Why Do New Ventures Succeed? An Analysis of New-Firm Survival and Success

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Abstract

The purpose of this study is to evaluate how different founder and firm characteristics affect new venture performance. This research uses survival proportional hazard functions, and limited-information maximum likelihood instrumental regressions to measure the marginal effects on revenues and employment. A particular emphasis of this study is to look at the connectivity of different types of capital to measure how networks influence firm-success. For instance, the existence of a particular type of advantage and a background characteristic should represent the use of one's network in securing success. The data used for this study come from the Kauffman Firm Survey (KFS), which surveys various firms' founders on their background and the state of the firm from 2004-2011. The expected result of this study is that the interaction terms that capture whether a founder is leveraging his or her network will be a much stronger predictor of the different measurements of success than any measure of a founder's background or the firm's connections and capital structures.

KEYWORDS: (Business Survival, Revenues, Venture Financing, Human Capital, Competitive Advantage, New Ventures, Firm Performance)
JEL CODES: (L25, L26, J24)

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Variable Glossary

lrevenues = Lagged Revenues
lemp = Lagged Employment
foundered = Founder Education Level
founderexp = Number of Business Founded by Founder
founderexpsameind = Founder Started a Business in a Relevant Industry
founderworkexp = Number of Years Spent in a Professional Environment
eqangels = Received Funding from Angel Investors
eqcompanies = Received Funding from a Company
eqvc = Received Funding from Venture Capitalists
debtfin = Financed the Company through Some Form of Debt
eqgovt = Received Funding from a Government Entity
eqfff = Raised Funding through Family and Friends
univcompadv = Has a Competitive Advantage Through a University Partnership
compcompadv = Has a Competitive Advantage Through a Company Partnership
patentcompadv = Has a Competitive Advantage Through a Patent
govlabcompadv = Has a Competitive Advantage Through a Government Lab or Research Center Partnership
foundhisp = Founder Identifies as Hispanic
foundamind = Founder Identifies as American-Indian
foundasian = Founder Identifies as Asian
foundblack = Founder Identifies as Black
foundwhite = Founder Identifies as White
foundmale = Founder Identifies as Male
foundage = Age Level of Founder
mining = Industry is Mining
con = Industry is Construction
ut = Industry is Utilities
manu = Industry is Manufacturing
tnw = Industry is Transportation and Warehousing
inf = Industry is Information
finser = Industry is Financial Services
re = Industry is Real Estate
profser = Industry is Professional Services
management = Industry is Management Services
wm = Industry is Waste Management
eduser = Industry is Education Services
rec = Industry is Recreation
food = Industry is Food/ Food Services
hightech = Founder Identifies Business as High-Tech
northeast = Business is Located in the Northeast
midwest = Business is Located in the Midwest
south = Business is Located in the South
totcr = Total Amount of Copyrights Owned by the Business
tottm = Total Amount of Trademarks Owned by the Business

totpatents = Total Amount of Patents Owned by the Business
totassets = Asset Level of the Business
totliab = Liability Level of the Business
totdebt = Debt Level of the Business
ednet =Interaction of University Partnership and Founder Education Level
indnet = Interaction of Company Partnership and Relevant Founder Experience
netfwex_2 = Interaction of Company Partnership and Professional Experience
netang_si= Interaction of Relevant Founder Experience and Angel Investment
netvc_si= Interaction of Relevant Founder Experience and VC Investment
netcomp_si= Interaction of Relevant Founder Experience and Company Investment

TABLE OF CONTENTS

1. INTRODUCTION

Over the past few decades, the rate at which startups fail has steadily climbed higher and higher, reaching 90% in 2012, and it has continued to rise since (Marmer et al 2012). The economic impact of startups is far reaching, as they account for as much as 50% of new job creation year-to-year across a host of industries (Fairlie et al. 2016). Although these hyper-competitive landscapes lead to drastic innovations, increases in efficiency, and massive returns to investment for some, the high rate of failure has had deep-seated negative effects for others. From the startup frenzy that is Silicon Valley, to startup-rich university towns, the positive and negative effects of new venture performance in the United States has far reaching implications on a macro-scale, affecting various industries, regions, and demographics. That said, on a personal level, loss of investment for venture-backers and career setbacks for the entrepreneurs themselves mean that venture-success is in the best interest for all invested parties.

The high rate of startup failure, combined with the massive upside of startup investment, has led to the development of specific types of investors, venture capitalists (VCs) and angel investors, that look exclusively at these high-risk investment scenarios. Looking at various factors such as industry, intellectual property, and all sorts of quantitative traits associated with the startup, many of these investors look very analytically at the traits of the firm in determining investment (Macmillan et al. 1985; Fulghieri and Sevilir 2009). Conversely, other investors look almost exclusively at the qualitative traits of the startup, which are predominantly traits of the founders, such as what kind of experience they have, where they went to school, and what sort of network and human capital that they may have acquired over the years. There are also investors who take a special interest in specific industries, as their investment decisions are informed largely by their familiarity and expertise in a certain field. These different kinds of investment philosophies in funding startups have likened startup investing to horse racing (Sandberg and Hofer, 1987). One can bet on the jockey, the entrepreneur; the horse, the product; or the race, the market. In practice, though, almost any investor has his or her decisions informed by all three of these philosophies.

Though venture capital financing is often considered a strong predictor of venture success, only a fraction of new ventures, around .5%, receive VC funding, and since around 10% of startups still do succeed in some capacity, VC investment is not the exclusive determinant of startup success (PwC Moneytree Report). That said, the questions asked by investors are relevant when one asks from an academic point of view: why do startups succeed?

While there is extensive academic research that tries to evaluate different variables' effect on startup success, there is little academic consensus on what constitutes new venture success (Baluku et al., 2016). Additionally, there is little research done on the connectivity of different types of variables. Reframing back to the horse-jockey-race analogy, it is difficult to look at each one of these variables in a vacuum. While partnerships with universities may be a distinct competitive advantage for a firm, the higher an education level that one has may make them more likely to have a such a partnership. The interaction of these two variables may act as an indicator for the network implied by the relationship (Sandberg and Hofer 1987). In sum, whether evaluating one's experience in starting a company, his or her education, or work in a related industry, there are interesting questions to be asked when looking at the jockey in the broader context of the race that they’re in and the horse that they’re riding. Looking at these relationships will give the academic community a fresh perspective in predicting who ultimately succeeds.

The goal of this study is to measure hazard rates and marginal effects of the interaction variables of founder characteristics, firm-financing, and competitive advantages. The findings illustrate how the founder’s accumulated human and social capital along with the types of competitive advantages their firms have and the types of financing of the firm, can explain the effects that various types of network capital have on the firm’s relative success. With highly significant interactions that display key combinations for startup survival, and strong predictors of revenues and employment, this study proposes both novel applications of interaction terms in predicting success and is one of the first studies to attempt to correct for sample bias in predicting subjective measurement of success.

The following literature review will give context as to where previous has focused and the conclusions it has drawn.

2. LITERATURE REVIEW

2.A. Overview

The evaluation of startups in the current literature has been a subject varying opinions. Due to the age of the business, the data that exists does not capture trends of performance, market share, and profitability which may be used to empirically evaluate older businesses (Cooper et al. 1994; Fablin and Grimes 2007). For this reason, the idea of how to measure firm success, not only how to determine it, is an argument in and of itself in economic literature (Baluku, Kikooma, Kibjanja 2016). Since success is subjective, research has diverged into two predominant areas: through indicator variables such as firm survival, sales, growth, turnover, and return on equity (standard metrics used in evaluating older ventures) and through financing (under the hypothesis that investment by a competitive source is a strong signal of success). From this perspective, success and financing outcome variables are inextricably linked, where one's level of success may be determined by investor interest and investment, which may breed further success (Baum and Silverman 2004; Cooper et al. 1994; Sanyal and Mann 2010).

2.B. Theoretically and Empirically Measuring Success

The distinction between theoretical and empirical analyses in this discipline is blurry. For instance, Audretsch and Mahmood (1995) confirmed that hazard models do not strictly apply, and that even simulations were limited by a lack of data. Similarly, Conti, Thursby, and Rothaermel (2011) created theoretical games of systems of equations, where different investors have their own preferences and different new-ventures have different likelihoods of success. Their estimation model is predicated on this system being solved, where there is an equilibrium between investor preferences, new-venture success likelihood, and information from which the asymmetry is built. In the context of the literature evaluated, creating one's own, or building off of a similar framework is more common than repurposing a theoretical framework. In sum, given the data a researcher has or the specific way they are asking a question, it makes sense to make alterations to the empirical implementation of theoretical ideas.

Typically, Cox proportional hazard functions are used to measure new-venture survival (Audretch and Mahmood 1995; Cader and Letherman 2009; Delmar and Shane, 2006). Depending on one's data and distribution of hazard rates, other survival-time regressions may be used (Bosma et al. 2002; Delmar and Shane 2006). That said, for other non-binary indicators, such as revenues, profits, or employment, more conventional maximum likelihood functions, such as time-series probits, logits, and tobits are used to measure subjective indicators of firm-success (Bosma et al., 2002; Delmar and Shane, 2006). When evaluating both survival and other metrics of success from a sample, there is inherent bias in the non-binary regressions as its panel variable is unbalanced or the time-series maximum-likelihood function regresses observations with missing values from failed firms. Different researchers have coped with and illustrated this bias in different ways (Bohmke, Morrey, Shannon 2005; Cader, Letherman 2009).

2.C. Financing Variables and Decisions as Indicators of Success

As discussed earlier, this notion of using financing variables to indicate success or position to succeed is a popular strain of thought (Baum and Silverman 2004; Ahmed and Cozzarin 2009; Davila et al. 2001; Huyghebaert et al. 2007; Yankov 2014). The earlier discussed notion of likening the investment scenario to horse-racing is very relevant. When investing in the race (the market), should the investor invest in the horse (the idea), the jockey (the entrepreneur), or the odds (financial criteria)? Although all aspects are understood to be important in determining whether the bet is made, Macmillan, Siegel, and Narasimha (1985) partially answer the question through surveying a sample of 102 venture capitalists. Their research stated characteristics that predict a higher likelihood of investment and basis to reject investment are that of the entrepreneur. The natural next step taken from this research was expanding the sample and scope of the question using variables that measure investment criteria through looking at the effects of the entrepreneur, industry, and the firm's strategy on venture-success (Gelderen 2004; Sandberg and Hofer 1987).

In their discussion on the role of VCs in biotech startups, Baum and Silverman (2004) argue that "financial intermediaries, such as venture capital firms (VCs) are perhaps the dominant source of selection shaping the environment within which new ventures evolve." One assumption they make is that VCs affect performance of startups in multiple ways. First, by identifying potential in the startup, they provide validation about the startup to the founders and the investment community. Second, they offer coaching to the startup, wherein they may provide resources that a startup needs to survive such as funding, portfolio company alliances, or advisors. Types of business alliances did correlate with more funding, as did intellectual capital, and human capital available to the startup. In terms of start-up performance, while IP and alliances did predict success, human capital had weak significance, suggesting that there may be some over-valuation of human-capital in predicting performance. Using financing as an indicator, the significant connection between the network capital of the startup and financing supports other studies that view such variables as being key to success.

So both Baum et al. (2004) and Macmillan et al. (1985) confirmed that founder characteristics are important in terms of whether a startup receives funding, but Baum questions whether there is strong connection between said human capital and startup performance. This opens up a discussion of the differences between human capital and social capital, and how each affect new-venture success (Bosma et al. 2005; Yankov et al. 2014; Larson 1992).

2.D. Human, Social, and Network Capital

One area that merges new-venture investing, firm characteristics, and entrepreneurial traits is using founder traits to determine the type and amount of funding that a startup may receive. In their research, Sanyal et al. (2010) discuss how the intersection of an entrepreneur's assets, the information that exist about the founders of a startup, and their characteristics may predict what type of financing they pursue or attain. For example, they find more educated entrepreneurs are more likely to pursue debt-financing and serial entrepreneurs are just as likely to self-fund, pursue external debt, or external equity due to mitigated information opacity.

Although it is well-accepted that innate entrepreneurial talent and luck both play a part in the outcome of a startup, Bosma, van Praag, Thurik, and de Wit (2002) quantified the effects of other forms of capital as opposed to talent. These authors argue that while these factors are important, that the amount of human capital, such as education or startup experience, and social capital, such close links to a geographic location or ties to industry professionals, should be evaluated too. To try and triangulate business performance, the authors used survival time, profit, and employment, where they found that human capital variables influences different parameters of performance in non-uniform ways. However, they do find that social capital unilaterally fosters entrepreneurial performance. These findings give credence to other works that emphasize networks as being both strong signals to investors and predictors of success.

Instead of evaluating human capital alongside social capital, as Bosma et al. (2002) do, Cooper, Giman-Gascon, and Woo (1994), discuss the effect that different types of human capital have on entrepreneurial performance, which they evaluate through 1) failure, 2) marginal survival, and 3) high growth. They split up human capital into general human capital, such as education level and demographics, and Management Know-How, such as past entrepreneurial experience and advisors. Interestingly, splitting human capital into different categories of variables induces interesting results. General Human Capital seemed to have more significant effects, while Management Know-How had a very weak effect on new-venture performance. These results are interesting given differing opinions on human capital's effects on venture-performance (Baum et al. 2004; Bosma et al. 2005; Yankov et al. 2014).

In their analyses, Delmar and Shane (2006) did a deep-dive into helping answer the question of investing on the horse of the jockey. They quantified startup performance through looking at new-venture sales and whether they survived, and hypothesized the effects that the founders' startup experience and industry experience would all have positive effects on startup survival and age, but that they would both be declining functions of age. This study offers a unique perspective of the diminishing effects of human and social capital as the company ages.

2.E. Interactive Effects

In their work, Sandberg and Hofer (1987) make the argument that it's imperative when evaluating new venture performance, to not only think in terms of who the entrepreneurs are, but also the industry structure, the firms' strategies, and the interactions of these variables. They found that the interactions between industry structure, business strategy, and entrepreneurial characteristics to be far more significant in the determination of new venture success. Put in the context of industry structure and venture strategy, characteristics of the entrepreneur had relatively little impact on new venture success. Interactive effects have been used elsewhere as well, illustrating decreasing returns to startup experience on sales and success as the firm ages and grows in size (Delmar and Shane 2006). In evaluating firm-success, interactive effects have given novel and insightful results, but have largely been under utilized.

2.F. Summary

In sum, the literature is divided in what defines startup success, what determines startup performance, and the role that the entrepreneur plays. There seems to be overwhelming support in the VC community for investing in the entrepreneur. Although economic literature does support that this is in fact where they focus, empirical evidence of this is not actually leading to stronger performance than the market or idea itself. Baluku et al. (2016) put it best, "there is no agreement among scholars of what constitutes startup capital and entrepreneurial success". This simple, but prevalent statement has framed the non-uniformity and inconsistency in what to study and how to study it, in order to answer in essence, the same question.

3. THEORY AND METHODS

3.A. Overview

The model evaluates different dependent variables through different regression methods. In order to evaluate firm-survival, a Proportional Cox Hazard function is used. For the models with lower bounds of 0, a limited information maximum likelihood (liml) instrumental variable regression is used. Due to selection bias present in the sample that comes from the observations suitable for the revenues and employment regression, it is necessary to instrument the survival term used in the regression to correct for endogeneity between survival and either revenues or employment (Cader and Letherman 2009; Boehmke et al. 2005). The model also features two primary interaction vectors of interest. The first vector is the interaction between the founder's human and social capital variables with the competitive advantage variables, to observe if there is an interactive effect between the capital of the founder with the advantages of his or her firm. The second vector of interest is the interaction between the founder's human and social capital variables with the venture financing variables, to observe the interactive effect between the founder's background and the type of financing on which the firm is structured.

3.B. Variable Selection

3.B.i. Dependent Variables

The proposed model has three dependent variables to measure different metrics of performance. For that reason, regressions are run with different variables that will collectively triangulate new-venture performance. The variables that are going to be used to triangulate new-venture-success are 1) survival, 2) revenues, and 3) employment.

These variables are often used to measure new-venture success (Baum and Silverman 2004; Bosma et al. 2002; Delmar and Shane 2006; Groenewegen and de Langen 2012; Cooper et al. 1994).

The survival variable is a binary outcome variable which is either 0 if the firm is no longer in business in its original form or 1 if the firm is still in business. The selection of firm-survival as a dependent variable is common in the literature (Cooper et al. 1994; Delmar and Shane 2004; Bosma et al. 2002). Survival is largely used due to the fact it offers the simplest perspective on whether a firm succeeds. Other variables used to measure firm-success do not capture this binary reality, as it is conceivable that a firm may have a million dollars in revenue and not survive.

This said, the literature also measures certain non-binary variables. To measure the economic success and impact that a firm may have, it is still necessary to measure the jobs that it creates, as well as amount of currency exchange that it generates. For this reason, it is necessary to use revenues and employment. There is literature that instead of revenues, used profits; however, this was due to the fact that negative profits were unobserved in the sample (Bosma et al. 2002; Bosma et al. 2005). Delmar et al. (2006) uses the same metric for this reason in evaluating new-venture performance, but they frame the variable as ‘sales’.

3. **B.ii. Predictor Variables**

Social and Human Capital

The variables from the sample that triangulate the social and human capital of the firm’s founder are the levels of education of the founder, how much professional experience they have, how many businesses they have started, and whether they have started a business in a relevant industry. These types of variables are used extensively across studies, having been significant predictors of the different dependent variables. Researchers have found significance in using these variables as predictors of new venture financing structure, firm-survival, firm-employment, and just about any variable used to measure firm-success (Delmar and Shane 2006; Sandberg and Hofer 1987; Sanyal and Mann 2010). These variables include both the skills that the entrepreneur may have acquired in their education and professional experience. Additionally, studies have found even stronger significance levels in the social capital variables of founders (Bosma et al. 2002). Measuring these variables is crucial to effectively gather network effects observed through interacting these variables.

Competitive Advantages

The competitive advantages of the firm are broken down into partnerships that the firm has with different entities (university, government lab or research center, private company, or a patent advantage). On one hand, these advantages are often seen as the result of receiving certain types of funding, such as VCs linking up portfolio companies or facilitating a connection to government (Baum and Silverman 2004). On another, pre-funding competitive advantages have been found to be one of the strongest predictors in receiving venture financing (Conti et al. 2013). All-in-all, these variables are key in measuring firm-networks, as they are the most tangible input the data set has for relationships that may cause success.

Venture Financing

This group of variables registers the reported financing breakdown of the firm. The specific types of financing of interest are Friends, Family, and Fools (FFF) money, Venture Capital (VC), Angel financing, Government Investment, or Debt. The breakdown of these variables are meant to capture the effects on performance that are implicit with different kinds of financing. Previous literature has found strong links between the entrepreneur and firm's financing, so this begs questions as to when both are accounted for, if either of these have effects on new venture success (Sanyal and Mann 2010; Baum and Silverman 2004). By including these variables, one can explore what the combination of founder capital and types of financing have on the success of the firm.

3.B.iii. Interaction Variables

A key focus of this study is to observe the interactive effects between the variables of interest in the model. In their evaluation of new venture performance as a function of a startup's strategy, industry, and entrepreneurial traits, Sanberg et al. (1987) found that the interactive effects between their three groups of interest were far greater and more significant than any of the variables in isolation. The interactive terms that this paper's model will evaluate will focus on two interactive vectors with the first being the product of the social and human capital with the competitive advantage terms. Interacting these two vectors should capture the effect that a startup whose entrepreneur(s) has a combined effect of an alliance and experience on whether its succeeds. The second interaction vector is between human capital with venture financing, with the intent of observing effects of human capital-based inclination to pursue one form of funding over another and if this has any bearing on the startup's success.

3.B.iv. Instrumental Variables

Survival

In creating the revenues and employment models, a survival variable is needed in order to inform the model if a firm has survived or not. Measuring this marginal effect will give clarity in evaluating the other coefficients. In order to correct for potential endogeneity between the survival variable and the outcome variable in the regressions, there needs to be a variable that is distinct yet still strongly correlated with survival. To do this, survival values are predicted from the proportional Cox Hazard function, stowed, and used then to instrument the corresponding revenues and employment iv-liml regressions.

3.B.v. Control Variables

This model will also contain controls to capture the effects of variables that if not accounted for may skew the results and detract from the model's overall fit.

Industry

The first group of control variables are industry specific controls, accounting for NAICS codes, as well as if the founder identifies the firm as high-tech. Not controlling for this would not account for whether a firm is in a high or low-growth industry, and may skew the results (Sandberg and Hofer 1987; Yankov et al. 2014). As Sandberg and Hofer (1987) pointed out, the industry in which the startup is in has a significant effect on whether a startup succeeds. Furthermore, the most significant variables in their study were the industry interactive terms. With many investors looking exclusively at specific industries, it is important to account for the fact that this selection bias in the investment process may not be explained by the venture financing variables (Sanyal and Mann 2010;

Cooper et al. 1994). Beyond being the subject of many studies and investment decisions, industry is understandably almost always used as a control in evaluating firm-success.

Founder Characteristics

The model will also contain founder characteristics, to control for non-human-capital based factors that a founder may bring to a startup that still may influence its performance, such as age, gender, and race. These were found to be statistically significant by Banir (2014) in his paper evaluating determinants of gender differentials in the entrepreneurial space. That said, while Barnir's may not be the most relevant in the context of this study, models that more closely resemble this study include such controls whenever the entrepreneur is eveluated (Bosma et al. 2002; Sandberg and Hofer 1987).

Business Health

Controlling for the business health at the time of observation is also needed, which will be controlled by various accounting variables. In their paper using asset specificity to predict and the financing structure of startups, Sanyal and Mann (2010) found asset specificity and general financial health to be strong predictors of the types of equity received. With other literature finding the type of venture financing as being predictive of startup success, it is necessary to control for asset specificity in order to do out best of isolating the marginal and interactive effects of the venture financing on the model's dependent variables (Sanyal and Mann 2010).

Region

As Sanyal and Mann (2010) point out in their study, there are higher densities of innovation in different parts of the country, so it is important to isolate regional effects.

These can strengthen or weaken access to funding, partnership capabilities, and the talent available to hire.

Intellectual Property

It is also worth controlling for the intellectual property (IP) that each startup has. This control vector is broken down into three variables, a sum of the firm's trademarks, copyrights, and patents developed or acquired. Conti, Thursby, and Rothaermel (2013) found that patents, especially in certain industries are significantly and largely predictive of new venture performance. Other studies use IP to control for novelty of a product and innovative capacity of the firm (Baum and Silverman 2004; Sanyal and Mann 2010).

3.C. Estimation Methods

3.C.i. Firm-Survival

The regression used in order to measure the effects of the variables of interest on whether or not the firm survives is a Survival model estimated with a Cox Proportional Hazard function. The Cox Proportional Hazard Function fits proportional hazards to the data using maximum likelihood methods. The theoretical concept of using a proportional hazard function to estimate firm-survival functions is that hazard rates are non-constant, unlike parametric hazard functions. Proportional hazard functions assume that there are different rates based on how the observations are grouped. The eventual results allow the Survival likelihood function to be maximized with respect to firm and founder traits. Delmar also has hazard function in his evaluation of new-firm survival; however instead of a continuous survival function, he uses piecewise exponentials to predict the hazard of failure.

3.C.ii. Revenue and Employment

Both the revenues and the employment measures have zero as the lower bound. Negative revenues and employment are both non-interpretable (Bosma et al. 2002). Therefore, both equations, per past studies, should be evaluated using a time-series tobit model. That said, due to the nature of the given data, it's difficult to use a time-series tobit. Because of the way that time-series tobit regressions treat border observations (by censoring them), the regression is problematic given the data. As will be discussed later in further detail, revenues are scaled 0-9 in different levels, where 0 is no revenue and 9 is $1,00,000+. By the nature of the sample, there are an overwhelming amount of border cases, meaning that a time-series tobit regression incorrectly illustrates the data.

Due to the nature of the data sampled, there is inherent selection bias among the observations in evaluating the predictors of the two variables. Since the data is in panel-format, when a firm would exit the survival regression, they do not exit the sample evaluated in the limited information maximum likelihood instrumental variable regression. Instead, where a survival observation may exit when *survival* = 0, other inputs such as revenues or employment carry 0 as its input and are continually regressed. If one were to simply drop the observations where *survival* = 0, though, the panel-time variable would become unbalanced.

For both of the reasons above, it is necessary to run a limited information maximum likelihood (liml) instrumental variable regression. In this model, an instrumental variable is selected that correlates with the variable expected to be endogenous, and regress it against the endogenous term. These results are used to solve an eigen-value matrix which allows the model to generate coefficients that are theoretically exogenous. The liml estimation techniques is a κ-class estimator of β, which minimizes κ as an eigenvalue under certain matrix constraints. The remainder of the estimation comes through estimating the data through maximum likelihood methods. The reason for choosing the liml regression, as opposed to a more conventional two-stage-least squares method, is due to the fact that regressing with maximum-likelihood methods allows one to remove non-normality and heteroskedasticity as potential issues in the results. The end result is a regression that should theoretically correct for the firm's survival, and the endogeneity from the survival term.

3.D. Estimation Strategy:

Although certain variables are included for reasons discussed above, it is still important to note that similar regressions to other researchers are ran on a data set where these analyses have not been performed on. For that reason, preliminary regressions are still needed in order to observe whether or not the model is specified correctly given the questions being asked and the data being analyzed.

3.E. Model Suitability and Specification:

The first regressions ran in the process are the Cox survival regressions, due to the need to predict a survival-hat variable in order to control for firms dropping out of the sample in the second set of regressions. After running the completely unrestricted model, one could observe that there are 22 variables in the first Cox proportional-hazard survival regression that are non-significant at the 15% level. This fully unspecified model can be found in Table I. All three of the business health variables – assets, liabilities, and debt – are insignificant with p-values of 1. Due to this, they were tested for multicollinearity.

Due to high correlation between total assets, total liabilities, and total debt, total debt was dropped. When the regression was run with only assets and liabilities, and then only assets, all of the returns from the regression have similarly insignificant results. Strangely, despite the p-values of 1, the business health variables have very small hazard ratios, which imply having more assets, liabilities, and debt strongly increases one's likelihood of survival. That said, the differing returns from the regression imply that such variables may be corrupted and should not be included in the regression moving forward.

In addition to the business health vector not having significance, the three dummy variables included to control for the region that a startup is in, were all insignificant. Individually, none of the three were significant anywhere below the 47% level. A test of joint-significance was performed in order to test for joint-significance of the regional variables, which reported a p-value of $p=0.7$, and gives evidence to reject the null hypothesis that they are jointly significant, and remove them from the sample.

Similarly to the regional controls, the controls for founder demographics were generally insignificant, with the exception of the founder's age being significant at a 3% level. The founder's gender is individually insignificant, with a p value of $p=0.876$, and was dropped. For the dummy variables controlling for the race demographics of the owner, significance levels range from around the 1% for if the founder is Hispanic to the 76% if the founder is American Indian, with values dispersed in between the two. The base group for this group of dummy variables is if the founder identifies as other. These variables were jointly significant.

Only three of fourteen industries were found to be statistically significant at the 15% level – Real Estate, Manufacturing, and Information. Plenty of the statistically insignificant industry controls, such as construction and mining do have meaningful hazard ratios, and simply omitting them would be problematic. For that reason, all the industry controls are kept in the regression moving forward. These, as well, are a group of dummy variables, with other services as the base group of these variables, which is derived from NAICS code 81. A f-test of joint significance was tested on these industry variables, which return a p-value of p=0.105, giving reason evidence to keep the industries in the model.

There are variables of interest, such as having venture capital equity and a government lab competitive advantage, that have values that are insignificant at the 15% level. That said, they remain in the regression because one of the goals of this evaluation is to compare their individual effects with the effects that occur from interacting them with other variables of interest.

The amount of businesses that one had founded was not statistically significant with a p-value of p=0.946, while having founded a business within the same industry is significant with a p-value of p=0.157. Due to the pronounced insignificance of how many businesses one had founded as opposed to having founded a business in a relevant industry, the amount of businesses founded by the founder is dropped. For purposes of the study having founded a business in a relevant industry captures similar network affects as just having founded a business. This leaves the final survival model as being:

$$h_{(t)} = h_{0(t)} \exp(\beta x_{humansocialcap} + \beta x_{financing} + \beta x_{compadv} + \beta x_{foundcont} + \beta x_{industry} + \beta x_{IP})$$

where $x_{humansocialcap}$ is comprised of founder education, whether the founder has started a business in a relevant industry, and the amount of years the founder has spent in the workforce. The financing vector, $x_{financing}$, is comprised of whether or not the company received FFF equity, government equity, angel equity, VC equity, or debt financing. The competitive advantage vector, $x_{compadv,}$ includes whether the company has a competitive advantage through a patent or a partnership with a university, company, or government lab or research center. The $x_{foundcont}$ contains the founder's age level and demographic controls, while the industry vector contains whether the company is in mining, construction, manufacturing, transportation and warehousing, information, financial services, real estate, professional services, management, waste management, educational services, recreations, food, and if they're high-tech. The IP vector is comprised of total copyrights, trademarks, and patents. Total patents is statistically insignificant in both regressions, but is included due to high significance of success measurements in past studies (Conti et al. 2011). This regression is run without any interactions, which can be seen in Table II.

For the regressions with interaction variables as predictive variables, the model takes special interest in certain interaction terms. The first interactions are between the amount of years of education of the founder and having a competitive advantage with a university and the interaction between whether a founder has started a business in a relevant industry and whether a company has a competitive advantage with a company-partnership. The remaining variables in the competitive advantage and human and social capital vectors are included in the model as well, but are not interacted with other variables. Additionally, measuring the interaction between the founder's work experience and whether the company has a competitive advantage through a partnership with another company should help give light to the network that the founder has accrued over time in securing an advantage.

For the regression with interaction terms between the human and social capital vector and the financing vector, there are also limited interaction variables of interest. Three of the interaction terms are that of whether the founder has started a business in a similar industry before, and whether they acquired funding from potentially industry-specific investors, such as Angels, VCs, or companies. This should proxy for one's past connections in the industry acting as a means of acquiring funding that allows them to succeed.

3.F. Data and Variable Creation

3.F.i. Data

The data used in this paper comes from the Kauffman Firm Survey (KFS), which was commissioned by the Ewing Marian Kauffman Foundation and was conducted every year from 2005-2012 by the Mathematica Policy Research. The sample observes 4,298 firms, registering questions on the founders and the firms spanning demographics, financials, strategy, organization, and more.

3.F.ii. Organization

The data set was downloaded in non-panel format. Each firm has an id number which was used to match and identify different years of the collected variables for each firm. The data was matched, transposed and put into the necessary panel format in the SAS software package. It was then exported to a .dta file to run the desired regressions in STATA.

3.F.iii. Variable Creation

Survival

The survival variable is derived from a combination of events in the data. The data set has a variable that explains why a company is no longer in business. If the firm answered that it merged or was acquired, then it was removed from the sample due to the difficulty in measuring why the firm merged or was acquired: was it over or underperforming? If they had not reported that it had gone out of business, and it was still reporting revenues in the final year of the model, the firm “survived” and was coded as 1 as opposed to failing, which is coded as 0. If the firm did not respond to the sample in consecutive years, it did not survive, while if the firm missed a year of reporting, it was removed from the sample.

Employment

The data set provides various employment variables, often detailing the breakdown of different total employment, types of employees, and degrees of employment. Due to insufficient entries in the latter two categories, the employment model simply uses total employment as its input.

Firm Finances

The firm finance variables, such as profits, revenues, assets, liabilities, etc., are all given by levels as opposed to numerical values. See Appendix A for ranges. Interpretations of the relevant financing variables are made accordingly.

Venture Financing

It is important to note that all of the venture financing variables are binary. Although there are questions which ask about the equity breakdown percentage, the entries are too few and far between in order to include those variables, as opposed whether or not the firm received the form of equity. The debt financing term is derived from the outstanding debt responses given by the respondents. If the firm has an outstanding business loan or a personal loan taken out on behalf of the business, it is coded as 1. Furthermore, the Friend, Family, and Fools (FFF) variable is made out of whether the firm is financed by the founder's spouse, parents, or friends, which are their own variables in the data set.

Competitive Advantages

It should be noted that the distinctions in the competitive advantages – whether through a patent, or a partnership with a university, company, or government lab – only began in 2007. This means that there were three years prior where these key variables were not reported. These distinctions were walked back over the previous three years if in 2007 one or more of these advantages were reported, and they had reported a competitive advantage in 2004-2006.

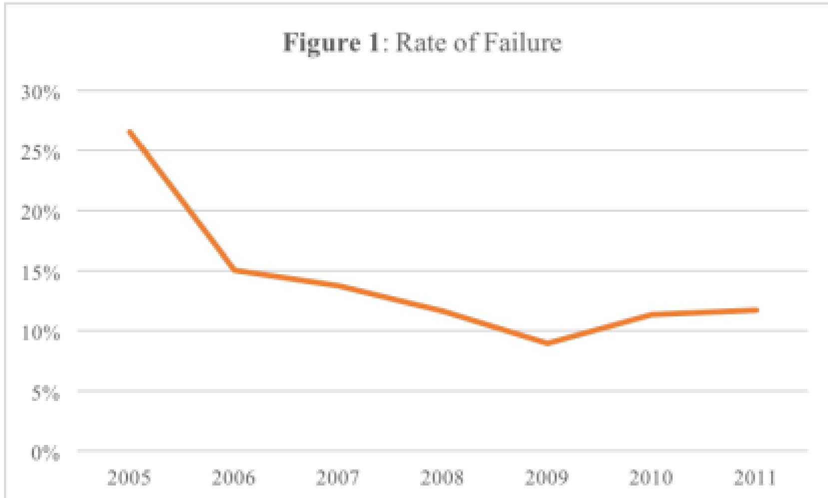
Other Controls

Other variables in the model that have interpretations that need to be clarified are founder age and founder education. Founder education levels and age-levels are given in Appendices B and C, respectively. It should also be noted that only the primary founder's controls and capital are included.

3.G. Summary Statistics

The most notable statistic is the survival rate of the firms in the sample. Of the 3,768 firms that begin in the sample, around 27% fail in the first year, while around 34% make it through the full eight years. It should be noted that the high failure rates (~90%)

noted before are specifically aimed at startups, while this is sample is more generally new ventures. The decline of firms in the can be seen in Figure 1.



The first year the statistics were recorded (2007), there were 95 (~2.5%) firms with university partnership competitive advantages, 337 (~8.9%) with company partnership competitive advantages, 115 (~3%) with patent competitive advantages, and 40 (~1.1%) with a government lab competitive advantage. These numbers typically drop as the years progress, but rise as a percentage of firms that have survived.

In the first year of the sample (2004), there are 69 firms that received angel investment (~1.8%), 44 with company equity (~1.1%), 18 (~0.5%) with government investment, 20 (~0.5%) with VC investment, 129 (~3.4%) with FFF investment, and about 2,011 (~53%) that pursued debt financing. Presumably, an observation that does not fall into any of these (or multiple of these) categories is self-funded. These number similarly decrease over time, but generally remain a similar percentage of the amount for surviving firms.

The median education level for founders is 6.26. To give context, education level 6 is an Associate's degree, while education level 7 is a Bachelor's degree. Approximately one in 5 (.17) founders have relevant founder experience. Additionally, the average founder has 12.7 years of professional experience.

In the first year, the median revenue level is 3.73, which to give context, level 3 is $1,001 - $3,000 and level 4 is $3,001 - $5,000. In the last year, of firms that are still alive, the median level is 7.25. Level 7 is $25,001 - $100,000, while level 8 is $100,001 - $1,000,000. In the first year of the sample, median employment is 1.5 employees, while in the last year , of surviving firms, median employment is about 4.1 employees.

Around 511 firms are considered high-tech at the beginning of the sample, ~13%, which increases as a percentage of surviving firms. The industries most strongly represented were manufacturing (18%) and professional services (25%). The most common founder demographic was white (82%) and the median age level is 3.55. Age level 3 is 35-44 and age level 4 is 45-54. The breakdown of the firms by industry can be found in Figure 2.

Figure 2: Firms by Industry

The following section will detail the regression analyses.

4.RESULTS AND REGRESSIONS

4.A. Survival Regression

4.A.i. Hazard Ratio Interpretation

An important concept to remember when interpreting the outputs of a Cox Proportional Hazard function, is that the outputs are given in hazard ratios. When interpreting a hazard ratio, one must keep in mind that interpretations are made with respect to the rest of the sample. For instance, in the context of the survival function, if a hazard ratio reported is 0.5, then there is a 50% less chance that observations in that group are experiencing an event, being failure. Another way to think the interpretation is that with a hazard ratio of 0.5, we estimate a 50% reduction in risk of failure. With this in mind, we progress with the interpretation of the model's results.

4.A.ii. Non-interaction Regression

One can find the full results for this regression in Table II.

Human and Social Capital

Although the founder's human and social capital vector is largely significant at the 15% level, the hazard ratios themselves are not particularly noteworthy. For instance, with a p-value of p=.026, the founder's education level is statistically significant; however, with a hazard ratio of 0.977, the effect is interpreted as companies with founder's that have higher levels of education are 2.3% less likely to experience failure. Furthermore, one variable that was particularly noteworthy in previous literature, and for industry investors, was whether the founder of a company had previously started a company in a related industry. With a hazard ratio of 1.08, significant at the 15% level, companies in that group could be interpreted as having an 8% greater chance of failing.

Similarly significant, the founder's work experience had a similarly non-meaningful hazard ratio of 0.99.

Firm-Financing

The firm-financing variables have more substantial hazard ratios than the human and social capital vector. If a firm is financed through angel investors, they have a hazard ratio of 0.28 (significant at the 3% level), meaning that they are 72% less likely to experience failure compared to those that do not. When a firm receives equity-financing from a company, it has a hazard ratio of 0.48, which is interpreted as being 52% less likely to fail then those that do not. This coefficient has a p-value of p=0.211, but this may be due the sample only having 149 samples that are financed this way. Equity financing through VCs has a very insignificant p-value of p=0.947 and a hazard ratio of 1.03, which can similarly be explained through there only being 66 observations, over the 8 years of the sample, where a firm receives VC financing. One of the strongest indicators of new-venture success from any of the regressions is debt financing, which is significant at the 0% level and garners a hazard ratio of 0.13. This means that one who seeks to finance his or her company through debt financing as opposed to not is 87% more likely not to experience failure. Those who receive financing from the government have a hazard rate of 3.64. This can be interpreted as government equity causing a 364% increase in likelihood of failing. It should be noted that despite a significant p-value, there are only 47 observations that have government equity financing. Lastly, those who receive Friends, Family, or Fools financing have a hazard ratio of 0.55 and a p-value of p=0.072. It seems that the strongest financing predictor of success is debt; however, if one does pursue equity, private equity is a much stronger predictor of survival than public equity.

Competitive Advantages

Perhaps the strongest predictors of new-venture survival were the competitive advantages. Having a competitive advantage through a university-partnership saw startup survival to be 32% more likely to survive with a hazard ratio of 0.68. Firm's that had a competitive advantage through partnerships with companies were 82.5% more likely to survive, which is significant at the 0% level. Firms that reported competitive advantages through having a patent had a hazard ratio of 0.51, meaning that they are 49% less likely to fail then those who do not have such a partnership. Although less significant and substantial than the other competitive advantages, having a partnership with a government lab or research center has a hazard ratio of 0.76 (24% less likely to fail), which is significant at the 25% level. These results give credence to the concept discussed in Bosma et al. (2002) that founder networks, social capital, and alliances are particularly strong predictors of startup success.

Controls

As discussed in the model specification section, there are many controls that are included due to joint-significance. The only demographic that has a hazard ratio of strong statistical significance is that of the Hispanic variables. With a hazard ratio of 1.28, founders who identify as Hispanic are 28% more likely to fail. Although they don't have p-values as significant, it is worth noting that across survival regressions, founders who are White and Asian both have hazard ratios in the general range of 0.80 to 0.86. Industries that are particularly note-worthy at the 15% significance level are real estate and information services, which per their hazard rates are 17% more likely to survive than the base group, which is a general NAICS code (81). Some industries that are significant at the 10% level are professional services, management services, and food services. These industries have hazard ratios of 0.89, 2.01, and 1.32, respectively. As far as intellectual property, the total amount of copyrights and trademarks are both statistically significant at the 1% level, or less. While total copyrights do not have a very influential hazard rate, being 0.93, those companies with more trademarks can expect a significant bump in their likelihood of survival, with a hazard rate of 0.63. Total Patents was included after the specification from the regression in Table I to Table II, because of the past significance that patents had in previous studies, but it carries over a similarly insignificant and non-influential hazard ratio. This does jive with other reported coefficients, as firms that are considered high-tech, which are most likely to pursue and acquire patents, have a similarly insignificant and non-influential hazard ratio. Additionally, there is very little correlation between claiming a patent as a competitive advantage and the total amount of patents owned by an entity (2.8%).

4.A.iii. Survival Human and Social Capital – Competitive Advantage

With respect to hazard ratios discussed in the previous regression, while there are marginal changes regression-to-regression, the objective of the interaction regressions is to observe the interactive effects of the variables. The hazard ratios and respective p-values of variables already discussed are reported in the relevant tables; however, with respect to their analysis, if they have been discussed, they will not be analyzed moving forward unless there is a noteworthy change in the coefficient that merits interpretation. One can find all of the survival interaction term results in Table III.

Founder Education – University Partnership

As discussed earlier on the Theory section, the methodology in including this variable is to measure the increased likelihood in survival that one may experience from the founder's time spent in the education system and the simultaneous occurrence of having a competitive advantage through a university partnership. This interaction should capture if a founder's network within the education system, and use of said network, yields a higher likelihood of survival. The varible has a hazard ratio of 0.89, which means that one with higher levels of education in the instance of a university-partnership advantage decreases the chances of failure by 11%, which is significant at 0%. Although this hazard rate is not more 'influential' in terms of chances of surviving when compared to whether the company simply has a university-partnership competitive advantage, it does have a p-value of 0.00, meaning that one can say with high confidence that the relationship captured with this interaction does in fact exist.

Founder Started a Business in Related Industry – Company Partnership

This interaction captures the effects that occur when a company has a competitive advantage through a partnership with another company and when the founder has started a business in related industry before the current venture. This hazard ratio illustrates some astounding effects that come from interacting the two variables. One can observe a large increase in a significance and drop in the hazard ratio when compared to the variable that only measures if the founder had previously started a business in a related industry. When compared to the hazard ratio of when a firm has a competitive advantage through a company partnership, one can see there is a comparable significance level, but the hazard ratio is lower by about 0.02. In sum, when a new-venture has both a partnership with a company and the founder has experience starting a company in the same industry, the venture is 85% less likely to fail than those that don't have this in its favor. This result shows strong empirical evidence for the increases in chances of survival associated with capturing one's having industry connections and actually using them.

Founder Work Experience (in Years) -- Company Partnership

Similarly like the previous interaction, founder work experience does not only measure accumulated professional knowledge that a founder may have gained, but also potential industry connections. Interacting this variable with whether the company had a competitive advantage through a company partnership measures the ability of founder's past knowledge and connections in conjunction with private-sector partnerships to deliver company survival. With a hazard ratio of 0.905, firms that have a founder with higher levels of work experience in conjunction with a company competitive advantage are 9.5% less likely to fail than other firms.

4.A.iv. Survival Human and Social Capital – Firm-Financing

Similar to the business health vector in the specification section, the interactions between angel financing and whether the firm's founder had started a business in a similar industry were non-interpretable, so the variable was omitted.

Founder Started a Business in Related Industry – Financing

These variables, measured to capture the connections that a founder may have acquired in previous ventures with investors, have intriguing results. The VC interaction term, with a hazard ratio of 0.55 can be interpreted as one who has both started a business in similar industry and has acquired VC funding, is 45% less likely to fail. That said, with a p-value of p=0.55, the hazard ratio is not statistically significant. Albeit, this hazard ratio and p-value come with only 18 observations where this combination is true, so this interaction should be earmarked for further research. It should be noted that this hazard ratio is substantially lower than either VC equity or whether the founder has started a company in a relevant industry before. Measuring a similar relationship as above, the company equity-relevant founder experience interaction seeks to quantify where one has industry connections, if such connections coincide with an industry investment, and how this affects whether the firm survives. Working with a small sample size of 62 observations, the hazard ratio is compelling as it is lower than both company equity investment and whether the founder started a business in a similar industry, at 0.41. Similarly to the interaction term with VC-financing, there is a high p-value of p=0.39, which does detract from the novelty of this result.

A trend that is in the way of truly measuring the effect of these variables is the amount of observations in the sample where both conditions are true. For that reason, as compelling as the hazard ratios are, the p-values detract from their validity, especially when compared to the other interactions.

4.B. Revenues and Employment Regressions

As discussed in the model section, there are significant bias issues when running a second stage to a survival regression, due to the fact that firms year-to-year are removed from the sample. That said, we are still curious in measuring the same variables marginal effects on a firm's revenues and employments, due to the binary nature of success versus failure. The different scales of success require careful measurement.

Due to these biases, revenues and employment are estimated with instrumental-variable limited-information maximum likelihood regressions. Survival is included and instrumented with survival predictions from the survival regressions. Additionally, in order to account for the effects of previous employment and revenue numbers, lagged employment and revenues are included as well. In order to maintain exogeneity in the model, variables are included that carry comparatively large coefficients. For example, in measuring revenues, survival's coefficient ranges from 3.12 to 3.31, which can be interpreted as surviving means that a firm experiences an increase of 3.12 to 3.31 revenue levels. By comparison, there is no other variable that has a coefficient greater than 1 revenue level. There are similar effects for survival in the employment regressions, as well as for the lagged revenues and lagged employment (though not as pronounced as survival).

Additionally, when interpreting the coefficients where revenues is the dependent variable, one should be cognizant of the fact that revenues are given in level values. Of observations that are generating revenues at all, the mean level is 6.82 and the standard deviation is 1.85 levels (through the whole period). Just to give the necessary context, level 6 is $10,001-$25,000 and level 7 is $25,001-$100,000. An increase in one standard deviation would put the revenue level at 8.67, which would be in the $100,001-$1,000,000 range. Also, for firms that are in business, the mean for employees is roughly three employees with a standard deviation of roughly six employees. This distribution of employees is largely skewed due to the fact that for one of these venture to be in business, it does not necessarily need to have employees.

4.B.i Non-Interactive Regression

The non-interactive revenues and employment regressions can be found in Tables IV and V, while the interaction term results can be found in Tables VI and VII.

Human and Social Capital

All three of the human and social capital variables were significant at the 5% level for revenues. While all marginal affects were relatively modest in terms of realized changes in revenues, the largest coefficient was expectedly having a founder with relevant founding experience. This coefficient of 0.06 can be interpreted as explaining an increase in 0.06 revenue levels.

In predicting employment levels, these variables were not as influential as they had been elsewhere. Work experience and founding experience both had results significant the 10% level, but they had coefficients of 0.003 and 0.067. These can be interpreted as for every increase in a year of work experience, companies' employment increases by 0.003 employees. Furthermore when a founder has relevant founding experience, employment is increased by 0.067 employees.

Firm-Financing

The most noteworthy coefficient from these variables was that of receiving angel equity, which was significant at the 0% level, and had a coefficient of 0.55. This means that receiving Angel Equity in aggregate yields an increase in revenue levels of 0.55, all else held constant. FFF equity, company equity, VC equity, and government equity all had coefficients that struggled with significance, the lowest of which was FFF equity, which had a p-value of $p=0.33$. Interestingly, the only variables with positive coefficients were angel and company equity.

Similarly to previous regressions, angel and government equity lead to significant positive increases in employment. That said, one of the most influential coefficient is VC equity. At a 2.5% significance level, VC equity has a coefficient of -0.81, meaning that employment is typically 0.81 employees lower than its counterparts. Interestingly, firms that have government financing have a coefficient of 1.81 (significant at a 0% level). Ceteris paribus, if a firm has government investment, they will have 1.81 more employees than their counterparts. This is the largest coefficient in this regression.

Competitive Advantages

The most intriguing competitive advantage variable was having a partnership with a university. With a coefficient of -0.44, statistically significant at the 0% level, having a partnership with a university saw an aggregate decrease in revenue of 0.44 levels. Patent and company competitive advantages both had positive coefficients, but neither were statistically significant. Government lab and research center competitive advantages saw firms realize a negative revenues coefficient, but it was also quite insignificant.

Competitive advantage variables as predictors of employment had largely small, statistically insignificant coefficients. The most notable was having a competitive advantage through a patent, which was significant at the 10% level, and had an aggregate increase in employment for firms where this was true of 0.21 employees.

Controls

With the base group being 'other' for race identifications, most race demographics were negative with respect to the base group, except for if the founder is white. That said, with a p-value of $p=0.69$, this coefficient was not statistically significant. The age of the founder was significant at the 0% level, with a coefficient of -0.05. The industries that saw the highest marginal effects on revenue, while maintaining statistical significance, were whether the firms were in manufacturing or were high-tech. They saw increases in 0.18 and 0.10 revenue levels, respectively at 0% and 2%

significance levels. Also, though instrumented, it is still worth pointing out the marginal effects of survival and lagged revenues. Surviving has a firm realize an increase in 3.27 revenue levels, while an increase in one revenue level in the previous year sees an aggregate increase in 0.55 revenue levels the next year.

Similarly to the controls on the revenues iv-liml regression, marginal effects on employment were largely not note-worthy. Certain industry variables such as transportation, or being high-tech, saw an increase in employment of about 0.15 employees, but there were typically no coefficients above 0.2 employees.

4.B.ii. Human and Social Capital – Competitive Advantage

Founder Education – University Partnership Interaction

The interaction term between university-partnership competitive advantages and founder education levels yields a coefficient of -0.05, statistically significant at the 0% level. Since having a competitive advantage with a university is binary, and founder education is not, one can interpret this as an increase in education level, given a university competitive advantage, there is a 0.05 drop in revenue levels.

The founder education level and university partnership competitive advantage interaction term garnered a relatively small (0.015) statistically insignificant ($p=0.3$) result. Having such a partnership was meaningful in predicting revenues or survival, but in the context of employment growth, it does not seem to be.

Founder Started a Business in Related Industry – Company Partnership Interaction

The concurrent existence of a founder with experience starting a business in a similar industry and a company competitive advantage sees revenues increase by 0.11

level compared to other companies who do not, all else held constant. This is a higher increase in revenue level compared to either variable individually.

The interaction between relevant founder experience and a company competitive advantage was significant (p=0.018) and did predict when these two conditions exits together that firms can expect an increase of 0.3 employees. Although not a large coefficient, it is much bigger than the sum of these two coefficients when regressed individually. The interaction between having a company competitive advantage and the amount work experience the founder has is statistically insignificant (p=0.96).

Founder Work Experience (in Years) -- Company Partnership Interaction

With a coefficient of 0.003, significant at the 15% level, this variable is not the strongest predictor of revenues. That said, given that in the existence of a company partnership, for every year that the founder has of professional experience, revenues increase by 0.003 levels. Given that the maximum in the sample for work experience is 45 years, this variables has the potential to increase revenues substantially.

The interaction between having a company competitive advantage and the amount work experience the founder has is statistically insignificant (p=0.96).

4.B.iii Human and Social Capital – Firm-Financing Interaction Regression

The interaction between experience starting a business in a relevant industry and angel equity versus VC equity was interesting. While the angel interaction term has a coefficient of 1.21 at a 0% significance level, VC equity has a coefficient of -1.39 at a 2.5% significance level. Both have significantly large effects on revenues in the sample. That said, both of these interaction terms have very low amounts of observations where both of these conditions are true.

The interaction terms between and relevant founder experience and angel, VC, and company financing variables are all statistically significant at the 0% level. With coefficients of 1.62 and 1.52 respectively, the angel and company interactions do strongly predict employment growth. The interaction with VC financing, though, has the most negative coefficient in the regression, where the existence of both conditions leads to roughly 3 less employees in a company.

4.C. Post-estimation:

There were various post-estimation techniques used to test the validity of the results. First, for each of the instrumental variables regression, the instrumented survival predictions were tested for endogeneity. This was done by estimating with instrumental two-stage-least-squares regressions, and then testing for endogeneity after the 2sls regression. Ideally, each would use its own predicted survival values; however, not all of these were exogenous. With that in mind, predicted values are used from similar regressions, where each final regression uses a survival prediction as an exogenous regressor. Additionally, a constructed Ramsey RESET test of proper specification was performed on each regression. All of the results signified correct specification, with the expectation of the non-interactive survival regression, which still has a p-value of 0.2.

Other tests performed were tests for autocorrelation and whether the outcome variables were truly stationary. For the test on autocorrelation of the outcome variables have large f-values and p-values of 0, so we must strongly reject the null hypothesis that there is no first order autocorrelation. Additionally, through preforming augmented Dickey-Fuller stationary tests, all of the estimates do not give evidence to reject the null hypothesis that all panels contain unit roots for the survival outcome variable. The revenues and employment outcome variables have inconclusive results with two estimate strongly rejecting the null hypothesis of all panels containing unit roots, while the other two estimates do not support this conclusion. For due-diligence, additional unit root tests are tested, namely the Harris-Tzavaliz unit-root test, which gives strong evidence to reject the null hypothesis of the panels containing unit roots, with a p-value of 0. Revenues and employment have the same results of supporting the notion that the panels are stationary. Additionally, due to using maximum-likelihood estimators in finding the coefficients, heteroskedasticity and non-normality are not issues when interpreting the coefficients and results.

It should also be noted that for the model where adjusted R-squared values do apply, the instrumental variable regressions, that the model does a good job of explaining the variation in the revenues and employment variables. With R-squared values of roughly 0.72 and 0.68 for revenues and employment, respectively, these values can be interpreted as 72% and 68% of the variation in the independent variable explaining revenues and employment, respectively.

4.D. Discussion:

4.D.i. General Themes

Some overarching themes from the regression analyses are that as standalone variables, human and social capital variables are not very strong predictors of firm success. That said, when interacted with competitive advantages and certain financing terms, the resulting network measurement of the founder and firm was substantial in determining new venture success. These finding are quite interesting, as these traits are often the highest standard in investment criteria, and entrepreneurial experience is held in very high esteem among entrepreneurs.

Competitive advantages, understandably, seemed to be the most unilaterally influential in predicting startup survival. That said, given firm-survival, they were not strong predictors of revenues and employment. As a general theme, though, it was difficult to analyze any coefficient as a predictor of revenue, because the coefficients were so dwarfed by the survival coefficient.

Depending on the type of financing that a firm received, they did have substantial differences in employment, though. From the limited sample, firms that were VC financed typically had fewer employees, while angel, company, and government equity all saw large, significant coefficients supporting employment growth. With respect to the interaction terms, they were generally very significant, influential predictors of firm survival. When regressed against more subjective measurements of firm success, though, they were much less influential.

4.D.ii. Noteworthy Coefficients and Ratios

The interaction terms between industry-relevant founder experience and company competitive advantages is very intriguing. With a hazard ratio of 0.15 at the 0% significance level, this implies that one’s ability to leverage his or her previous industry-network into a meaningful advantage is important when predicting survival. Being 85% less likely to fail was one of the most significant predictors of new-venture survival (along with debt financing). Although, not quite as significant or influential in the regressions on revenues and employment, the industry-network interaction term also has marginal effects of an increase in 0.11 revenue levels and 0.3 employees. As noted above, while these marginal effects may seem small, for the instrumental variable regressions that have survival in the regression and lagged outcome variables, the marginal effects are largely dominated by those two variables.

Another input with an eye-catching coefficients is the government-financing variables. Though having low amounts of observations throughout the sample, it often still posted significant and influential coefficients. For instance, in the Cox regression, it posted the highest hazard ratio of any variable, meaning that government equity investment was the one trait that was the strongest predictor of venture-failure. That said, in the instance where the firm did in fact survive, it was the single strongest predicting trait of job creation, year-to-year. Again, a small sample size of government invested firms means that interpretations and discussions need to be made with a grain of salt, but this does have strong implications for policy creation. This could be due to government governance heavily emphasizing employment growth, potentially at the expense of the firm's security.

One last coefficient that stood out in the regressions was debt-financing being such a strong predictor of venture survival. From the point of view of venture-investment acting as a proxy of venture success, its hazard ratio of 0.13 is puzzling. Albeit, the equity investment and debt financing terms are not mutually exclusive, but the notion that one's willingness (and ability) to take out debt to finance the business is very interesting. It does bring up the thought, though, that if a founder is at a crossroads wherein he or she can either take on debt to finance the business, or go out of business, it makes sense that such a high percentage of firms that survive have at some point taken on debt.

5. RESEARCH LIMITATIONS

There are some major limitations encountered in acquiring the presented results. First of all, the fact that revenues in the sample are only given in levels detracts from the interpretability of the coefficients. The revenues inputs are simply indicator variables and the interpretations need to be taken with a grain of salt. Also, the survival variable is manufactured, as discussed in the Theory and Methods section, and while a lot of effort and careful consideration was put into its creation, it is not an original variable in the given data. There are also some underlying issues with the employment data, with it being skewed. See the results discussion for further detail.

Furthermore, with respect to the interpretations of the revenues and employment regression, the coefficients of the variables of interest are largely dwarfed by the survival coefficient. Due the nature of the regression that is being run, it's necessary to include survival in order to indicate whether the firm should be experiencing revenues or employment. There are ways that survival and maximum likelihood functions can be tied together, but they were not applicable (Bohmke et al. 2005).

An underlying theme in the data which likely is influencing the results is that while this data seems to be a representative sample of debt and equity distributions across new-ventures, the amount of observations that have equity financing are lacking. Despite significance for a lot of these variables, their coefficients need to be interpreted with this in mind. For instance, there are 66 observations with VC equity over 8 years, and only 18 when it is interacted with relevant industry experience. Given that comparing VC-financed firms to other businesses is one of the most enticing and relevant analyses to be performed, having so few applicable observations is a sore spot for the study.

6. CONCLUSION

The results of this regression are novel in multiple ways. First, using instrumental variables in order to correct for selection bias in the sample, we are able to see theoretically non-biased results to predict revenues and employment, with interaction variables that had never been used to do so. Second, to the author's knowledge, using interaction variables between human and social capital with competitive advantages, to measure network capital leveraged by the entrepreneur, has never been done before.

The significance and low hazard ratios of the competitive advantage and human and social capital vector are very interesting. Given that the human and social capital hazard ratios are not very substantial, being 85% less likely to fail, per the interaction, has more to do with a founder's ability and willingness to leverage industry connections and knowledge into tangible advantages, as opposed to either input in isolation.

The major findings of this study should predominantly inform the two major stakeholders in new ventures – entrepreneurs and investors. While the observations made with respect to different types of firm-equity-financing are largely lacking, entrepreneurs can still take away that success is much less related to one's personal levels of experience than typically thought. Instead, when starting a business or building a team of cofounders, entrepreneurs should be just as cognizant of the network that they may collectively have and their ability to leverage the network into creating a successful company. Additionally, it's worth pointing out that even in the instance where there would have been enough financing-interaction observations to yield significant and meaningful results, entrepreneur's often still take money wherever they may be able to get it to keep their businesses afloat.

For investors, these findings do in sense give validation to the concept of investing in the entrepreneur versus the idea. On one hand, conventional social and human capital variables, while significant, were largely not meaningful in finding measurable advantages (the lowest hazard ratio was 0.977). The interaction terms in the regression do illustrate that an entrepreneur's network and use of one's network is a very strong predictor of venture performance. Being aware of this as opposed to simply asking 'have they started a business before' or 'how many years of professional experience do they have', should yield more accurate results. This study tries to illustrate that it's the natural next step from the above questions, in other words, 'what have they taken away from their experiences', that acts as the predictor of a stronger and safer investment.

Changing focus, a lot of the policy implications that can be taken away from this study come in the form of two major takeaways. Although a limited sample size, government equity was the strongest predictor of failure in all the regressions taken, registering an increased likelihood of failure of 364%. So, making sure that the vetting process for government investment is held to a similar standard as private equity investment, in terms of investment criteria, should certainly be implemented. Furthermore, one of the strongest predictors of employment was government equity, yielding 1.81 more employees than their counterparts. If this is concerted policy effort (vis-à-vis business security for employment growth) then such decisions should be revaluated. Lastly, possibly the strongest group of predictors of success, in terms of survival, revenues, and employment, were the competitive advantages that the firms had.

Implementing policies that help induce more collaboration and partnerships, whether through tax incentives, business classifications, or grants, could see a strong increase in overall new-venture survival, and firm-success.

In conclusion, although some variables do not explicitly agree with past literature, and while there are notable data limitations with respect to equity, revenues, and employment variables, the major results do an excellent job of giving credence to past research and give substantial fodder for further research. Moving forward, researchers should keep in mind the influential and significant hazard ratios of interactive terms in predicting success. Additionally, given the issues at hand, building a data set which emphasizes collecting more equity observations and detailed financials could really expand on this research. This research both addressed contradictions in the literature, affirmed beliefs, and raised issues for further analysis.

Table I:

Stcox Survival Regression – Unspecified

Variable	Hazard Ratios	Standard Errors	Z-Statistic
Human and Social Cap.			
foundered	1.0109	0.0102	1.07
founderexp	1.0000	0.0145	0.00
founderexpsameind	1.0723	0.0666	1.12
founderworkexp	0.9970	0.0022	-1.35
Venture Financing			
eqangels	0.3457*	0.2040	-1.80
eqcompanies	0.4548	0.2639	-1.36
eqvc	0.7113	0.3664	-0.66
debtfin	0.2386***	0.0165	-20.78
eqgovt	1.6723	1.0252	0.84
eqfff	0.5961	0.1967	-1.57
Comp. Adv.			
univcompadv	0.5925	0.1365	-2.27
compcompadv	0.2749***	0.0463	-7.66
patentcompadv	0.6469	0.1812	-1.56
govlabcompadv	0.7864	0.1879	-1.01
Found. Cont.			
foundhisp	1.0597	0.0964	0.64
foundamind	0.9034	0.1097	-0.84
foundasian	0.8559	0.1159	-1.15
foundblack	0.9522	0.1036	-0.45
foundwhite	1.0633	0.0982	0.67
foundmale	0.9732	0.0453	-0.58
foundage	0.9714	0.0192	-1.46
Industry			
mining	0.7242	0.5142	-0.45
con	0.5967	0.3467	-0.89
ut	1.0498	0.0840	0.61
manu	1.1043	0.0711	1.54
tnw	1.0183	0.1325	0.14
inf	0.8280	0.0987	-1.58
finser	0.8885	0.0975	-1.08

re	0.7978*	0.0962	-1.87
profser	0.9660	0.0617	-0.54
management	1.0614	0.3792	0.17
wm	0.9108	0.0755	-1.13
eduser	0.8553	0.2323	-0.58
rec	1.1255	0.1651	0.81
food	1.0566	0.1645	0.35
hightech	1.0514	0.0725	0.73
Region			
northeast	0.9313	0.0616	-1.08
midwest	0.9940	0.0567	-0.11
south	1.0134	0.0533	0.25
IP			
totcr	0.9648	0.0169	-2.04
tottm	0.8080719***	0.0521	-3.31
totpatents	0.9998	0.0010	-0.16
Bus. Health			
totassets	0.0000	.	.
totliab	0.0000	.	.
totdebt	0.0000	.	.

Note: 1) * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table II:

Stcox Survival Regression - Specified (Non-interactive)

Variable	Hazard Ratios	Standard Errors	Z-Statistic
Human and Social Cap.			
foundered	0.9774**	0.0091	-2.46
founderexpsameind	1.0842	0.0550	1.59
founderworkexp	0.9903***	0.0020	-4.82
Venture Financing			
eqangels	0.2885**	0.1739	-2.06
eqcompanies	0.4845	0.2525	-1.39
eqvc	1.0343	0.4776	0.07
debtfin	0.1381***	0.0093	-29.38
eqgovt	3.6150***	1.4939	3.11
eqfff	0.5581**	0.1623	-2.01
Comp. Adv.			
univcompadv	0.6829***	0.1583	-1.65
compcompadv	0.1751***	0.0283	-10.76
patentcompadv	0.5071	0.1332	-2.59
govlabcompadv	0.7629	0.1830	-1.13
Found. Cont.			
foundhisp	1.2867***	0.1022	3.17
foundamind	0.9757	0.0987	-0.24
foundasian	0.8589	0.1068	-1.22
foundblack	1.1175	0.1065	1.17
foundwhite	0.8641	0.0698	-1.81
foundage	0.9601***	0.0171	-2.28
Industry			
mining	1.2445	0.7350	0.37
con	0.6574	0.3340	-0.83
ut	1.1000	0.0771	1.36
manu	1.0302	0.0605	0.51
tnw	1.0937	0.1260	0.78
inf	0.8324	0.0938	-1.63
finser	1.0458	0.1014	0.46
re	0.8250*	0.0962	-1.65
profser	0.8898**	0.0519	-2

management	2.0140***	0.4724	2.98
wm	0.9563	0.0727	-0.59
eduser	0.8693	0.2271	-0.54
rec	0.9518	0.1277	-0.37
food	1.3191**	0.1743	2.1
hightech	1.0171	0.0632	0.27
IP			
totcr	0.9330**	0.0283	-2.29
tottm	0.6316***	0.0765	-3.8
totpatents	0.9998***	0.0000	-4.2

Note:* indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table III:

Survival Interaction Term Results

Interaction Variables	Hazard Ratio	Standard Errors	Z-statistic
Human and Social Cap - Comp. Adv.			
ednet (univ * founded)	0.8944***	0.0256	-3.9
indnet (rel ind exp. * comp)	0.1516***	0.0537	-5.33
netfwex_2 (worexp * comp)	0.9047***	0.0125	-7.25
Human and Social Cap - Venture Fin.			
netvc_si (rel ind exp * eqvc)	0.5478	0.5419	-0.61
netcomp_si (rel ind exp * eqcomp)	0.4074	0.4322	-0.85

Note: * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table IV:

LIML Instrumental Variable Revenues Regression - Specified (Non-interactive)

Variable	Hazard Ratios	Standard Errors	Z-Statistic
2sls Controls			
survival	3.2717***	0.3270	10.01
lrevenues	0.5279***	0.0193	27.41
Human and Social Cap.			
foundered	0.0146**	0.0059	2.47
founderexpsameind	0.0636*	0.0331	1.92
founderworkexp	0.0025**	0.0012	2.08
Venture Financing			
eqangels	0.5504***	0.1840	2.99
eqcompanies	0.0728	0.2435	0.3
eqvc	-0.0677	0.3760	-0.18
debtfin	-0.1650	0.1411	-1.17
eqgovt	-0.2496	0.4721	-0.53
eqfff	-0.1227	0.1614	-0.76
Comp. Adv.			
univcompadv	-0.4439	0.1160	-3.83
compcompadv	0.0777	0.0824	0.94
patentcompadv	0.0961	0.1405	0.68
govlabcompadv	-0.0515	0.0988	-0.52
Found. Cont.			
foundhisp	-0.0578	0.0556	-1.04
foundamind	-0.1884**	0.0767	-2.46
foundasian	-0.1383*	0.0820	-1.69
foundblack	-0.1033*	0.0604	-1.71
foundwhite	0.0226	0.0515	0.44
foundage	-0.0539***	0.0123	-4.37
Industry			
mining	-0.0579	0.3437	-0.17
con	-0.6093	0.4339	-1.4
ut	0.0177	0.0496	0.36
manu	0.1789***	0.0372	4.81
tnw	0.1095	0.0771	1.42
inf	-0.0495	0.0633	-0.78

finser	-0.0882	0.0692	-1.27
re	-0.2149***	0.0737	-2.92
profser	0.0506	0.0352	1.44
management	0.1566	0.2387	0.66
wm	-0.0752	0.0486	-1.55
eduser	-0.1387	0.1540	-0.9
rec	-0.0393	0.0766	-0.51
food	-0.0163	0.0977	-0.17
hightech	0.0975**	0.0458	2.13
IP			
totcr	0.0010	0.0021	0.47
tottm	0.0000	0.0000	1.64
totpatents	0.0000	0.0000	-0.49
Constant	-0.5996***	0.0771	-7.77

Note: * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table V:

LIML Instrumental Variable Employment Regression - Specified (Non-interactive)

Variable	Hazard Ratios	Standard Errors	Z-Statistic
2sls Controls			
survival	1.1931***	0.4297	2.78
lemp	0.8733***	0.0221	39.45
Human and Social Cap.			
foundered	0.0027	0.0080	0.33
founderexpsameind	0.0683	0.0515	1.33
founderworkexp	0.0030*	0.0016	1.92
Venture Financing			
eqangels	0.3142	0.3284	0.96
eqcompanies	0.4597	0.3040	1.51
eqvc	-0.8155	0.5249	-1.55
debtfin	-0.0741	0.2315	-0.32
eqgovt	1.8068	1.1797	1.53
eqfff	0.0028	0.2418	0.01
Comp. Adv.			
univcompadv	0.1380	0.1800	0.77
compcompadv	-0.1120	0.1397	-0.8
patentcompadv	0.2197	0.2797	0.79
govlabcompadv	-0.0103	0.1998	-0.05
Found. Cont.			
foundhisp	0.1021	0.0821	1.24
foundamind	-0.0742	0.0849	-0.87
foundasian	0.0244	0.1313	0.19
foundblack	0.1587	0.1021	1.55
foundwhite	0.0373	0.0872	0.43
foundage	-0.0506***	0.0170	-2.98
Industry			
mining	-0.0578	0.1878	-0.31
con	-0.4177**	0.1962	-2.13
ut	0.0770	0.0697	1.11
manu	0.0569	0.0515	1.1
tnw	0.1670	0.1068	1.56
inf	-0.0664	0.0797	-0.83

finser	-0.0348	0.0686	-0.51
re	-0.0342	0.0706	-0.48
profser	-0.0610	0.0426	-1.43
management	0.1127	0.5029	0.22
wm	-0.0781	0.0581	-1.34
eduser	-0.1812	0.1502	-1.21
rec	-0.0811	0.0756	-1.07
food	-0.4938**	0.1967	-2.51
hightech	0.1121	0.0753	1.49
IP			
totcr	-0.0023	0.0029	-0.78
tottm	0.0001*	0.0001	1.71
totpatents	0.0000	0.0000	-0.75
Constant	-0.4328***	0.1218	-3.55

Note: * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table VI:

Revenues Interaction Term Results

Interaction Variables	Coefficients	Standard Errors	t-statistic
Human and Social Cap - Comp. Adv.			
ednet (univ * founded)	-0.0525***	0.0145	-3.63
indnet (rel ind exp. * comp)	0.1179*	0.1157	1.02
netfwex_2 (worexp * comp)	0.0037	0.0030	1.27
Human and Social Cap - Venture Fin.			
netang_si (rel in exp * eqangels)	1.2132***	0.2775	4.37
netvc_si (rel ind exp * eqvc)	-1.399*	0.7909	-1.77
netcomp_si (rel ind exp *eqcomp)	0.2391	0.3613	0.66

Note: * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Table VII:

Employment Interaction Term Results

Interactions	Coefficients	Standard Errors	t-statistic
Human and Social Cap - Comp. Adv.			
ednet (univ * founded)	0.0186	0.0209	0.89
indnet (rel ind exp. * comp)	0.3370*	0.1955	1.72
netfwex_2 (worexp * comp)	0.0009	0.0042	0.21
Human and Social Cap - Venture Fin.			
netang_si (rel in exp * eqangels)	1.6156***	0.6413	2.52
netvc_si (rel ind exp * eqvc)	-3.0751***	1.2444	-2.47
netcomp_si (rel ind exp * eqcomp)	1.5152***	0.5509	2.75

Note: * indicates significance the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. 2) Reference variable names and meaning in the variable glossary.

Appendix A:

Level	Range
1	$500 or less
2	$501 - $1000
3	$1,001 - $3,000
4	$3,001 - $5,000
5	$5,001 - $10,000
6	$10,001 - $25,000
7	$25,001 - $100,000
8	$100,001 - $1,000,000
9	$1,000,000+

Appendix B:

Level	Education
1	Less than 9th grade
2	Some high school, but no diploma
3	High school graduate (diploma or GED)
4	Technical Trade or Vocational Degree
5	Some college, but no degree
6	Associate's degree
7	Bachelor's degree:
8	Some graduate school but no degree
9	Master's degree
10	Professional school or doctorate

Appendix C:

Level	Age
1	18-24
2	25-34
3	35-44
4	45-54
5	55-64
6	65-74
7	75+

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