Innovation, Survival and Growth: Evidence from a Cohort of US Startups (2004-2011) *

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August 25, 2019

Draft

Abstract

The launch of new business ventures is an important source of dynamism for both advanced and transitioning economies. However, survival prospects are low and many new business ventures remain small. Yet, the empirical evidence from administrative level data suggests that much of aggregate employment and productivity gains stem from a small subset of successful, including high-growth, startups; however, these data often lack information on firm strategy, financing, innovation activities and founder characteristics, among other variables. Using a novel detailed survey dataset, the Kauffman Firm Survey, we study a representative cohort of American startup firms launched in 2004 over an eight-year period until 2011; overlapping with the business cycle pre and post the Great Recession of 2008-2009. Considering a rich set of firm-level factors including financing conditions, we examine the role of innovation —measured by the firms industrial technology sector, patenting and R&D, as well as whether it introduces any new products to market —in driving firm survival and performance. We also investigate the role of innovation in securing external financing as a potential mechanism for early stage firm growth.

Key Words: new firm entry, duration models, entrepreneurial finance, innovation, entrepreneurship.

JEL Classification: C41, C14, D21, L60.

*Acknowledgements: We are grateful for helpful comments from seminar participants at CEA, CERDI. Disclaimer: Certain data included herein are derived from the Kauffman Firm Survey. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Ewing Marion Kauffman Foundation.

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1 Introduction

A main theoretical prediction of firm dynamics and entrepreneurship literature emphasizes that mature, large firms tend to stagnate whereas new, young firms tend to grow very quickly conditional on survival, resulting in an important source of reallocation and aggregate productivity growth for both advanced and transitioning economies, Foster, Haltiwanger, and Krizan (2002), and Earle and Brown (2010). For example, Haltiwanger, Jarmin, and Miranda (2010) find that a significant contribution of both gross and net job creation stems from the launch of new firms in the US and that conditional on survival, young businesses grow quickly in an up-or-out dynamic. However, Decker, Haltiwanger, Jarmin, and Miranda (2016) have recently documented a decline in business dynamics, or firm turnover, driven by declining business start-up rates and a decreasing role of dynamic young firms in the economy. Further, much of the aggregate gains stem from a small subset of successful, often high-growth, firms. Understanding the systemic factors (or barriers) driving the creation of innovative, young firms remains an important public policy concern heightened by the fact that since the onset of Great Recession, both job creation and firm startup rates have remained historically low. While many studies have examined firm survival for mature, corporate firms, few have shed light on the dynamics facing new, young firms from time of birth through its early stages; see Huynh, Petrunia, and Voia (2012). A major challenge for entrepreneurs starting or running a business in the initial years lies is the inability to obtain external business financing in light of too short a history of performance and securing clients and stable revenue.

In this paper, we use a novel dataset that tracks a representative sample of firms from a cohort of US-based startups, and that provides an inside view of early stage firms and their founders and contribute to a growing literature on the dynamics of young entrepreneurial firms through the lens of empirical microeconomic evidence. Recent similar studies are Zarutskie (), [cite others]. To put our study in context with more popular and selective studies on startups, it is important to distinguish between the drivers of survival and performance for the median, or typical, new firm compared to that of high growth (or unicorn) startups that are in the right tail of the distribution for instance, startups that are borne out of incubators and seek outside equity investment with the goal of obtaining an exit or public company status that provide equity investors with returns on their investment large enough to compensate for risk. Because of the rarity of the later, our study can be interpreted as focusing on the middle of the distribution. For instance out of our sample of 4000 firms, fewer than 1 percent obtain any form of outside equity over an eight-year period. Almost all of these startups launch from the founders home, are financed principally by its founder(s) and less than half launch with outside debt (formal bank issued debt). A major strand of the literature focuses on the role of finance, such as credit constraints of early stage firms and sources of funding via debt or equity. Another strand deals with the role of the founder, human capital, firm strategy and innovation. In our paper, we attempt to disentangle the role of financial variables from the degree of innovation of the firm (in terms of its sector and whether the firm has introduced a new product to market). A growing hypothesis in the literature highlights the role of innovation in young firms conditional on entry in driving performance; our work seeks to contribute to this literature using a novel dataset for the United States. For example, Arrighetti and Vivarelli (1999) and Vivarelli and Audretsch (1998) find that more innovative new entrant firms tend to enjoy superior post-entry performance. Mairesse and Mohnen (2010) show how qualitative questions in surveys can provide information on firm innovation activities.

Our study aims to highlight some of the potential mechanisms driving the dynamics of new business ventures and inform how they might impact broader aggregate variables. First, we study the factors that drive firm survival, with a particular focus on initial firm financing as well technological intensity of the firm sector. A measure of technological intensity serves as a proxy for firm innovation activities, or its proximity to the technological frontier. Further, as a by-product, we are able to shed light on the effect of the Great Recession in heightening firm exits or shutdowns. As a preview, results suggest that a firms initial financial position characterized by a greater reliance on formal debt financing positively affected survival in normal times, but the effect reverses during the crisis. Our results shed light on the role of financial frictions and highlight strong statistical differences in the hazard rates according to firm technological intensity.

Second, we carry out a set of regressions that explore the link between firm level innovation and growth, conditional on our sample of surviving firms. Our measures of innovation include whether a firm performs R&D, whether it is in a high-tech sector, and additionally, whether it brings product innovations to the market. The later measure becomes available in the survey beginning in 2008 the firms fifth year of operation. Applying a difference-in-difference framework, we assess the impact of innovation activity occurring through the firms observed lifespan on performance from a before-after perspective exploiting the longitudinal nature of our data. A series of robustness checks test for selection and the concern of parallel trends in the diff-in-diff approach; given a lack of suitable IVs and an experimental setting. One potential mechanism we evaluate lies in the role between financing and innovation strategy; in other words, a firms attempt to innovate and build competitive advantage potentially influences its ability to apply for and secure additional rounds of external financing over time; simultaneously affecting and driving growth.

The rest of the paper continues as follows. Section II provides an overview of the literature on firm survival. Section III describes the data and Section IV reviews our empirical methodology. Section V discusses our results and Section VI concludes.

2 Connection to the literature

2.1 The role of finance

A distinguishing feature of young, startup firms is the opaqueness and information asymmetry surrounding their future business plans and survival prospects, Robb and Robinson (2014). The extent to which young, startup firms are unable to access sufficient financial capital and the resulting effects on performance and survival remain largely unknown. The effect of financing constraints can operate through various channels. Stiglitz and Weiss (1981) showed that banks ration credit due to information asymmetries. In seminal papers, Stiglitz and Weiss (1981) showed that banks ration credit due to information asymmetries and Berger and Udell (1992) documented evidence of credit constraints using data from survey of loan officers. Evans and Jovanovic (1989) test whether entrepreneurs are more likely to be wealthy and in their theoretical model some projects become unprofitable for a financially constrained entrepreneur. Cabral and Mata (2003) show how much of the distribution of firm size evolution can be accounted for by initial startup financial constraints. Myers and Majluf (1984) predicted a pecking order theory where firms prefer to finance investment beginning with internal funds, then debt and then equity so as to minimize adverse selection. Berger and Udell (1992) provides evidence of credit constraints using data from survey of loan officers. For practical purposes, Kaplan and Zingales (2000) suggests using a measure of credit-score as an exogenous measure of firm financial constraints.

The literature has also emphasized the importance of firm startup financial capital and leverage. Does capital structure drive firm performance or does firm performance drive capital structure? Zingales (1998) addressed this issue in a period of deregulation in the trucking industry and showed how some inefficient firms survive due to deep pockets. A central prediction from the finance literature posits that entrepreneurs will rely on a greater share of debt financing to the extent that their business venture inspires a greater degree of certainty. Zetlin-Jones and Shourideh (2012) find that most investment financed by privately held firms is financed through borrowing. However, greater leverage may adversely affect a firms chances of survival, as discussed in Zingales (1998). Firms may eventually suffer from debt overhang, unable to finance new projects, or, they may fall victim to predation by deep-pocketed competitors. In contrast, high leverage could work in favor of firms survival by forcing early restructuring. Furthermore, high leverage may indicate a firms aggressive expansion strategy.

While the financing mix is important for understanding the plight of young firms, little is known about the role of initial financing levels and a young firms ability to navigate and surmount challenges in its early stages, see Huynh, Petrunia, and Voia (2012). When entrepreneurs are initially encouraged to invest in ambitious, lengthy projects in a growing economy, changing economic conditions can sometimes render those plans unsustainable. Redeploying the invested capital to more productive pursuits can entail a painful adjustment process, sometimes forcing a firm to shut down. As a result, firms that launch with ample initial financing may also be more likely to miss-employ that capital compared to leaner startups that expand in a more cautious manner. The interaction between the supply of credit and entrepreneurial overconfidence could be a potentially important factor in business cycle fluctuations.

Using data on corporate firms, Spaliara and Tsoukas (2013) find that survival is more sensitive to financial indicators during a period of crisis as compared to more tranquil times. To the extent that the recession was triggered by a financial crisis as opposed to traditional demand or supply side factors, the direction of causality should flow from the firms financial position to its performance and survival. Young firms with a greater reliance on formal outside debt or short term liquidity provisions would be more adversely affected in the event that their banking relationship deteriorated or future access to funding was reduced. Furthermore, to the extent that the policy response was aimed towards larger financial institutions, which do not typically specialize in small business lending, suggest that the financial crisis adverse affect on young, startup firms may have been amplified. Using the same data as in this paper, Berger, Cerqueiro, and Penas (2014) find that a greater small bank geographical presence improves the survival prospects of young firms in normal times, but that this effect disappeared during the financial crisis.

Are startup firms born in booms different than those that emerge during recessions or periods of slow economic growth? In a study of US manufacturing plants over the period 1972-1997, Lee and Mukoyama (2008) find that the entry rate is much more cyclical than the exit rate (higher in booms), and entering plants average size and productivity vary significantly over the business cycle. In particular, plants entering in booms are significantly smaller and less productive than plants entering in recessions (relative to incumbents) - only highly productive plants enter during recessions. In contrast, the authors do not find much evidence of selection on exit. While such empirical evidence may indicate the presence of barriers to entry, an alternative view is that overoptimistic entrepreneurs find it easier to launch new ventures in good times, despite their poor prospects.

A historical feature of the US banking sector is its presence of a large number of small, local financial institutions which have been found to specialize in forming lending relationships with small and young businesses. For example, Petersen and Rajan (2002) find that distance matters for provision of funds to small firms (though declining with improvements in information technology). A priori, the depth of the banking sector in the US might suggest that credit markets have largely filled the niche of providing finance to startups, however the evidence is mixed and many argue that a market failure (still) exists. Policy interventions have been enacted such as SBA loan programs. Recently, Brown and Earle (2013) have evaluated some of these interventions and found positive effects on job creation.

2.2 Firm age, size and survival patterns

The theoretical literature on firm dynamics and entrepreneurship has shed light on conditional relationships between firm age and size for survival, firm entry and exit via selection and learning, and the role of financial frictions; Evans (1987), Jovanovic (1982), Hopenhayn (1992), Cooley and Quadrini (2001). In particular, these models describe how firms learn about their productivity and costs over time, driving exit. Initial constraints in firm size causes growth to be high for young firms, in contrast with mature firms that have attained efficient scale. Financial frictions, or a firms capital structure, can account for additional heterogeneity in firm performance across age and size cohorts. Firms can taken on more debt to grow faster, but face higher probability of default given variability in profits.

Empirical studies on firm survival typically find negative duration dependence, the longer a firm operates the more likely it is to survive. This is consistent with a model where firms learn about their competitiveness as they age. Mature, older firms have very low failure rates. However, survival dynamics for in the early years of a firms startup is more complex. Initially, a firm may undergo a honeymoon period for several years where business failure is infrequent. Eventually, firms uncover adverse market conditions, or face unsustainable financing, and firm exit peaks. Thereafter, firm exit rates decrease steadily with age, see Parker (2009) for a more detailed discussion. Under this hypothesis, startup firm hazard rates should follow an inverse U-shaped pattern.

2.3 Innovation measurement & Firm Performance

Innovation increases product quality and make firms more competitive, which increases their revenue and size and forces existing firms producing old and obsolete versions of the product to exit the market. Without innovation, models of firm dynamics typically predict that firms stagnate after reaching a certain size. A large empirical literature mainly using data for OECD countries documents a robust positive relationship between firm-level innovation and productivity (Hall, 2011); innovation and employment (Harrison et al., 2008), as well as some innovation inputs, such as R&D, and productivity (Hall et al., 2011).

Innovation is commonly seen as the work of highly educated labor in research and development (R&D) intensive companies with strong ties to the scientific community (Farberger et al 2010). However, innovation in a broader sense also characterizes attempts to try out new or improved products, processes, or experiment with alternate ways to do things (Bell and Pavitt, 1993; Kline and Rosenberg, 1986). This is a process of technology adoption, imitation and adaptation far from the technological frontier, where firms adopt incremental (as opposed to radical) changes (Fagerberg et al. 2010). It is also a process that requires the combination of different innovation outputs, modes of innovation, in addition to product and processes, such as marketing or organizational innovations (Bell and Pavitt, 1993).

The innovation process entails the transformation of knowledge capital or innovation inputs, both tangible and intangible such as training, equipment, R&D or intellectual property acquisitions into innovation outcomes such as the introduction of new and improved products, new production processes, or organizational changes. To measure innovation, one can focus on both measuring inputs and innovation activities, and/or measuring innovation outcomes. The early innovation measurement literature focused on a specific set of innovation inputs that were easier to quantify, for instance R&D, or the intensity of the technology used. These early efforts were followed by the implementation of the Oslo Manual type of surveys, which mainly focus on measuring innovation outcomes such as product/process improvements or patents at the firm level. Under the Oslo manual, innovation is principally defined as whether the firm introduces a new product to market, a measure which is self-reported. In contrast, firms in the high-tech sector are defined based on whether their ISIC industry has a larger than average share of R&D, or higher shares of employment in STEM fields. See Cirera and Maloney (2017) for a more detailed discussion.

3 The Kauffman Firm Survey

Almost a half a million startup firms are launched annually in the United States. Yet, little comprehensive data exists that allow researchers to study firms at their most interesting stage: initial years from launch. Existing databases, such as Compustat and Amadeus, track mature, established firms and generally do not contain information beyond that obtained from publicly available financial statements. Some past surveys of startup firms in the US are Survey of Small Business Finances and Panel Study of Entrepreneurial Dynamics I and II.

To bridge the gap, the Ewing Marion Kaufman Foundation commissioned a longitudinal study of new businesses in the US, known as the Kauffman Firm Survey (KFS). The survey follows 4,928 firms that launched in 2004 annually until 2011. The survey questionnaire contains detailed information on the firm, including industry, physical location, employment, profits, intellectual property, business strategy, and financial capital, as well as information on business owners, including age, gender, race, ethnicity, education, previous industry experience, and previous start-up experience. The initial survey design called for 5,000 interviews, with a target of 3,000 interviews for high-technology businesses given particular interest in these firms among researchers. While data is collected on firm location, the small samples at the geographic level, such as by county, limit the ability to relate variation in local economic conditions to firm level outcomes.

The sampling frame for the panel of business startups was created using Dun & Bradstreets (D&B) database of business establishments that started in 2004 in the United States, which totaled roughly two hundred and fifty-thousand firms. D&B maintains a large commercial database of businesses compiled through various public and industry sources. Year of launch is defined as the first year the business began operations and took steps to incorporate itself; as a result, a firm's first year may not always entail sales or hiring employees.

In order to obtain a larger sample of startups in high-technology fields, the data was partitioned into strata according to industrial technology categories, based on a classification scheme developed by Hadlock, Heckler, and Gannon (1991). Table A.6 provides the final classifications of high and medium technology businesses, determined according to each industrys respective share of employment in research and development (R&D) using data from the BLS Occupational Employment Statistics program and based on three-digit level Standard Industry Classification (SIC) code. DesRoches, Barton, Ballou, Potter, Zhao, Santos, and Sebastian (2007) provide additional details.

The US Census Bureau and Bureau of Labor Statistics maintain large confidential micro databases of business establishments, which also contain data on young, new firms. The Census Bureaus Longitudinal Business Database (LBD) is a longitudinal database covering all employer establishments and firms in the US non-farm private economy while the BLSs Business Employment Dynamics (BED) data are compiled from records from a federal-state cooperative program known as Quarterly Census of Employment and Wages (QCEW). The QCEW is based on quarterly unemployment insurance (UI) reports (and taxes) required to be sent by businesses. The QCEW is also the employment benchmark for several BLS products such as Job Openings and Labor Turnover Survey (JOLTS). Importantly, a major exclusion of UI coverage are self-employed workers. It follows that BED does not contain information on establishments with zero employment. In both LBD and BED, an establishment is defined as an economic unit that produces goods or services, usually at a single physical location, and engages predominantly in one activity. A firm is a legal business, and may consist of multiple establishments. Firm-level data can be compiled by aggregating establishments under common ownership using employer tax identification numbers.

Figure 1 displays the number of new establishments born as well as jobs created by establishments less than 1 year old annually since 1994. Figure 3 compares survival rates between establishments in the BED with firms in the KFS. Survival rates for cohorts of new business establishments are displayed by year of birth. While some of these new establishments may not coincide with new firms, the survival rates track fairly closely the survival rates for the firms launched in 2004 in the KFS. To improve the comparison, the survival rates for KFS firms are conditioned on firms with positive employment in the startup year. Unlike the KFS, there are no sampling error issues with the BED data. Whereas shutdown for BED is defined as establishments that revert to no employment for four consecutive quarters, firms in the KFS are deemed to shutdown based on direct reporting to the annual followup survey.

Figure 2 plots the number of employees across the entire cohort of startup firms in our sample over time separately for all firms and surviving firms only. The number of total employees climbs rapidly in 2005 but begins to fall in 2006 as firms exit. In contrast, the total number of employees across surviving firms exhibits a more steady, gradual increase over time.

3.1 Overview of Firms in KFS

A challenge of empirical studies of entrepreneurship is distinguishing between types of entrepreneurs. Using data from the Statistics of the U.S. Business (SUSB) compiled by the U.S. Census Bureau, Hurst and Pugsley (2011) finds that most small businesses have little intention to grow or innovate. An advantage of the KFS is its oversampling of high-technology firms, which also are likely to be high-growth innovative firms, in contrast to typical startups that eventually fall in the small business category. According to Table A.7, entrepreneurs in technology industries are more likely to have higher levels of human capital, to invest in R&D and to introduce a new product to market. Interestingly, however, on average they tend to start up at a smaller size, as measured by total assets.

Table A.2 provides a count of firm exit by year throughout the time period of study. By 2011 over half of the firms in the initial baseline year report shutting down their business, which is consistent with empirical estimates on new firm survival. Table A.3 breaks down the number of firms by two-digit industry according to the NAICS classification. Professional services, manufacturing and the retail sector make up the three largest industries.

3.2 Financing Decisions

The standard life-cycle theory of small firm finance assumes that young startups initially rely on informal channels of credit followed by increasingly formal sources as the firm establishes its business history. Robb and Robinson (2014) finds that the sample of startup firms in the KFS display a heavy reliance on formal debt financing, in line with the notion that startups also seek financing where capital is more readily available, Cosh, Cumming, and Hughes (2009). Similarly, we investigate firms financial decisions based on both the type (debt vs. equity) and source (informal vs. formal). Capital can be provided by the business owner, an insider (family, friend), or an outside (formal lending institution or venture capital, angel financing).

While we focus on the source of finance, an important distinction raised by Robb and Robinson (2014) is the role of risk-bearing vs. liquidity. For instance, a business loan might be obtained via the founder pledging personal assets in the form of collateral, and as a result, the loan serves as an equity-like instrument for the founder. Personal bank loans obtained by the owner are classified as outside debt. Table A.1 provides an overview of the mean levels of initial financing by type. We observe that the two main sources of financing are owner equity and outside debt. While roughly 40% of firms report some level of outside debt, the average amount is considerably larger than that reported by owner equity. In other words, outside debt is important for firms which obtain it. Owner debt plays a role for some firms but the average reported amount is small. A handful of firms do report receiving large sums of financing via outside equity. Overall, we observe that outside financing is more reliant on debt, while inside financing is composed mostly of equity.

As a potential mechanism to understand firm exit, Table A.5 provides the evolution of average firm capital injections over time for the three most popular sources of finance. Initially in 2005 and 2006, the average amount of new capital obtained is similar between firms that survive and those that eventually fail. However, beginning in 2007, the average capital injections for exiting firms begins to drastically decrease, suggesting a precursor to firm exit is the inability to raise funds.

3.3 Firm-level innovation activities

In addition to sector level differences between firms in terms of intensity of technological inputs, the survey introduced questions beginning in calendar year 2009, or in the sixth wave of data collection, that asked firms about their innovation activities; namely, whether the firm introduced any new or significantly improved product or service and whether the innovation was new to the firm or new to the market (regional/national). From the later, we obtain a measure of novelty that distinguishes from imitation. Conditional on surviving firms, Table 1 provides a breakdown of reported firm-level innovation in the year it occurs by sector technological intensity. Further, it reports shares of firms that engage in R&D.

We observe overall large rates in innovation, patenting and R&D for firms in the medium and high tech sectors. Most innovation activity occurred in 2009, potentially due to censoring as this was also the first year the question was introduced in the survey. Our initial prior is that firms launching product innovations sooner are more likely to display positive effects on growth measures. Further, not all firms introduce innovations, even in the medium or high tech sector, and not all product innovations are potentially driven by R&D. Similarly, some firms invest in R&D but have yet to introduce any product innovation. In summary, Table 1 provides summary statistics of our set of innovation measures that form part of our treatment effects approach in the next section.

4 Empirical Methodology & Hypotheses

As described in the previous section, the Kauffman Firm survey tracks a cohort of startup firms that launch in 2004 until 2011. We first study firm-level survival prospects over the period using a workhorse duration model. Second, we estimate a series of growth regressions that condition on the sample of surviving firms up to 2011; including the predicted survival rates as an explanatory variable. Our growth measures capture performance of the firm over an eight year time span which includes the Great Recession of 2008-2009.

4.1 Survival

Duration models are used extensively in the literature to estimate the hazard rate, or instantaneous probability of exit, for firms. Unlike logit models, they can account for right-censoring which can be important when observing firms for shorter time periods. See Cameron and Trivedi (2005) for a more complete discussion. The workhorse duration model is the semi-parametric (Cox) proportional hazards model, defined as:

$$h(t) = h_0(t)\phi(X, \beta) \tag{1}$$

where $h_0(t)$ is called the baseline hazard and is a function of t only with all covariates set to zero. $h(t)$ represents the rate of failure at time t given that a firm survived in $t-1$. $\phi(X, \beta)$ can be interpreted as a scaling factor, and does not depend on t, typically specified in exponential form $exp()$ (Alternatively, accelerated failure time models allow the covariates to affect the hazard multiplicatively). The advantage of this approach is that the parameters β can be estimated, or identified, without explicitly modeling the functional form of the baseline hazard (via partial likelihood). An important assumption in Cox models is the proportionality assumption, that is the effect from a covariate on the baseline hazard must be proportional over time, or in other words invariant. When the PH test fails, the suggested approach is to include the variable that failed the PH test as well as an interaction term with a time variable in a new regression.

We do not include time-varying firm specific covariates to avoid any feedback or endogeneity issues with respect to survival and as a result, the firm-level covariates are based on a firm's initial conditions. However, we include a time-period dummy variable to capture the role of the Great Recession on firms' hazard rates. The crisis dummy is constructed to take the value of 1 in years 2007-2009 and the value 0 otherwise. We interact this variable with the firms's initial financial conditions, its outside debt ratio and startup capital level.

Our empirical approach is not immune from potential omitted variable bias, or unobserved heterogeneity. The role of the entrepreneur in firm performance is typically void in economic studies given the difficulty in observing measures of ability and talent. As a result, even a model with a comprehensive set of observables may fail to fully explain the variability in the data. One way to address the issue of unobserved firm-specific attributes is to employ (shared) frailty models, which allow for the presence of a latent multiplicative effect on the hazard function. While firm specific factors are important in duration models, unobserved heterogeneity can lead to misrepresentation of the overall firm hazard rate. When thinking about the role of the entrepreneur, observing information that captures ability and talent is typically sparse. Hurst and Pugsley (2011) find that many small business owners, including a share of young startups, do not have ambitions of growing their business or innovating.

The explanatory variables included in our specification control for firm-specific characteristics as well as local factors, according to the available data and informed by theory. Business characteristics (industry dummies, business location, legal status), founders demographics (education, gender) and initial financing conditions, such as startup capital (total debt + equity), and leverage (measured as the ratio of outside debt to total debt and equity). We use number of employees as well as startup capital to proxy for initial firm size. While the cohort of firms in our study all begin with the same, we include the founders number of years of work experience. Work experience has been found in the literature to play an important role in explaining unobserved factors in firm performance. An entrepreneur with more work experience might possess greater knowledge or be better able to evaluate a potential business opportunity. Furthermore, work experience might also correlate with the founders net worth, and ability to raise external finance.

4.2 Growth

In the previous section we study survival prospects of our cohort of startup firms over the 2004-2012 period conditional on initial conditions and degree of firm level innovation measured by sector R&D intensity. In this section, we condition our sample to firms that survive until 2011 and evaluate their performance from year of birth using a series of reduced form OLS or binary outcome regressions. In these set of estimates, we are able to exploit additional survey questions that were added to the survey beginning in 2009 related to firm innovation activities for each calendar year; outlined in Table 1. Specifically, these questions ask the firm whether they introduced any new and improved product or service and its degree of novelty, such as whether it is new to the firm or a regional market. As a result, we investigate the extent to which innovation outputs positively affects the growth of the firm beyond measures such as R&D and the firm's technology sector. Because the firm reports introducing product innovations beginning in 2009, roughly midway through its observed lifespan, our model setup could be viewed as applying a diff-in-diff framework where the dependent variable is measured in terms of a growth rate pre and post intervention; see Ci, Galdo, Voia, and Worswick (2015). Our measures of firm growth are in terms of final year observations relative to startup year for revenues, number of full-time employees as well as whether the firm experiences positive employment growth.

In these growth regressions, our set of predictors are time-invariant features of the firm and characteristics of the founder as well as initial financing and size conditions. Our treatment variable, whether the firm introduces a product innovation during its early years, is potentially endogenous. Startup firms that innovate in their early years may launch with more resources or unobserved factors that drive a firm to innovate would also affect performance simultaneously. While panel data models would alleviate some of the endogeneity by differencing out omitted factors, our limited time frame and because the impact from time of innovation could span multiple years limit their appeal. Further, the available set of time varying predictors are largely limited to the evolution of firm financing which are also endogenous. To provide some indication of whether selection may be occurring, we estimate a set of regressions that evaluate whether innovative firms are larger or obtain greater levels of initial financing at year of birth. To test the parallel trends assumption, we employ the same set of growth regressions using growth rates derived from the pre-intervention period (2004-2008).

While we lack a quasi-experimental setting to truly ascertain a causal impact from innovation, our estimates can be interpreted as a reduced form overall average impact after accounting for other available factors and conditional on survival. The contribution from our findings stems from providing evidence on firm performance using information on firm-related innovation activities that are largely unavailable in other data sources.

5 Results

5.1 Innovation and Survival

Column 1 of Table 1 presents the results from our benchmark model. A coefficient of can be interpreted as raising or lowering the hazard by a factor of $1 + \delta$. Figure 4 evaluates the fit of our benchmark model relative to the empirical hazard. Overall, the estimated hazard tracks the empirical hazard closely, and we find that the semi-parametric Cox does a better job than a less flexible parametric model. However, we are less able to fit the data for 2011 due to censoring. The baseline hazard provides the results of the model assuming all coefficients are set to zero, which can be interpreted as accounting for the overall risk of firm exit not due to any firm-specific factor. Overall, the explanatory variables have expected signs. Work experience, initial labor productivity, and credit riskiness of the firm are all significant at the one percent level. A percent increase in labor productivity translates to roughly an 8 percent decrease in the firm hazard rate.

The effects from initial financial conditions are less obvious. A higher initial outside debt ratio appears to lower the firm hazard rate, but is not statistically significant. The results indicate some evidence that firms that startup with greater levels of financial capital have an increasing risk of failure. However, when we interact these variables with the Crisis dummy, a clearer picture emerges of what is driving the results from the benchmark model. The effects of the financial variables are exacerbated when interacted with the economic crisis, and play a lesser role pre and post crisis. A higher level of the outside debt ratio lowers the firms hazard rate during normal times, but negative affects the hazard rate during the economic crisis. The estimated coefficient switches from -0.320 to 0.566 in column 2. For startup capital, the effects are intensified when interacted with the economic crisis, but otherwise display muted effects not significantly different than zero. For example, the effect on firms with startup capital in excess of $100,000 switches from -0.078 to 0.593 in column 3. The results are consistent in the model which includes the full set of interactions, in column 4.

The finding that firms with greater levels of initial startup capital were more adversely affected during the Great Recession might be surprising or counter-intuitive at first glance but is in line with findings from the literature. In a study of banking crises and industry financial dependence, Kroszner, Laeven, and Klingebiel (2007) find that financially dependent firms grow faster in normal times but are hit harder in crisis times. The Great Recession proved to be an especially turbulent and uncertain time, and business plans that otherwise seemed a priori reasonable may have turned out to be unrealistic in light of the shock to the economy and financial system. In contrast, firms that raised smaller levels of initial financing were more likely to grow in stages and raise additional capital as their economic prospects improved, without overextending their business at the same time.

5.2 Innovation and Growth

In this section, we present results from a set of regressions that evaluate the link between firm innovation and the resulting effects on firm performance over the time period 2004-2008. Performance over the observed time period is measured in terms of growth in log revenues, the number of full-time employees and whether the firm displays positive employment growth. Because many firms launch with no revenue or employment in the first year, we use the first year where such measures become positive and adjust the growth rate based on the number of years to 2011. Our estimation sample comprises roughly 2,000 firm that survive until 2011; innovation activities, our set of treatment variables, are reported in calendar years 2009 to 2011. We use a similar set of controls based on initial conditions of the firm and its principal founder, including state and industry effects. Regressions are implemented using appropriate survey weights.

Table 3 presents our set of growth regressions for sales and employment (where we model employment in terms of change in levels and whether growth is positive). Our set of innovation predictors include R&D and patent activities, whether the firm is in the high-tech sector, and whether it reports introducing a new product to market in each year of 2009 to 2011. Further, we classify product innovation according to three types: overall product innovation (new to the firm or regional market), product innovation that is new to the market, and product innovation that coincides with R&D. In this way, we attempt to isolate differential effects according to the degree of novelty.

Overall, we do not find any effect from R&D while patents display a negative effect for employment growth. Firms in the high and medium tech sector display strong positive employment effects in terms of hiring new workers. In terms of our product innovation measures, the evidence is mixed but in general we find positive statistical effects for some measures depending on year. When conditioning on degree of novelty, we tend to see larger effects in terms of coefficient magnitude. An empirical challenge lies in the nature of innovation and the time lag to impact from introducing a new product to market; fewer firms are introducing innovations later in their lifecycle such as in 2010 and 2011 which creates a censoring problem as we only observe firm performance up until 2011.

Overall, we observe that the R^2 is around 0.1 for the revenue growth regressions indicating that our set of controls only explain some of the variation. Previous startup experience has some marginally statistical effect but years of work experience has no effect or possibly negative. Years of experience correlates with founder age and the literature finds that successful startups are sometimes launched by younger entrepreneurs as well as older ones with greater experience depending on the industry and context; pointing to the overall difficulty of any predictor in having direct effects that hold on average. Among the financial variables, firms in the highest category of initial startup capital display statistically positive effects for all our growth measures. Initial outside debt ratio has a statistically negative effect on change in the number of employees. We also include initial levels of employment which tend to be positively correlated with employment growth suggesting the role of persistence with initial startup size; however, we do not find an effect on revenue growth.

Table 4 reports estimates on the parallel trends assumption; using growth over the pre-intervention period of 2004-2008. In other words, we assess to what extent firms that are introducing new products reported in 2009 to 2011 are displaying higher growth rates a priori. Further, given that these set of innovation survey questions were introduced in 2009, it is possible that reported innovations may have in fact occurred sooner. Partially confirming this intuition, we find statistically positive effects for some measures of product innovation by year when growth is considered as a binary measure of employment growth; and little effect otherwise. Growth measures during the pre-intervention period are also highly affected by the Great Recession; we observe that firms in the highest levels of initial financing display more modest effects than when compared to the entire period as found in Table 3.

Table 5 further evaluates whether firms that eventually engage in product innovation in their early years start off larger or obtaining greater levels of initial financing. We find only weak evidence that these firms have more employees at startup (coefficient magnitude of 0.393) and no evidence for initial revenues. We find a statistical effect at the five percent level, however, for initial levels of financing (log 0.3) which points to a potential channel whereby innovation interacts with financing; innovative firms are more likely to obtain outside financing which feeds into firm performance measured by size (labor and sales). In contrast, we find strong statistical negative effects for firms in the medium or high tech sector on initial levels of financing.

To investigate further the potential mechanism from the role of finance, Table 6 relates the level of total outside debt financing the firm receives over its lifespan post year of entry to its initial conditions and whether the firm innovates in subsequent years. Here we find statistical effects at the one percent level for firms that report innovation in 2009 [log 1.13]; however the magnitude of the effect is lowered when conditioning on novelty possibly pointing to the riskiness embedded in innovation. With respect to other effects, there is some persistence in terms of firms that obtain higher initial levels of financing receive greater injections of outside debt in subsequent year. We observe that patents exhibit a marginally negative effect possibly in line with the literature that finds highly skewed patent valuations.

6 Conclusion

[to be updated]

Conventional wisdom holds that young, startup firms face poor survival prospects; let alone the prospect for growth and contributing to broader economic gains. We use a longitudinal representative panel of small US start-up firms for the period 2004-2011 to investigate how a firms initial conditions affect survival in normal times and crisis times. We find that initial financing conditions play a heightened role during crisis times. Specifically, firms with higher reliance on formal debt financing are more at risk of failure during the financial crisis, controlling for other factors. As a result, we provide empirical evidence of liquidity and credit shocks affects firm survival and performance, and that a potential policy intervention may have mitigated some exit of efficient firms.

As a by-product of our empirical estimates, we also highlight the importance of firm heterogeneity, in particular between firms in the high-tech sector vs. traditional businesses. The fact that the empirical hazard rate for high-tech firms quickly reaches its peak suggests that these later firms more quickly learn about their demand and survival prospects, as predicted by the theoretical literature.

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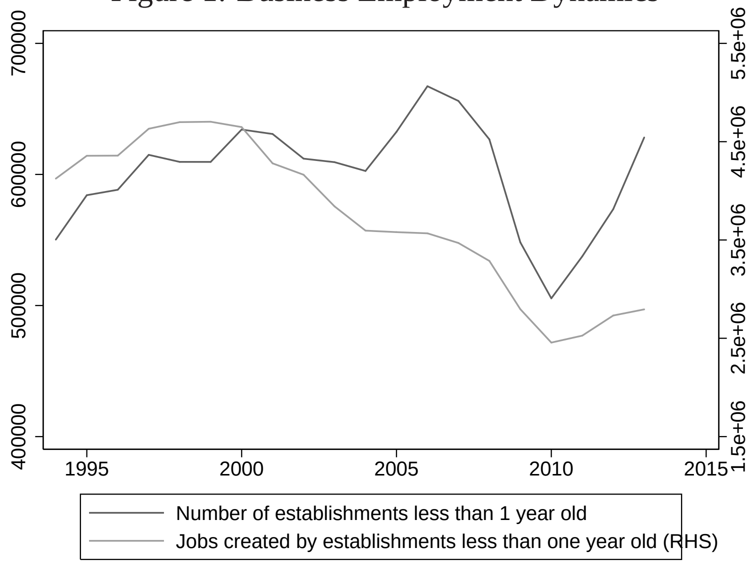
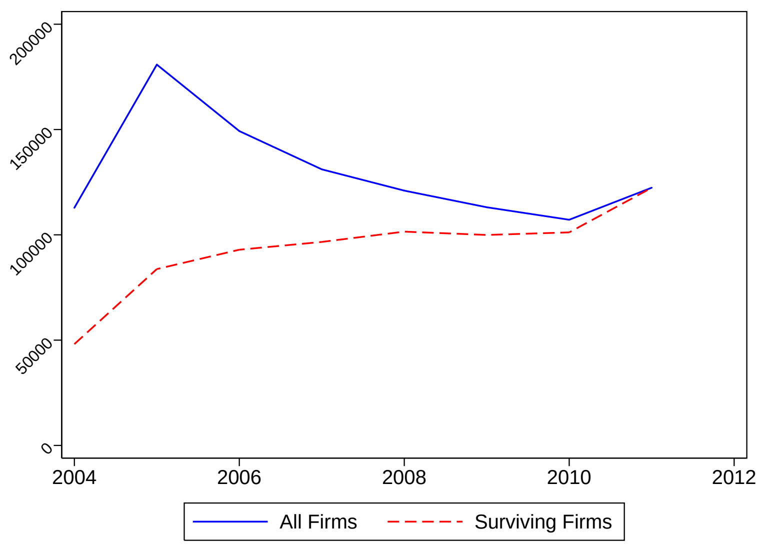
Figure 1: Business Employment Dynamics



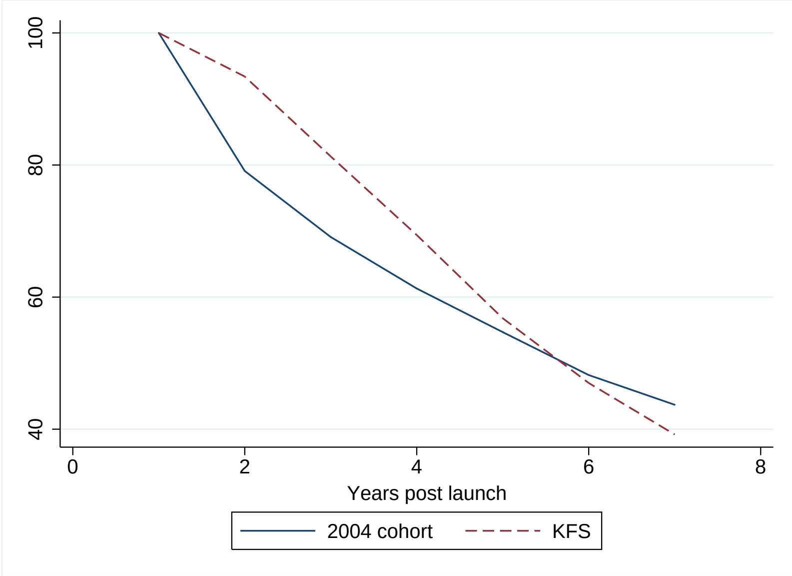
Source: Bureau of Labor Statistics Business Employment Dynamics (BED)

Figure 2: Total Stock of Employees from Entering 2004 Cohort of Startup Firms



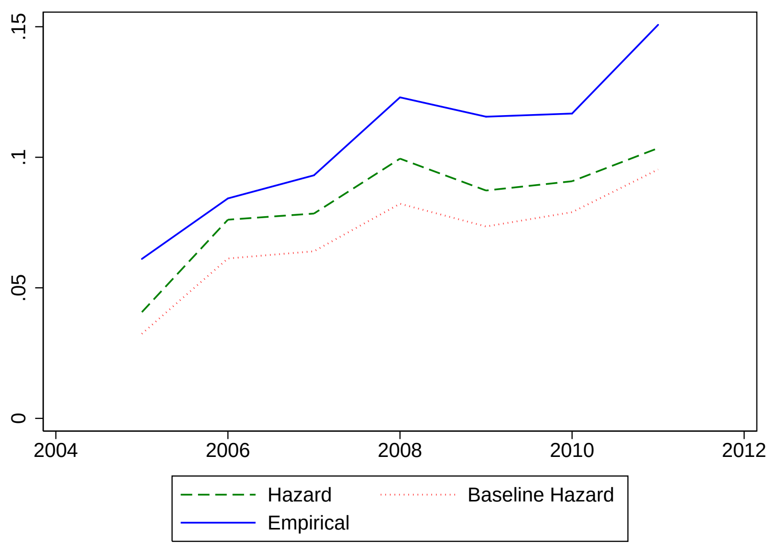
Note: Based on weighted count of 62,452 startup firms in Kauffman Firm Survey.

Figure 3: Survival Rates of Establishments and Firms in KFS



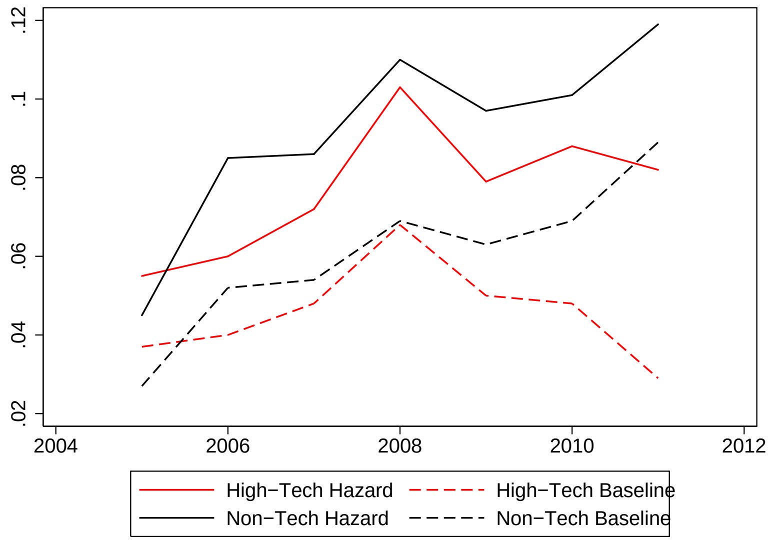
Note: Year of birth for new establishments in BED defined by positive employment for the first time in the database, while failure is defined by no employment in four consecutive quarters. Employment changes are measured from the third month of the previous quarter to the third month of the current quarter.

Figure 4: Hazards



Note: Baseline and hazard rates based on benchmark model. Empirical hazard based on raw data count.

Figure 5: Hazards: High-Tech vs. Non-Tech



Note: Baseline and hazard rates based on benchmark model. Empirical hazard based on raw data count.

Table 1: Innovation rates

	High Tech	All Other
Product innovation - New to the firm		
2009	22.7	17.2
2010	9.9	8.8
2011	7.8	6.4
Cumulative	40.4	32.4
Product innovation - New to the market		
2009	12.7	11.0
2010	5.4	3.6
2011	3.5	3.0
Cumulative	21.6	17.6
Product innovation - backed by R&D		
2009	11.5	7.3
2010	3.6	1.8
2011	2.6	1.6
Cumulative	17.7	10.7
Patents in First year	5.90	2.00
Performs R&D	25.7	17.3

Note: Based on conditional sample of 2,007 surviving firms in Kauffman Firm Survey. All numbers are sample weighted and in percentage terms.

Table 2: New Firm Survival

	1	2	3	4
Outside Debt Ratio	-0.112	-0.320***	-0.111	-0.291**
	0.1	0.12	0.1	0.12
Outside Debt Ratio x Crisis		0.566***		0.489***
		0.18		0.19
5,000 $<$ Startup Capital $\leq$ 10,000	0.176*	0.179*	-0.045	-0.04
	0.11	0.11	0.13	0.13
10,000 $<$ Startup Capital $\leq$ 25,000	0.145	0.147	0.055	0.066
	0.09	0.09	0.11	0.11
25,000 $<$ Startup Capital $\leq$ 100,000	0.231**	0.234**	0.092	0.12
	0.1	0.1	0.11	0.11
Startup Capital $>$ 100,000	0.108	0.112	-0.078	-0.018
	0.11	0.11	0.13	0.13
5,000 $<$ Startup Capital $\leq$ 10,000 $\times$ Crisis			0.680***	0.671***
			0.22	0.22
10,000 $<$ Startup Capital $\leq$ 25,000 $\times$ Crisis			0.319	0.292
			0.2	0.2
25,000 $<$ Startup Capital $\leq$ 100,000 $\times$ Crisis			0.466**	0.388**
			0.19	0.19
Startup Capital $>$ 100,000 $\times$ Crisis			0.593***	0.429**
			0.19	0.2
High Credit Risk	0.488***	0.488***	0.488***	0.488***
	0.1	0.1	0.1	0.1
Work Experience	-0.103***	-0.103***	-0.103***	-0.103***
	0.02	0.02	0.02	0.02
High Tech	-0.068	0.067	0.066	0.066
	0.08	0.08	0.08	0.08
0 $<$ Employees $\leq$ 5	-0.081	-0.081	-0.081	-0.081
	0.06	0.06	0.06	0.06
5 $<$ Employees $\leq$ 10	-0.188*	-0.189*	-0.190*	-0.190*
	0.11	0.11	0.11	0.11
Employees $>$ 10	-0.272**	-0.270**	-0.270**	-0.270**
	0.13	0.13	0.13	0.13
Labor Productivity	-0.081***	-0.082***	-0.081***	-0.081***
	0.02	0.02	0.02	0.02
N	3,525	3,525	3,525	3,525
Log-likelihood	-12350	-12345	-12342	-12339

Note: Cox regression results are reported. The dependent variable is a dummy equal to one if the firm fails, and zero otherwise. *, **, *** denotes statistical significance at the 10, 5 and 1 % levels respectively.

Table 3: Growth: 2004-2011

	Revenue			Employee Growth (probit)			Change in # FT Employees		
logownerworkexp	-0.131*	-0.126*	-0.113*	-0.020	-0.019	-0.022	-0.040	-0.036	-0.067
	0.07	0.07	0.07	0.02	0.02	0.02	0.13	0.14	0.13
$0 < \text{Empl} \leq 5$	-0.100	-0.104	-0.083	0.104***	0.104***	0.102***	0.505**	0.486**	0.468*
	0.16	0.16	0.16	0.04	0.04	0.04	0.25	0.25	0.25
$5 < \text{Empl} \leq 10$	-0.360	-0.368	-0.317	0.255***	0.251***	0.246***	1.664***	1.618***	1.562***
	0.24	0.24	0.24	0.06	0.06	0.06	0.51	0.51	0.51
$\text{Empl} > 10$	0.215	0.216	0.275	0.206***	0.206***	0.206***	5.787***	5.779***	5.737***
	0.30	0.30	0.31	0.07	0.07	0.07	0.94	0.93	0.93
Outside debt ratio	-0.056	-0.041	-0.038	-0.069	-0.067	-0.063	-1.280***	-1.298***	-1.322***
	0.19	0.19	0.19	0.05	0.05	0.05	0.46	0.46	0.46
$5K < SC \leq 10K$	-0.111	-0.110	-0.147	0.020	0.021	0.020	-0.207	-0.255	-0.205
	0.22	0.23	0.23	0.06	0.06	0.06	0.39	0.38	0.39
$10K < SC \leq 25K$	0.207	0.209	0.227	0.141***	0.144***	0.151***	0.288	0.310	0.376
	0.17	0.17	0.17	0.04	0.04	0.04	0.28	0.28	0.28
$25K < SC \leq 100K$	0.064	0.055	0.062	0.129***	0.131***	0.139***	0.181	0.180	0.245
	0.19	0.19	0.19	0.05	0.05	0.05	0.41	0.42	0.41
$SC > 100K$	0.494**	0.486**	0.515**	0.114**	0.114**	0.117**	0.991**	0.972**	0.994**
	0.21	0.21	0.21	0.05	0.05	0.05	0.48	0.49	0.50
high credit	0.594	0.633	0.541	0.117	0.126	0.125	-0.996	-0.942	-0.863
	0.41	0.40	0.42	0.09	0.09	0.09	0.66	0.66	0.65
High medium tech	0.059	0.060	0.073	0.003	0.006	0.004	0.805***	0.816***	0.805***
	0.14	0.14	0.14	0.03	0.04	0.04	0.29	0.28	0.29
Has patent	-0.022	0.004	0.057	-0.267***	-0.265***	-0.285***	-1.419	-1.392	-1.628*
	0.34	0.32	0.34	0.09	0.09	0.09	0.97	0.99	0.90
R&D	-0.239	-0.206	0.047	-0.026	-0.026	-0.123	1.036	0.993	0.245
	0.38	0.39	0.42	0.10	0.10	0.11	0.85	0.83	0.93
innov 2009	0.259			0.093**			0.347		
	0.16			0.04			0.32		
innov 2010	0.563***			0.112**			1.061**		
	0.21			0.05			0.52		
innov 2011	0.255			0.014			0.211		
	0.26			0.06			0.54		
novelty 2009		0.248			0.118***			0.744*	
		0.18			0.04			0.40	
novelty 2010		0.672**			0.107			0.588	
		0.30			0.07			0.63	
novelty 2011		0.254			-0.030			0.151	
		0.48			0.08			0.90	
innov2009rd			-0.104			0.200***			0.917
			0.34			0.07			0.65
innov2010rd			-0.326			0.195**			1.783
			0.43			0.09			1.09
innov2011rd			-0.174			0.118			1.992*
			0.52			0.11			1.11
N	1749	1749	1749	1916	1916	1916	1916	1916	1916
R2	0.1	0.1	0.1						

Note: Columns 1-3 report OLS estimates where the dependent variable is log revenue growth.. Columns 4-6 report probit marginal effects where the dependent variable is whether the firm displays positive employment growth. Columns 7-9 report negative binomial regression estimates where the dependent variable is change in number of full-time employees (re-scaled). All growth measures are based on 2011 numbers relative to 2004. *, **, *** denotes statistical significance at the 10, 5 and 1 % levels respectively.

Table 4: Growth Parallel Trend (pre-intervention): 2004-2008

	Revenue			Employee Growth (probit)			Change in # FT Employees		
logownerworkexp	-0.105*	-0.106*	-0.097*	-0.001	0.002	-0.005	0.185	0.187	0.157
	0.06	0.06	0.06	0.02	0.02	0.02	0.13	0.14	0.14
$0 < \text{Empl} \leq 5$	0.098	0.096	0.116	0.191***	0.191***	0.186***	0.737***	0.731***	0.705***
	0.14	0.14	0.14	0.04	0.04	0.04	0.24	0.24	0.25
$5 < \text{Empl} \leq 10$	-0.159	-0.161	-0.116	0.312***	0.317***	0.306***	1.947***	1.957***	1.887***
	0.19	0.19	0.19	0.06	0.06	0.06	0.42	0.42	0.43
$\text{Empl} > 10$	0.213	0.190	0.259	0.319***	0.320***	0.316***	6.309***	6.294***	6.231***
	0.26	0.26	0.27	0.07	0.07	0.07	0.90	0.90	0.90
outside debt ratio	-0.163	-0.160	-0.154	-0.056	-0.049	-0.054	-1.202***	-1.207***	-1.241***
	0.18	0.18	0.18	0.06	0.05	0.05	0.40	0.39	0.39
$5K < SC \leq 10K$	-0.020	-0.004	-0.018	-0.010	-0.010	-0.001	-0.314	-0.319	-0.295
	0.19	0.19	0.19	0.06	0.06	0.05	0.33	0.33	0.33
$10K < SC \leq 25K$	0.168	0.163	0.171	0.099**	0.103**	0.113***	0.324	0.331	0.371
	0.16	0.16	0.16	0.04	0.04	0.04	0.26	0.26	0.26
$25K < SC \leq 100K$	-0.025	-0.024	-0.016	0.138***	0.141***	0.156***	0.349	0.358	0.409
	0.17	0.17	0.17	0.05	0.05	0.05	0.40	0.40	0.40
$SC > 100K$	0.298	0.297	0.311*	0.087*	0.089*	0.092*	1.011**	1.020**	0.981**
	0.18	0.18	0.18	0.05	0.05	0.05	0.45	0.45	0.45
high credit	0.246	0.253	0.207	-0.009	-0.014	0.011	-1.237**	-1.267**	-1.150*
	0.36	0.36	0.36	0.09	0.09	0.09	0.62	0.64	0.64
High medium tech	0.128	0.131	0.132	0.040	0.046	0.039	0.191	0.202	0.174
	0.12	0.12	0.12	0.03	0.03	0.03	0.27	0.26	0.26
Has patent	0.015	0.001	0.056	-0.308***	-0.310***	-0.338***	-0.235	-0.272	-0.438
	0.29	0.29	0.29	0.08	0.08	0.09	1.12	1.10	1.01
R&D	-0.183	-0.211	-0.034	0.067	0.082	-0.072	1.624**	1.598**	0.676
	0.32	0.32	0.36	0.10	0.11	0.11	0.76	0.76	0.95
innov2009	0.146			0.117***			-0.033		
	0.15			0.04			0.30		
innov2010	-0.111			0.059			-0.278		
	0.19			0.05			0.44		
innov2011	0.132			0.144***			0.315		
	0.17			0.06			0.52		
novelty2009		0.284*			0.145***			0.220	
		0.17			0.04			0.37	
novelty2010		0.190			0.071			-0.253	
		0.29			0.07			0.63	
novelty2011		0.248			0.183**			0.395	
		0.30			0.09			0.95	
innov2009rd			-0.038			0.247***			1.094*
			0.30			0.07			0.66
innov2010rd			-0.395			0.248***			1.050
			0.32			0.09			1.03
innov2011rd			-0.005			0.311***			2.864**
			0.46			0.11			1.12
N	1735	1735	1735	1916	1916	1916	1916	1916	1916
r2	0.1	0.1	0.1						

Note: Columns 1-3 report OLS estimates where the dependent variable is log revenue growth.. Columns 4-6 report probit marginal effects where the dependent variable is whether the firm displays positive employment growth. Columns 7-9 report negative binomial regression estimates where the dependent variable is change in number of full-time employees (re-scaled). All growth measures are based on 2011 numbers relative to 2004. *, **, *** denotes statistical significance at the 10, 5 and 1 % levels respectively.

Table 5: Selection

	Revenue			Employees			Finance		
logownerworkexp	0.244***	0.243***	0.243***	0.301***	0.303***	0.305***	-0.169***	-0.168***	-0.168**
	0.04	0.04	0.04	0.08	0.08	0.08	0.06	0.06	0.06
$0 < \text{Empl} \leq 5$	0.429***	0.431***	0.425***				0.531***	0.534***	0.540**
	0.10	0.10	0.10				0.16	0.16	0.16
$5 < \text{Empl} \leq 10$	1.125***	1.131***	1.116***				0.995***	0.999***	1.013**
	0.17	0.17	0.17				0.29	0.29	0.29
$\text{Empl} > 10$	1.733***	1.739***	1.722***				1.820***	1.831***	1.847**
	0.22	0.22	0.22				0.34	0.34	0.34
outside debt ratio	-0.056	-0.058	-0.054	0.595	0.604	0.590			
	0.15	0.15	0.15	0.41	0.42	0.42			
$5K < SC \leq 10K$	0.330*	0.329*	0.330*	-0.312*	-0.309*	-0.308*			
	0.18	0.18	0.18	0.18	0.18	0.18			
$10K < SC \leq 25K$	0.466***	0.466***	0.463***	-0.238*	-0.231*	-0.216			
	0.14	0.14	0.14	0.14	0.14	0.14			
$25K < SC \leq 100K$	0.976***	0.975***	0.973***	0.210	0.220	0.234			
	0.14	0.13	0.13	0.25	0.25	0.25			
$SC > 100K$	1.088***	1.088***	1.083***	2.099***	2.099***	2.143***			
	0.17	0.17	0.17	0.37	0.37	0.38			
high credit	-0.121	-0.123	-0.119	0.748**	0.764**	0.758**			
	0.24	0.24	0.24	0.34	0.34	0.34			
High medium tech	0.141	0.139	0.139	0.348	0.357	0.365	-0.478***	-0.471***	-0.471**
	0.11	0.11	0.11	0.24	0.24	0.25	0.17	0.17	0.17
Has patent	-1.074***	-1.071***	-1.089***	1.123	1.112	1.162	0.114	0.112	0.118
	0.35	0.35	0.35	0.71	0.71	0.71	0.50	0.50	0.50
R&D	0.021	0.030	-0.065	-0.181	-0.178	0.246	-0.091	-0.037	0.014
	0.13	0.13	0.21	0.36	0.37	0.66	0.20	0.20	0.30
innovall	-0.062			0.429*			0.319**		
	0.10			0.25			0.15		
noveltyall		-0.111			0.507			0.165	
		0.12			0.35			0.19	
innovallrd			0.105			-0.479			-0.013
			0.25			0.66			0.36
N	1784.000	1784.000	1784.000	1918.000	1918.000	1918.000	1991.000	1991.000	1991.00
r2	0.4	0.4	0.4	0.2	0.2	0.1	0.2	0.2	0.2

Note: OLS regression results are reported. Dependent variable in columns 1 and 2 is log revenue of the firm in the first year of operation; log number of employees in initial year in columns 3 and 4; log initial financing in columns 5 and 6. *, **, *** denotes statistical significance at the 10, 5 and 1 % levels respectively.

Table 6: Finance: Outside debt injections over 2005 to 2011

	M1	M2
logownerworkexp	-0.031	-0.019
	0.09	0.09
$5 < \text{Empl} \leq 10$	1.480***	1.512***
	0.43	0.42
$\text{Empl} > 10$	1.848***	1.910***
	0.53	0.53
outsidedebtratio	2.686***	2.692***
	0.37	0.37
$5K < SC \leq 10K$	0.652	0.703*
	0.42	0.42
$10K < SC \leq 25K$	1.649***	1.735***
	0.34	0.34
$25K < SC \leq 100K$	2.190***	2.305***
	0.35	0.35
$SC > 100K$	2.732***	2.820***
	0.42	0.42
highcredit	1.575***	-1.526***
	0.53	0.53
High medium tech	-0.03	0.023
	0.28	0.28
$0 < \text{Empl} \leq 5$	0.579**	0.593**
	0.25	0.25
Has patent	-1.394*	-1.319*
	0.76	0.75
innov 2009	1.131***	
	0.26	
innov 2010	0.304	
	0.41	
innov 2011	0.808**	
	0.4	
novelty 2009	0.896***	
		0.32
novelty 2010	-0.599	
		0.56
novelty2011	-0.181	
		0.6
N	1937	1937
r2	0.3	0.3

Note: OLS regression results are reported. The dependent variable is log total debt injections of the firm over the period 2005 to 2011. *, **, *** denotes statistical significance at the 10, 5 and 1 % levels respectively.

A Appendix

Table A.1: Sources of Financing for 2004 startups

	All Firms	Mean if >0	Count	Survive	Fail
Owner Equity	29,188	38,951	3789	25,898	26,819
Owner Debt	2,592	10,441	1473	2,400	2,690
Inside Equity	579	43,865	215	264	698
Inside Debt	2,512	43,179	545	2,452	1,993
Outside Equity	3,655	550,496	267	2,725	3,576
Outside Debt	33,416	120,406	1814	39,299	28,352
Total Capital	91,646	105,887	4340	91,226	87,617

Note: Based on sample of 4,216 firms in Kauffman Firm Survey. Numbers displayed are in average dollar terms.

Table A.2: Firm Exits

	Unweighted		Weighted	
	Survive	Fail	Survive	Fail
2005		301		4653
2006		366		5979
2007		343		5330
2008		383		5752
2009		293		4443
2010		249		3807
2011	2007	274	28109	4379
Total	2007	2209	28109	34343

Note: Based on 4,216 firms in baseline year in Kauffman Firm Survey.

Table A.3: Composition of Startup Firms by Industry

		Startup Year		Survive Until 2011	
Industry	NAICS	Unweighted	Weighted	Unweighted	Weighted
Construction	23	308	6503	134	2817
Manufacturing	31, 32, 33	589	3734	304	1758
Wholesale Trade	42	186	3426	85	1531
Retail	44, 45	465	9332	165	3263
Transportation, Warehousing	48,49	96	1804	41	761
Information	51	142	1967	66	844
Finance, Insurance	52	164	3376	69	1411
Real Estate, Rental, Leasing	53	159	3310	84	1720
Professional Services	54,55,61	1091	10943	590	5894
Waste Management, Remediation	56	306	6080	141	2820
Health Care, Social Assistance	62	95	1937	41	798
Arts, Entertainment, Recreation	71	92	1536	47	724
Accomodation, Food Services	72	88	1740	31	590
Other Services	81, 11, 21 22, 92	435	6766	209	3178
Total		4216	62452	2007	28109

Note: Based on 4,216 firms in baseline year in Kauffman Firm Survey.

Table A.4: Statistics by All, Surviving and Exiting Firms

Panel A: All Firms

	Mean	Median	Sd	25th perc	75th perc	n
Outside Debt Ratio	0.20	0.32	0.33	0.00	0.34	4043
Credit Risk	3.21	3.13	0.72	2.75	3.67	4204
Productivity	9.74	9.92	1.86	8.65	11.04	2620
Employees	1.93	1.00	5.16	0.00	2.00	4216
Startup Capital	9.18	9.90	3.67	8.29	11.41	4216

Panel B: Surviving Firms

	Mean	Median	Sd	25th perc	75th perc	n
Outside Debt Ratio	0.21	0.00	0.33	0.00	0.39	1929
Credit Risk	3.03	3.00	0.70	2.63	3.50	2005
Productivity	9.89	10.09	1.84	8.90	11.13	1301
Employees	1.85	1.00	4.38	0.00	2.00	2007
Startup Capital	9.15	9.90	3.77	8.29	11.51	2007

Panel C: Exiting Firms

	Mean	Median	Sd	25th perc	75th perc	n
Outside Debt Ratio	0.19	0.00	0.31	0.00	0.33	2114
Credit Risk	3.36	3.29	0.70	3.00	3.80	2199
Productivity	9.61	9.90	1.87	8.52	11.00	1319
Employees	2.00	1.00	5.69	0.00	2.00	2209
Startup Capital	9.20	9.90	3.60	8.29	11.34	2209

Note: Outside debt ratio is measured as initial outside debt to total startup financing. Credit risk ranges from 1 to 5 where 5 implies the firm is high risk. Productivity is the log of the firm's total initial wage bill to total revenue in the first year. Startup capital is the log of total financing obtained in dollars.

Table A.5: Capital Injections: Surviving vs Exiting Firms

		All Firms	Mean if > 0	Count	Survive	Fail
2005	Owner Equity	10,157	29,358	1878	9,912	9,337
	Owner Debt	2,310	11,899	933	2,096	2,679
	Outside Debt	22,503	83,239	1318	23,733	21,602
2006	Owner Equity	5,584	25,562	1283	6,720	3,909
	Owner Debt	1,926	11,953	812	2,067	1,837
	Outside Debt	25,063	81,709	1330	25,283	19,948
2007	Owner Equity	3,587	24,766	941	4,970	1,639
	Owner Debt	1,513	13,547	631	2,106	1,138
	Outside Debt	20,383	82,280	1194	23,647	12,037
2008	Owner Equity	3,056	27,700	770	5,321	866
	Owner Debt	1,420	14,212	575	2,333	636
	Outside Debt	19,015	95,296	1077	27,105	6,155
2009	Owner Equity	1,902	27,458	590	4,175	271
	Owner Debt	1,082	13,453	505	1,868	143
	Outside Debt	14,733	94,466	932	25,904	2,067
2010	Owner Equity	1,418	22,021	491	3,073	10
	Owner Debt	750	14,781	386	1,542	4
	Outside Debt	9,845	99,554	756	22,081	207

Note: Based on sample of 4,216 firms in Kauffman Firm Survey. Numbers displayed are in average dollar terms.

Table A.6: Technology Sampling Strata Definitions

Technology Sampling Stratum	SIC Code	Industry
High	28	Chemicals and allied products
	35	Industrial machinery and equipment
	36	Electrical and electronic equipment
	38	Instruments and related products
Medium	131	Crude petroleum and natural gas operations
	211	Cigarettes
	229	Miscellaneous textile goods
	261	Pulp mills
	267	Miscellaneous converted paper products
	291	Petroleum refining
	299	Miscellaneous petroleum and coal products
	335	Nonferrous rolling and drawing
	348	Ordnance and accessories, not elsewhere classified
	371	Motor vehicles and equipment
	372	Aircraft and parts
	376	Guided missiles, space vehicles, parts
	379	Miscellaneous transportation equipment
	737	Computer and data processing services
	871	Engineering and architectural services
	873	Research and testing services
	874	Management and public relations
	899	Services, not elsewhere classified
None		All other

Source: KFS Baseline Methodology Report.

Table A.7: High Tech vs low tech

	Non-Tech	Medium, High-Tech
Bachelor	0.24	0.28
Graduate	0.20	0.37
Years Work Experience	10.1	13.9
Startup FT Employees	2.95	3.30
Revenue > 0	0.64	0.66
Revenue ($)	228,495	318,927
ROA	0.52	0.66
Total Assets ($)	372,639	216,289
Patents	0.02	0.05
R&D	0.16	0.27
New Product	0.25	0.31
Univ Coop	0.09	0.12
Survive to 2011	0.44	0.53
N	2894	2034

Note: Based on 4,298 firms in baseline year. Numbers reported are shares or averages dollar amounts. Statistics are all significantly different at 5 percent level across columns.