1 ~ 4 of Table 8 demonstrate 3-digit NAICS fixed effects, which suggest that in most sub-industries, experiences in any industry increase the likelihood of venturing success. Both "same sector" businesses and "other sectors" businesses lower exit rates. Thus, the entrepreneur who

receives a high degree of community attention from closely-related retail sub-sectors is more likely to engage in entrepreneurial finance for serial venturing. Hypothesis 3 is supported, accordingly.

The exception is restaurants. In restaurants, it is really only past restaurant experience, i.e. experience in "same sector" that raises success. In restaurants, other forms of experience lower success. In the other sub-industries, any past experience raises success. Through these robustness checks, we confirmed our main findings.

In addition, column 5 and 6 of Table 8 show 3-digit NAICS fixed effects, which indicate that an entrepreneur who engages in a high degree of retail community spanning (i.e., to share resources and to transfer technical knowhow across retail sub-sectors) is more likely to engage in entrepreneurial finance. The interaction terms between number of retail ventures and economic cycle and geography could refer to the social ties built and developed by the serial entrepreneurs, while the squared functions of those interactions further clarify the nonlinear nature of entrepreneur-community spanning process. Hence, Hypothesis 4 is supported.

Results for Angel-Fund Financing

To further test the alternative financing vehicle for retail entrepreneur, we examine whether the retail ventures received financing supports from angel investors or not. We define these measures through data collected from three angel funds X, Y, Z; we cross-checked with as many ventures directly as possible. Both indicator variables for financing events and counts of financing rounds are taken into account.

Regarding the consequences of entrepreneurial finance for start-ups, we first compare the subsequent outcomes of funded ventures with non-funded ventures. Table 9 to 11quantify the relationship between angel group financing and outcomes. We focus on the 130 ventures that are used in our border analysis. This sample restriction removes both very low quality and very high quality ventures, focusing on ventures that are similar in quality and for which funding prospects

were quite uncertain at the time of the pitch.

Insert Table 9 about here

Table 9 considers our outcome variables for venture success. In the first column, we regress a dummy variable for whether the venture was alive in 2010 on the indicator for whether the firm received funding from the angel group. In Panel A, we include only a constant and the funding dummy variable; in Panel B we control for angel group, industry, and year fixed effects (controlling for the year that the venture approached the angel group). The coefficients on the indicator variables are 0.20 and 0.25, both statistically significant at the 1% level. Firms that received angel funding are 20%-25% more likely to survive for at least four years.

Column 2 shows that funded ventures are also 9%-11% more likely to undergo a successful exit by December 2010. In unreported specifications, we also disaggregated this result into a 4%-7% higher likelihood of successful acquisition and a 4%-5% higher likelihood of going public. Finally, Column 3 finds that the funded ventures are 16%-19% more likely to be successful, where success represents achieving 75 employees or a successful exit by December 2010. Columns 4 and 5 show that this venture success result does not depend substantially on the threshold used to measure employment success. These additional outcomes are all statistically significant and precisely measured. Moreover, reflecting the use of indicator variables, they are very robust to modest changes in sample composition.

Insert Table 10 about here

Table 10 considers our metrics of venture operations and growth using a similar specification

to Table 3a. The first column finds that funded ventures have 19-20 more employees in 2010 than unfunded ventures. This estimate is again statistically significant. Column 2 shows that this higher employment level in 2010 is not due to funded ventures having greater employment at the time of the pitch. Median regressions find an employment growth of 13.0 (5.2) employees.

Column 3 shows that funded ventures are 16%-18% more likely to have a granted patent. Columns 4 and 5 consider improvements and growth in web traffic performance. Funded ventures are 12%-16% more likely to have improved web performance, but these estimates are not precisely measured. On the other hand, our intensive measure of firm performance, the log ratio of web site ranks, finds a more powerful effect. Funded ventures show on average 32%-39% greater improvements in web rank than unfunded ventures in recent years.

Insert Table 11 about here

Finally, Table 11 analyzes whether angel funding leads to other financing. Panels A and B consider indicator variables for types of financing activity, while Panels C and D consider counts of financing rounds. The first column begins with whether the venture ever receives professional venture capital financing. This starting point provides background on whether alternative financing to the angel group was easily available. We find that funded ventures are 70% more likely to receive some form of venture financing than start-ups rejected by the angel groups. On average, they have 1.6-2.1 more financing rounds. These estimates suggest that rejected deals found it reasonably difficult to obtain venture financing at all.

The estimates in Column 1 use data on venture financing that we developed from multiple sources, including contacting the venture directly. Column 2 shows similar results, but with somewhat lower elasticities, when we use only data that we obtain from searching VentureXpert.

We will return to this estimation when discussing Table 4‘s expanded sample.

Column 3 returns to the financing data used in Column 1 and removes the current angel financing event. Thus, we now compare the probability of a funded venture obtaining further financing to the probability of a rejected deal obtaining any financing. Even after excluding the current angel financing event, the ventures funded by the angel groups are 21%-27% more likely to obtain later financing and have on average 0.8-1.2 more financing rounds.

The last two columns quantify the role of the angel groups in these subsequent financing events. Column 4 counts deals that include investors other than the original angel groups. In comparison of Column 3 and 4, we found that most of the additional financing events included outside investors. Column 5 alternatively counts deals that only include outside investors. The effects here are a third to a half of their magnitude in Column 3. Funding by these two angel groups aids access to follow-on financing, with a substantial portion of the subsequent deals syndicated by the angel groups with other venture financiers.

Of course, we cannot tell from this analysis whether angel-backed firms pursue different growth or investment strategies and thus have to rely on more external funding. Alternatively, the powerful relationships could reflect a supply effect where angel group investors and board members provide networks, connections, and introductions that help ventures access additional funding.

Overall, the results in Tables 9 to 11 suggest that angel funding by these three angel groups is associated with improved venture performance. That is, serial ventures could benefit from alternative financing vehicles such as the angel fund, which is based more on social ties and community attention, as suggested by Hypotheses one to four.

There are limitations for the interpreting our results. We first consider only ventures that approach our angel investors, rather than attempting to draw similar firms from the full population of business activities to compare to funded ventures. This step helps ensure ex ante comparable

treatment and control groups in that all the ventures are seeking high growth. Second, we substantially narrow even this distribution of prospective deals until we have a group of companies that are ex ante comparable. This removes heterogeneous quality in the ventures that approach the angel investors.

Discussions

Some patterns prevail for the establishments of large firms as well, however. Like those of small owners, establishments of large owners that are opened during a recession or associated with a national brand are much more successful. In fact, the positive effect of opening during recession is even greater for the establishments of large owners than for those of small owners. Being associated with a national brand, which almost half of these establishments are, is not as beneficial to large owners, but being located in an urban environment, which 95 percent of these establishments are, increases their survival, contrary to the effect we found for the establishments of small business owners. Establishments opened by sole proprietors are far less successful.

There are also very few such establishments in the set of large owner establishments in retail: less than one percent of these establishments are owned by proprietors, whereas 69 percent of new establishments of small owners were opened by such owners. The reason might be due to the proprietor's overconfidence in market entry without considering business cycle and competitive intensity. Cain et al. (2015) critically examined the notion that 'overconfidence' explains excess market entry: Entry into different markets is not driven by confidence in one's own absolute skill, but by confidence in one's skill relative to that of others. Overconfidence in relative skill is driven by neglecting competitors or by systematic errors made.

In contrast, entrepreneurs are often described as overconfident even when entering difficult markets such as biotech and mobile computing. How do entrepreneurs maintain confidence in difficult tasks? Cain et al.'s (2015) laboratory experiments reconciled literature by separating types of overconfidence and identifying what type is most prominent in each type of task.

If entrepreneurs overestimate their absolute performance, the problem of excess entry might be exacerbated when tasks are difficult. However, studies of market entry games (Dorfman, et al., 2013) have found excess entry into markets with easy tasks, at the expense of entry to markets comprising difficult tasks, which suggests that overplacement may be at fault. Camerer and Lovallo (1999) also suggested overplacement as the culprit for excess entry: They gave participants the choice to enter a contest that would be determined either by skill or by chance. Participants were more willing to enter the contest when it was based on skill, estimating that their performance would lead to positive expected payoffs for themselves but negative payoffs for other entrants.

Moreover, the primary difference between large owners and small owners is that establishments opened by large owners survive longer. The mean duration of a new establishment is just over 1200 days, or 3.3 years, for small owners, but almost twice that, at 2100 days, or 5.75 years, for large owners. Therefore, when we look at data on the stock of existing stores, we see evidence that chain stores are a big part of the market (Basker et al., 2012; Jarmin et al., 2009). Because of these longer durations, large owners operate about 10 percent of all retail establishments at any point in time even though they open only five percent of the new establishments.

Overconfidence arising from past success could explain the reason why small owners condition their venture success on business cycle and competitive intensity. Overconfidence leads to investment in unprofitable ventures, introduction of overly risky product innovations, ill-fated market entries, competitive blind spots, failures to learn from experience, overvaluation of businesses (i.e., Astebro, Jeffrey & Adomdza, 2007; Simon & Houghton, 2003). Entrepreneurs are often quite confident, despite high probabilities of failure in economic downturn.

Conclusions

Typical captial-raising sources for new ventures are venture capitalists and banks. When barriers for entry and exit are low, venturing activities become intensified and fund-raising efforts turn to be difficult. Entrepreneurial start-ups suffer high rates of business failure, or under-entry

(Artinger & Powell, 2016). Thus, does serial venturing show high re-entry rates an exemption? This inquiry calls for attention to the linkage between social innovation of capital acquisition, serial entrepreneurship, and venture success.

This paper confirmed the importance of entrepreneurs' social ties and community attention, which nurture their experiential learning. Such learning from serial venturing has significant impact on entrepreneurial success. Founders could benefit from such capital acquisition alternatives based on social ties. Our findings are also consistent with Mitteness et al.'s (2016) results that conditions existed when angels exerted the extra effort required to form relations with dissimilar others, such as community members.

The success in the first venture may signal reputation effect to capital providers. This paper modeled and simulated the diffusion of the social tie-based entrepreneurial financing alternatives on the one hand, and analyzed empirically the duration of serial venturing conditioned on the reputation effect of entrepreneurship, on the other. Our Bayesian model estimation sheds insight on diffusion patterns, while our findings show the route that entrepreneurs achieve serial venture success measured as duration of ownership controlled by the founder. Bayesian bootstrap estimation procedures discussed above help (1) to determine the relative roles of basic information transmission versus other forms of peer influence, and (2) to distinguish financing information passing by serial entrepreneurs and first-time startup founders.

As shown in the Weibull proportional hazard rate model, the probability of exiting from business falls with past experience at starting new ventures, which supports the reputation effect of serial venturing. Small retail entrepreneurs may create fewer jobs per business than large tech entrepreneurs, but small retail is economically important because there are so many establishments. The businesses of small owners may be short-lived but they are prevalent.

To conclude, this paper identified an unexpected pattern underlying serial ventures for small business owners in retail. That is, the new business that they open is more likely to survive if their

previous business has been closed than if their previous business remains open. Ownership is sequential. This could be a feature of retail ownership – where most owners are small proprietors and therefore unable to maintain more than one business at a time. Finally, angel funding by these three angel groups is associated with improved venture performance. That is, serial ventures could benefit from alternative financing vehicles such as the angel fund, which is based more on social ties and community attention.

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Table 1: Number of Retail Establishments, and Entry and Exit, by Year

Year	Total establishments on July 4th	Establishments Opened Jan. 1 to Dec. 31	Establishments Closed Jan. 1 to Dec. 31
1990	362218	96798	65825
1991	398044	113171	75466
1992	448176	138925	100373
1993	476462	137260	126442
1994	480257	131263	107545
1995	495524	129451	132853
1996	493850	115859	111184
1997	495244	108357	98381
1998	508433	111272	123683
1999	501515	113882	119866
2000	492420	105998	101733
2001	493239	106183	96218
2002	511594	119080	107765
2003	524427	119918	103943
2004	535528	112690	119264
2005	527771	106480	123905
2006	511260	106678	103753
2007	510715	105125	101933
2008	509918	91976	87467
2009	514593	92125	91503
2010	519145	98492	79264
2011	544377	91328	36083

Table 2: Statistical Descriptions

Variable	Mean	Std. Dev.	Min	Max
Duration (in days)	1217.721	1359.501	30	8034
Businesses opened before: all	.455	1.133	0	19
Businesses opened before: still open	.142	.706	0	19
Businesses opened before: now closed	.313	.776	0	19
Businesses opened after current business	.460	1.105	0	19
Urban establishment	.822			
National chain	.020			
Opened in recession	.104			
Corporation	.220			
Proprietorship	.687			
Partnership	.093			
Survives 1 year (n = 2244729)	.723			
Survives 2 years (n = 2150542)	.533			
Survives 3 years (n = 2063097	.411			

Number of observations: 2331988 except as noted. The number of observations used to calculate the survival rates is reduced to the set of businesses that start one, two or three years prior to the end of our data period to ensure we can observe a full year, two-year or three-year survival.

Table 5: Weibull Duration Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Number Opened Before	0.980***	0.954***			0.957***	0.916***
	(0.001)	(0.002)			(0.003)	(0.003)
Squared (Number Opened Before)		1.004***				1.009***
		(0.000)				(0.001)
Number Opened Before Still Open			1.003	1.017***		
			(0.003)	(0.004)		
Sq. (Number Opened Before Still Open)				0.998***		
				(0.001)		
Number Opened Before but Closed			0.962***	0.924***		
			(0.001)	(0.002)		
Sq. (Number Opened Before but Closed)				1.011***		
				(0.000)		
Opened in recession	0.919***	0.919***	0.919***	0.919***	0.922***	0.920***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Major Chain	0.735***	0.733***	0.726***	0.724***	0.724***	0.724***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Urban Establishment	1.211***	1.212***	1.210***	1.210***	1.200***	1.198***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Proprietorship	1.672***	1.675***	1.682***	1.685***	1.672***	1.675***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Partnership	1.755***	1.752***	1.757***	1.757***	1.755***	1.753***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Number Opened Before * Recession					0.992***	1.002
					(0.003)	(0.005)
Number Opened Before * Chain					1.018***	1.028***
					(0.006)	(0.010)
Number Opened Before * Urban					1.027***	1.046***
					(0.003)	(0.004)
Sq. (Number Opened Before * Recession)						0.998***
						(0.001)
Sq. (Number Opened Before * Chain)						0.997**
						(0.001)
Sq. (Number Opened Before * Urban)						0.995***
						(0.001)
Number of obs	2,331,988	2,331,988	2,331,988	2,331,988	2,331,988	2,331,988
No. of failures	1,849,592	1,849,592	1,849,592	1,849,592	1,849,592	1,849,592
p (Weibull)	0.88	0.88	0.88	0.88	0.88	0.88

Notes: Standard errors, clustered at the owner level, in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$