Utilizing the Kauffman Firm Survey to Predict Growth in Venture Size and Scope among Small Firm Startups: 2004 Startups Tracked through 2008

by

Timothy Bates, Alicia Robb & Simon Parker
Beacon Economics
San Rafael, CA 94901

for

Office of Advocacy
www.sba.gov/advocacy

under contract number SBA-HQ-10-M-0210

Release Date: April 2013

Table of Contents

List of Tables

Executive Summary

What determines whether a startup venture grows and survives or stagnates and dies? This study attempts to delineate the new-venture entrants and very young firms destined to achieve only modest growth (or worse) from those most likely to grow considerably. Although no simple formula accurately sorts the gazelles from firms generating little or no growth, certain factors stand out repeatedly in our analytical exercises identifying firm and owner traits and strategies that explain growth patterns among young small businesses. On the positive side, firms with groups of three or more owners tend to grow faster than businesses with fewer owners. This finding supports our hypothesis that larger teams of owners provide a greater depth of experience and expertise, relative to other firms, and this larger talent pool enhances venture growth. Next, we hypothesized that greater investment of financial capital in young businesses translates into a higher likelihood of firm growth than lower investment and weaker capitalization; our empirical findings support this. On the negative side, we hypothesized that ventures whose owners were less growth motivated would indeed experience less actual firm growth than others, and our findings, once again, supported our hypothesis.

Another expected determinant of strong venture growth included firm ownership of intellectual property. While this was not apparent in the earliest years of venture operation, beyond year three, ownership of intellectual property indeed predicted higher growth for both high-tech businesses and financial-capital-intensive firms generally. Firm credit score, a measure of credit market access, was expected to affect access to capital (in the sense that a low score restricted access while a high score enhanced it) and this, in turn, would enhance growth; higher credit scores often did in fact explain higher venture growth, and vice versa for low scores. Owner educational background, finally, was an erratic predictor of small-business growth patterns.

Our analysis of small-firm growth dynamics proceeded by separating business startups and young ventures into subgroups appropriate for analysis. Small business startups are indisputably an unusually diverse group, ranging from self-employed workers in labor-intensive service industries (child care, for example) to highly educated and specialized professionals, to cutting-edge high-tech firms attempting to compete in global markets. Firms with growth potential, we hypothesized, are broadly those run by owners possessing appropriate expertise and accessing sufficient financial capital to sustain venture growth. Specific owner and firm traits and strategies that enhance growth, nonetheless, are not homogeneous across industry types. Using Kauffman Firm Survey (KFS) data, we created three overlapping business groupings – 1) high-tech firms, 2) financial-capital-intensive firms, and 3) human-capital-intensive firms. Firms not fitting into any of these categories were dropped. Using annual changes in number of workers (including owners) attached to a specific firm as our measure of venture growth over the 2004-2008 time period, we attempted to explain growth patterns using several econometric techniques employing as explanatory variables various firm and owner traits and strategies.

At the point of venture startup, owner education and relevant work experience are poor predictors of subsequent firm growth, yet the advanced education and experience possessed by the owner team are key sources of vitally important expertise, without which firm success is unlikely. Although the weak explanatory power of these key traits seems paradoxical, in fact no paradox exists. Owners having strong human-capital endowments – particularly those with graduate degrees and extensive applicable work experience – are the subset of entrepreneurial candidates likely to have the most attractive opportunities to pursue salaried employment. When they do launch startups, they often pursue a "toe-in-the-water" approach. Stated differently, they frequently start out very small to get a sense of what the prospects of their business startup may be, since their full-time commitment to the entrepreneurship alternative often requires both investing substantial capital and quitting one's salaried employment. As owners assess the performance of their young ventures, they must decide whether to 1) commit fully to entrepreneurship, 2) maintain a steady course of small-scale operation, or, alternatively, 3) abandon entrepreneurship altogether. Conditional on satisfactory venture performance and their assessment that future prospects are strong, entrepreneurs start to invest increasingly in their firms. As a result, venture performance outcomes (survival with growth, survival without growth, and firm closure) eventually clarify and take shape.

Highly educated and experienced owners of young ventures, in other words, often choose to keep their businesses in operation only when outcomes and prospects are positive. Absent these traits, the high opportunity costs of pursuing firm ownership full-time encourage them to cut their losses. The closure of a young firm often implies not failure but, rather, a pragmatic assessment of the folly of quitting salaried employment and risking loss of one's small-business financial investment in the face of limited prospects. To test whether owner human-capital traits ultimately do predict venture growth patterns, we therefore estimated a "survive-and-prosper" model, which entailed econometrically explaining small-business growth, conditional upon the firm remaining in business. This was done by examining growth among firms in the KFS database that 1) had already been in operation for three years and 2) remained in operation through yearend 2008. We effectively sought to explain growth among firms whose owners were most often beyond the exploratory startup phase of operation and indeed committed to the entrepreneurship path. Beyond putting a toe in the water, these owners had plunged in. Owners with undergraduate degrees as well as graduate or professional training, according to our survive-and-prosper model findings, were outperforming significantly their less-educated counterparts. Enhanced venture performance overall was associated positively with the owner's level of educational attainment, firm capitalization, and access to financial capital, findings which carry important implications for practitioners and policy makers seeking to promote venture growth in an environment of sustainable entrepreneurship.

A. Overview

What determines whether a startup venture grows and survives or stagnates and dies? Can we delineate the entrants destined to create little value from those most likely to grow to considerable size while creating substantial employment and payroll as well as increased wealth for their owners? Successful venture capitalists of course typically earn their livelihood by selecting young ventures having considerable growth potential and investing equity capital to acquire ownership stakes in those promising firms. Scholars analyzing databases of startup ventures with the objective of identifying the likely winners have had, to date, rather less success than the venture capital funds (Parker, 2009). Perhaps this is due to the quality of the databases available to support scholarly research of venture growth dynamics. Alternatively, the methodologies employed have perhaps been insufficiently creative to date. Is the task undoable? Findings of this study indeed identify key factors that accurately predict growth among startups and very young ventures, yet, while our study results provide insights into small-firm growth dynamics, we do not claim to have discovered a clear-cut profile sorting the swift from the laggard.

This study attempts to delineate the new-venture entrants and very young firms destined to achieve only modest growth (or worse) from those most likely to grow considerably. This is the key issue driving our empirical analysis of Kauffman Firm Survey (KFS) data. We first organize the data into firm subsets appropriate for analysis, which entails 1) defining useful industry-specific and factor-intensive subsets of businesses and 2) delineating actual business startups from nascent businesses.[1] Next,

[1] For this analysis, "nascent firms" were defined as those that did not meet a trivial sales threshold of $5,000 annually.

we created various control variables appropriate for investigating firm growth dynamics. We then undertake the tasks of 1) estimating regression models explaining specific measures of firm growth, and 2) generating summary statistics capable of illuminating both the nature of the underlying KFS small-firm data and the nature of the challenges presented by our task of seeking to understand venture growth dynamics.

Explaining venture growth is not easy, yet our results revealed certain clear patterns. Our findings indicate that understanding small-firm growth dynamics is particularly useful for clarifying the challenges facing young high-tech firms. The underlying high-tech businesses themselves are often going through difficulty as they initially attempt to transition from nascent status to active venture operation. Among those "started" in 2004, for example, nearly 20 percent had not yet generated any sales revenues at all by 2007.[2] Clearly, there are many paths from nascent status to successful venture operation, and the various paths entrepreneurs are pursuing vary across the broad industry groupings under consideration.

B. Creating Useful Analysis Files

Using KFS data, we created three overlapping business groupings: 1) high-tech firms, 2) financial-capital-intensive firms, and 3) human-capital-intensive firms. The KFS data were designed, in part, to facilitate analysis of high-tech firms, which were oversampled. We have used the high-tech firm definitions employed by the creators of KFS both because they are reasonable and because resulting firm weights embedded in the KFS database allow us to correct for high-tech venture overrepresentation when we

[2] There is no perfect – or even widely accepted – technique for delineating nascent firms from active young businesses. We investigated several alternative filtering techniques and chose ultimately to equate nascent status with trivial sales revenue generation of $5,000 annually.

are mixing high-tech firms with other business types not overrepresented in the database. We have identified and defined financial-capital-intensive firms using Annual Capital Expenditure Survey (ACES) data to determine average firm fixed private capital for 11 broad industry groups. Those emerging as financial-capital intensive (those firms well above the all-industry average regarding capital intensity) included 1) manufacturing, 2) wholesaling, 3) professional services, and 4) finance/insurance/real estate (FIRE).

We next defined human-capital-intensive firms using 2000 census of population PUMS data to determine entrepreneurs' educational attainment by industry. Those firms emerging as human-capital intensive (well above the all-industry average regarding owner educational attainment) included 1) professional services, 2) business services, 3) finance, insurance, and real estate (FIRE), and 4) entertainment/recreation services. Industries ranked as neither financial- or human-capital intensive included 1) personal services, 2) repair services, 3) food/health/child-care services, 4) construction, 5) transportation, and 6) retail. Among the latter, the industry group most closely approaching the human- and financial-capital threshold values used to determine factor intensity was retailing. Health-related services are, in some instances, included in the professional services grouping – and thus defined as human- and financial-capital intensive – while others fit into the food/health/child-care category.

Next task: every small-firm/self-employed database we know of has peculiarities that must be scrutinized carefully before "firms" included in the database are accepted as firms appropriate for analysis (Bates, 1997). The KFS database includes numerous small firms considered by the database designers to be startups in 2004 that we consider to be nascent firms. Among the 4,022 firms in the KFS data in 2004, 46.5 percent of them had zero sales revenues that year, and an additional 9.2 percent had revenues exceeding zero but under $5000. We did not drop all of the zero-revenue and very-low-revenue ventures from our analysis files. Instead, we defined a threshold concept, "base year" and firms with very low or zero revenues in 2004 were eligible for entry into our analysis files only when their sales exceeded our sales revenues threshold value of $5,000 annually.

Thus, data describing firms with 2004 revenues of zero and 2005 revenues of $6,600 entered into our analysis files as follows: 2004 data were excluded but 2005 data were included, because 2005 revenues had exceeded our threshold for filtering out nascent ventures. We have experimented by imposing sales revenue thresholds of both $3,000 and $5,000: 53.5 percent of the 4,022 KFS firms failed to meet a $3,000 revenue threshold in 2004 and 55.5 percent of them did not meet a $5,000 threshold. As noted below, we employed other threshold variables periodically in the course of our analysis to observe how our empirical results changed as differing thresholds were applied to the KFS data. Our analysis of growth is therefore conducted solely for firms graduating from nascent status, and their first year of inclusion in our analysis files may therefore reflect 2004 data, or 2005 or 2006 or later data; indeed, a few never did reach threshold revenue levels. For a firm **not** classified as nascent in 2004, our analysis consists of analyzing firm growth from 2004 through yearend 2008.

For firms exiting nascent status in 2005 or later years, the year of entry into our analysis files is their base-year 2005 (or later) data, and growth of such firms extends from their base year through 2008. All of our various applications of sales revenue thresholds and periodic inclusion of surviving firms only in our analysis files reduced effective small-firm sample sizes, but these samples were nonetheless sufficiently large to support statistically valid data analysis. The KFS database, fortunately, provides lots of observations, even in such subsets as women- and minority-owned businesses, which constituted roughly 30 percent and 21 percent, respectively, of the firms we analyzed. Regarding thresholds, note that a firm's revenues may exceed our threshold value in an earlier year but fall below it in later years; such firms are retained in the analysis files while they remain active (as opposed to closed) ventures. Alternatively, a firm going out of business and shutting down operations is included in our analysis files and growth of such firms is conducted from their base year through their year of discontinuance. Some of our specific regression estimations of growth, however, apply only to surviving firms still active in 2008, and such regression exercises are flagged in the text.

Next, it is noteworthy that the KFS time-series data under consideration terminate at yearend 2008, a year noted as a recession year in the aggregate U.S. economy. Since three related factors – the reality of economic recessionary conditions generally, the contraction of credit availability for small business specifically, and the recession's varying regional impact – may bias our analysis of firm growth, we added state-specific annual macro-control variables to our KFS analysis files. Two types were added: 1) state-specific annual unemployment rates, and 2) state-specific measures of the change in the state-wide unemployment rate for the current year versus the previous calendar year. In our regression analysis of growth, estimated coefficients of these macro-control variables have varied in size and are statistically insignificant, except in the case of high-tech firm growth. Thus, recession-induced bias limiting venture growth appears to have had impacts on our empirical findings that may not be captured well by these macro-control variables. Recessionary impacts are nonetheless present and are more likely picked up by explanatory variables sensitive to credit-market conditions, such as firm credit scores.

C. Data Analysis and Interpretation of Empirical Results

We begin our analysis of venture growth by presenting summary statistics describing firm and owner traits and strategies employed separately for 1) high-tech firms, 2) human-capital-intensive small businesses, and 3) financial-capital-intensive young ventures. We next proceed along three distinct paths regarding the econometric models used to explain small-firm growth patterns. First, we estimate three sets of regression models explaining changes in worker numbers separately for 1) high-tech firms, 2) financial-capital-intensive firms, and 3) human-capital-intensive ventures through 2008 for progressively smaller subsets of firms. The first set of econometric models examines those firms surpassing the $5,000 gross annual sales threshold (Table 4), while the second adds an additional threshold, 20 hours per week worked by a firm owner (Table 5), and the third explains changes in worker numbers solely for those firms meeting sales and work hours thresholds *and* achieving at least five-fold growth through yearend 2008 (Table 6).

Our second distinct path of econometric analysis proceeds by examining firms meeting the threshold values regarding owner hours worked and sales revenues, but changes in worker numbers are analyzed across two distinct phases of the small-firm life cycle – the learning phase (Table 7) and the growth phase (Table 8). Our third and final path of econometric analysis involves reanalyzing the growth phase of the small-business life cycle using a fundamentally different approach; Cox regressions are utilized to estimate a competing risk model of venture outcomes. Relative to the alternative of a firm surviving and prospering, we explain the competing risks of either surviving without prospering or closing (Table 9); we then explain, relative to the alternative of closing, the competing risk of surviving, either with or without prospering (Table 10).

1. Overview of Actual Firm Growth Patterns

Tables 1 through 3 report statistics of owner traits, firm traits, and firm outcomes that summarize how our various groupings of growing firms and their owners differ from firms generating either no or negative growth in annual sales revenues through yearend 2008. Each table breaks firms/owners into three overlapping groups reporting growth in sales revenues from their base year through 2008 as follows: “3X” firms have at least tripled their annual sales revenues between their base year and 2008; “4X” firms have at least quadrupled their sales revenues; “5X” firms have grown their annual sales revenues at least five-fold; “no or negative growth” firms, in contrast, have experienced either no or negative sales growth from their base year through 2008. Firms expanding their base-year sales by more than zero but less than three-fold through 2008 are excluded from the statistics in Tables 1 through 3.

A comparison of the firm/owner/outcome traits reported in columns three and four of Table 1, for example, permits the reader to observe how high-tech firms expanding their revenues at least five-fold through 2008 differed from corresponding high-tech firms generating no sales growth whatsoever through 2008. Particularly noteworthy is the fact that owners of the 5X firms were more likely to possess graduate degrees and work more hours each week than the no-growth comparison group of owners. The 5X firms described in Table 1 were initially smaller (mean sales under $60,000), less profitable (mean profits of negative $25,582) and less well capitalized (mean startup capital of $155,900) than the corresponding no-growth firms. (Their corresponding means for base-year sales, profits, and startup capital were $524,000, $50,172, and $250,200 respectively.)

Table 1: Business, Owner, and Outcome Traits among Firms Meeting Sales Thresholds*: High-tech Firms* (mean values unless otherwise stated)

	3X Growth	**4X Growth**	**5X Growth**	**No Growth**
A. Owner Traits:				
Education (%):				
No college	4.6%	5.7%	5.4%	3.0%
Some college	21.6%	25.1%	27.2%	25.8%
College grad	34.8%	27.3%	27.8%	42.1%
Graduate degree	37.4%	39.9%	39.6%	28.0%
Other Traits:				
Owner age	44.2	44.1	44.3	45.5
Prev. startup experience (%)	52.8%	53.6%	54.1%	52.7%
Hrs. worked/week	49.8	51.4	51.3	41.3
Yrs. previous industry exper. (%)	14.2	13.4	13.4	17.9
Female (%)	11.2%	10.5%	11.6%	12.0%
B. Firm Traits:				
2004 # employees	4.8	5.0	5.0	11.6
2004 revenue ($000)	$191.0	$83.4	$59.5	$524.0
2004 net profit	($4,027)	($22,046)	($25,582)	$50,172
Startup capital ($000)	$150.6	$160.5	$155.9	$250.2
Credit score	48.4	47.2	46.4	44.4
Outside financing ratio	16.4%	14.8%	13.2%	13.3%
Owns intellectual property (%)	40.3%	40.5%	40.2%	32.4%
Team ownership (%)	28.1%	32.4%	29.2%	9.9%
Incorporated (%)	80.1%	81.0%	82.1%	74.6%
Home based (%)	42.2%	45.2%	45.7%	56.2%
C. 2008 Outcomes:				
Revenue ($000)	$1,224.4	$1,339.7	$1,360.5	$321.6
# employees	11.5	12.5	13.4	6.4
Net profit	($35,490)	($90,614)	($93,014)	$826
Total assets ($000)	$908.2	$1,061.6	$1,111.7	$324.9
Home based (%)	25.1%	26.3%	25.4%	55.6%
Incorporated (%)	86.9%	87.0%	87.6%	78.9%
N	154	125	105	71

All three categories of growing firms summarized in Table 1 indeed were initially smaller firms than their no-growth counterparts: the smaller their initial size and the greater their reported losses (negative profits), the more rapid their subsequent growth through yearend 2008. Similarly, a comparison of high-tech firms reporting higher growth rates (Table 1) reveals in every instance that higher growth in sales revenues through 2008 corresponded to lower initial firm profitability. Thus, the no/negative growth high-tech firms on average generated profits of over $50,000 and sales of over $500,000 in their base year, while 3X growth firms produced profits of minus $4,000 on sales of $191,000, and 5X growth firms produced losses exceeding $25,000 on sales of a mere $59,500 initially. Base-year sales performance and profitability was thus consistently INVERSELY related to subsequent growth in firm sales revenues.

A comparison of firms exhibiting differing growth patterns reveals other interesting differences in initial firm characteristics. The growing firms consistently reported a higher incidence of intellectual property ownership initially, in comparison to the no-growth high-tech firms. Further, team ownership (three or more owners) was consistently more widespread among the growing firm subgroups, in comparison to the low rate of team ownership typifying the no-growth high-tech ventures (where less than one in ten reported team ownership). Through yearend 2008, the 5X high-tech firms had grown their average revenues from under $60,000 (base year) to $1.36 million, a twenty-two-fold increase in annual sales, while their employee numbers grew from 5.0 initially to an average of 13.4 in 2008. Summary statistics portray growing high-tech firms as having owners who are better educated (graduate versus undergraduate degree) and who work longer hours, in comparison to owners of no/negative growth firms.

The growing high-tech firms, in summary, exhibit a higher incidence of intellectual property ownership and team ownership, relative to their no-growth counterparts, and they started out smaller, less well capitalized and less profitable than their no-growth counterparts. High growth, however, certainly does produce continuing challenges, a point emphasized by the fact that the higher the firm growth through 2008, the greater the operating losses: the data show that high-tech firms that grew five-fold or more generated average profits of minus $93,014 in 2008, while their no-growth counterparts managed, on average, to report slim positive profits. How can high growth be sustained when it coexists with such persistent negative profitability? The answer is unclear.

Table 2 statistics describe owner and firm traits and outcomes for subsets of firms in human-capital-intensive lines of business. Relative to the high-tech firms, those in the human-capital-intensive fields – whether growing or not growing – report female ownership with greater relative frequency. The growing firm groups, once again, stand out in the sense that owners worked, on average, longer hours than the no/negative growth firm owners. Yet, other owner traits – educational background, age, experience – exhibit only small differences across the growing and no-growth groups of firms. Firm traits of the growing firms in the human-capital-intensive fields include smaller initial firm size, somewhat larger capitalization, higher credit scores, more team ownership, and complete absence of base-year net profits, relative to the no/negative growth ventures.

Table 2: Business, Owner, and Outcome Traits among Firms Meeting Sales Thresholds*: Human-Capital Intensive Firms* (mean values unless otherwise stated)

	3X Growth	4X Growth	5X Growth	No Growth
A. Owner Traits:				
Education (%):				
No college	6.4%	7.8%	5.9%	9.4%
Some college	23.9%	23.1%	25.5%	24.2%
College grad	39.4%	40.7%	42.7%	40.9%
Graduate degree	28.3%	27.0%	24.4%	23.0%
Other traits (%):				
Owner age	44.4	44.2	44.1	46.3
Prev. startup experience	46.8%	48.6%	47.3%	44.3%
Hrs. worked/week	46.3	47.8	48.2	38.1
Yrs. previous industry exper.	13.4	13.1	13.1	13.8
Female	29.2%	29.6%	30.4%	24.8%
B. Firm Traits:				
2004 # employees	4.5	4.7	5.0	6.1
2004 revenue ($000)	$83.8	$77.0	$70.0	$326.8
2004 net profit	($2,654)	($7,181)	($8,170)	$48,529
Startup capital ($000)	$159.2	$107.4	$114.3	$98.9
Credit score	48.4	44.3	44.9	38.9
Outside financing ratio	16.4%	17.4%	16.9%	17.1%
Owns intellectual property (%)	27.5%	27.7%	28.6%	22.7%
Team ownership (%)	16.2%	17.4%	18.2%	8.8%
Incorporated (%)	68.2%	67.2%	66.6%	58.1%
Home based (%)	48.5%	45.2%	46.6%	63.1%
C. 2008 Outcomes:				
Revenue ($000)	$856.6	$1,018.9	$1,106.6	$179.3
# employees	9.8	11.1	11.7	4.4
Net profit	$86,210	$93,145	$97,216	$19,471
Total assets ($000)	$499.2	$598.4	$671.2	$268.9
Home based (%)	39.0%	37.2%	35.3%	65.9%
Incorporated (%)	72.7%	72.2%	71.2%	58.7%
N	303	232	195	277

The consistent pattern of negative profitability typifying growing firms initially is unexpected and noteworthy (see Tables 1 and 2). The fastest growing (5X) firms described in Table 2, once again, report both the smallest initial size and largest base-year operating losses (sales of $70,000 and profits of minus $8,170), in comparison to other firm subgroups, while the no-growth firms were initially the largest and most profitable (mean sales and profits were $326,800 and $48,529 respectively). By 2008 yearend, the 5X firms in human-capital-intensive fields were generating average sales and profits of $1.106 million and $97,216 respectively, which certainly indicates that these growing firms are far more capable of achieving sustainable growth, relative to their money-losing high-tech 5X counterparts.

Among both the high-tech and human-capital-intensive firm subgroups examined thus far, being initially fat and happy (relatively large and profitable) is certainly a powerful predictor of a likely failure to generate growth in subsequent years. This message is driven home by the fact that the same pattern recurs in Table 3's statistics describing firms in financial-capital-intensive fields. These statistics portray the highest-growth firms (5X) reporting initial mean values of sales revenues and profits of under $90,000 and minus $13,393 respectively, while the no/negative growth subset of firms reported base-year mean sales and profits of nearly $470,000 and $50,000 respectively. Once again, the fastest growing firm subset initially exhibits both the smallest average firm size (measured by sales) and the largest operating losses of any venture subgroup described in Table 3.

Table 3: Business, Owner, and Outcome Traits among Firms Meeting Sales Thresholds: *Financial-Capital Intensive Firms* (mean values unless otherwise stated)

	3X Growth	4X Growth	5X Growth	No Growth
A. Owner Traits:				
Education (%):				
No college	6.0%	7.1%	7.5%	11.4%
Some college	27.7%	27.9%	28.1%	25.4%
College grad.	41.6%	40.6%	42.1%	40.3%
Graduate degree	22.0%	22.5%	20.1%	20.3%
Other traits:				
Owner age	44.9	44.7	44.7	45.8
Prev. startup exper.	49.3%	52.1%	53.3%	43.6%
Hrs. worked/week	46.3	47.8	47.8	40.5
Yrs. previous industry exper. (%)	13.2	13.0	13.0	14.1
Female (%)	28.5%	24.5%	27.1%	23.5%
B. Firm Traits:				
2004 # employees	4.3	4.6	4.7	5.4
2004 revenue ($000)	$101.5	$98.6	$87.7	$469.2
2004 net profit	($7,980)	($12,552)	($13,939)	$49,773
Startup capital ($000)	$171.9	$118.6	$119.8	$115.8
Credit score	48.1	48.5	48.5	41.8
Outside financing ratio	17.8%	17.1%	16.6%	19.5%
Owns intellectual property (%)	27.7%	29.2%	27.3%	24.5%
Team ownership (%)	18.3%	20.0%	20.4%	10.1%
Incorporated (%)	68.8%	68.6%	66.6%	59.6%
Home based (%)	43.3%	41.7%	42.9%	58.0%
C. 2008 Outcomes				
Revenue ($000)	$1,159.1	$1,301.5	$1,380.4	$296.1
# employees	9.9	11.1	11.5	5.0
Net profit	$28,030	$17,798	$15,369	$26,163
Total assets ($000)	$545.4	$592.8	$634.4	$372.2
Home based (%)	31.8%	28.4%	28.3%	58.4%
Incorporated (%)	75.2%	74.9%	72.6%	61.4%
N	419	340	289	320

In summary, all of the subgroups of growing firms in Tables 1, 2, and 3 report owners who work, on average, longer hours per week, in comparison with owners of no/negative growth firms. Other specific differences across groups of financial-capital-intensive ventures are less noteworthy – higher credit scores, smaller initial firm size, and a higher incidence of team ownership typify the growing subgroups of firms, relative to their no-growth counterparts. All of the differences in firm and owner traits and venture outcomes are, of course, not necessarily indicative of causal relationships between these traits and firm growth patterns through time. Many of the traits that are correlated to firm growth, or the lack thereof, are correlated, as well, with each other. Firms with multiple owners, for example, are attached to firms more likely to own intellectual property in comparison to single-owner firms.

It is also worth noting that firm sales is not an ideal measure of venture growth; it is used in these summary statistics precisely because we wish NOT to use our preferred measure of growth – numbers of workers – in the summary statistics section of this progress report. Yet the pronounced differences in firm and owner traits and firm outcomes discussed above are certainly noteworthy and thought provoking. We will revisit these patterns as we undertake our econometric analysis of growth in numbers of firm workers across time.

2. Establishing Measures of Firm Growth

Our econometric exercises seek to explain growth in the number of firm workers over the time period from which the individual small business exceeded our threshold value regarding sales revenues (base year) through yearend 2008, the final year of the KFS time-series data. The base year restriction, as noted above, is imposed to net out nascent firms from the analysis frame. The dependent variable, “number of workers” is defined various ways; all variants of the dependent variable are derived from following general definition of the number of workers: it includes the number of paid employees plus the number of working owners. The actual dependent variable used in regression analysis is the ***change*** in the number of workers from the base year to the following year, and then from the base-year plus one to the year after that, and so forth through 2008; this change may be logged or unlogged.[3] Tables 4 and 5 describe the outcomes of regression exercises explaining the unlogged change in number of workers. Note that many nascent firms never made the transition to active firm status and many that successfully transitioned to active status were no longer in existence by 2008. These firms are excluded from the regression findings reported in his study.

Our analysis of the dependent variable, changes in the number of workers attached to a firm over the course of the KFS time series, is not primarily concerned with understanding the behavior of the average firm; we want to understand the behavior of firms experiencing rapid growth in worker numbers, and thus we are particularly interested in outliers – those experiencing particularly large, positive deviations from the mean change in numbers of workers. Thus, we do not want to rein in the outliers and we therefore prefer the unlogged to the logged version of our dependent variable.

Our initial attempt to model firm-specific changes in worker numbers employed a logged dependent variable – log of the number of workers in the base year plus one,

[3] Our preferred form of the dependent variable is unlogged, meaning the change in worker numbers was not subjected to logarithmic transformation. Log transformations are applied to dependent-variable values in empirical studies like our present undertaking for many reasons, one of which is the fact that regression exercises of small business outcomes often attempt to model values of the dependent variable for the "typical" firm being analyzed. Additionally, logged dependent variables often conform to the normal distribution assumptions much better than their unlogged counterparts, and these assumptions are common underpinnings of regression analysis techniques. Regression analysis by its very nature explains deviations from variable mean values. When explaining deviations from the mean value of chosen dependent variables, researchers interested in the typical firm are often concerned that outliers (very large deviations from the mean) might skew the findings of regression analysis; regression outcomes heavily skewed by outliers may therefore do a poor job of illuminating the nature of the average firm under consideration. The log transformation process reins in the outliers, often resulting in a "better fit."

minus log of the number of workers in the previous year, and so forth through 2008. In this exercise, "workers" were defined as paid employees. Thus, we analyzed all of the KFS data – nascent firms and active firms alike. Using firm and owner traits as explanatory variables, we generated regression analysis outcomes in which three explanatory variables emerged as statistically significant determinants of annual changes in worker numbers, relative to the previous year. They were 1) owner hours worked, 2) team ownership (three or more owners), and 3) home-based businesses: greater owner hours and team ownership predicted higher growth in worker numbers, while the home-based business trait predicted lower growth. Thus, a firm with one owner running the business out of his/her personal residence and working few hours per week generated less growth in worker numbers through 2008, while firms with the opposite traits produced more growth, holding other factors constant.

Since the majority of the firms possessing the three statistically significant low-growth traits also reported zero sales revenues in 2004, a logical inference is that many of them were not really active firms at all but, rather, nascent operations that might or might not ultimately make the transition to active firm status. We decided to weed out the nascent firms and focus our analysis upon active small-business startups past the nascent stage that were genuinely committed to operating as "real" business ventures. There is no perfect – or even widely accepted – technique for delineating nascent firms from active young businesses, so we investigated several alternative filtering techniques, and chose ultimately to equate nascent status with trivial sales revenue generation; thus, our $5,000 sales threshold emerged.

3. Hypotheses Guiding the Analysis of Firm Growth

Our hypothesized causal relationships between firm and owner traits and firm growth patterns include the following:

a. Young venture growth is not adequately captured by one-size-fits-all econometric models using founder and firm traits (plus strategic choices) to explain venture growth for an all-inclusive population of firms operating in widely varying industries (Parker, 2009; Lofstrom and Bates, forthcoming). Thus, we proceed by explaining venture growth for select subsets of firms.

b. Highly educated, appropriately experienced founders are likely to achieve higher rates of venture growth than poorly educated, inexperienced founders for two reasons. First, those with strong human capital are expected to self-select into types of ventures having higher growth prospects than the lines of business which founders with weak human capital self-select into. Second, stronger human capital facilitates successful venture operation and expansion.

c. Additionally, we hypothesize that a larger venture owner team size acts as a positive growth factor since a larger pool is expected to provide a greater depth of human capital, in comparison to a single-owner venture (Bates, 1997; Parker, 2009).

d. Greater access to, and investment of financial capital is expected to translate into a higher likelihood of firm growth than weaker capitalization (Parker, 2009). Further, access to capital, we hypothesize, is incorrectly measured by merely observing the capital resources invested by the founders at startup.

e. A greater degree of innovation is expected to translate into stronger venture growth prospects than a smaller degree or an absence of innovation. This hypothesis must be viewed through the lens of our first hypothesis above, in the sense that its relevance is expected to vary across industry sectors.

f. Young ventures experience rapid growth most often when their founders expect them to grow substantially. In contrast, some founders are less growth oriented, citing motivations like "want to be my own boss" for starting a new business, while setting low growth goals for their firms.

Before we turn to the actual regression analysis outcomes and discuss how these hypothesized determinants of growth patterns in fact performed when applied to the KFS data, it is instructive to contrast our approach to the criteria which venture capitalists commonly apply when they seek to identify firms with strong growth potential that may be attractive investments. Hypothesis e (above) regarding innovation highlights important limitations of the quantitative statistical models we rely upon in this report to identify young ventures having strong growth potential. When firms in the KFS database own patents, trademarks, or copyrights, we recognize this fact by including the explanatory variable, intellectual property, in our econometric analysis of venture growth. General partners of venture capital funds, in contrast, delve deeply into the nature of that intellectual property, using their expertise and the services of other experts to determine the likely commercial value of that intellectual property. They evaluate, furthermore, the likelihood that the management team of the company owning the relevant intellectual property will successfully use such assets to create and market valuable products derived from their intellectual property.

The bottom line is this: we are employing a crude variable – whether or not a particular firm owns intellectual property – while talented venture capitalists are developing sophisticated understandings of the value of such property as business assets. The likely outcome of an econometric model relying upon a crude measure of such a business asset versus a venture capital fund utilizing sophisticated measures is predictable: the fund is more likely to identify viable small-business growth prospects than an econometric model analyzing KFS data.

Qualitative aspects of several key determinants of small-venture prospects, whether intellectual property or the caliber of the human capital possessed by the firm's management team, are crudely proxied by KFS small-business data or related data on small firms (Dun & Bradstreet data, Census Bureau data, and the like) widely used in econometric analyses of small-business outcomes. The econometric analysis modeling small-firm outcomes is simply one tool and insights gained from this line of research frequently need to be supplemented with other analyses using complementary approaches. Our challenge going forward is to improve the sophistication of these databases to make them more useful tools for understanding small-business dynamics. Temptations to rely upon econometric findings to the exclusion of other methods should be resisted by those seeking to understand small business behavior.

4. Econometric Analysis of Firm Growth Patterns through Yearend 2008

We first sought to explain venture growth among firms of all sizes, including small businesses in our analysis subject only to the condition that their sales revenues exceeded zero. Our initial empirical results forthcoming from these regression models explaining growth in worker numbers for all firms (results not reported) were extremely weak: owner educational background measures had no explanatory power for delineating faster from slower growing firms, nor did the dollar amount of financial capital invested in the firm. In other words, the regression findings suggested that high-tech firms (or financial- and human-capital intensive firms) whose owner(s) lacked college degrees and invested little or no financial capital are just as likely as the firms of highly educated owners investing significant capital to achieve high growth. Furthermore, presence or absence of intellectual property ownership did not matter, nor did credit scores, team ownership, or many other traits normally associated with firm and/or owner strength. Does anything predict enhanced growth prospects? Indeed, owner hours worked was directly related to positive firm growth outcomes (and statistically significant). The only other measure of owner human-capital quality emerging as statistically significant – owner's prior work experience in the field in which the small firm operates – emerged as a negative predictor of firm growth in the financial-capital-intensive venture subgroup.

The outcomes of our next set of regression exercises explaining the unlogged change in firm-specific worker numbers through 2008 for KFS firms meeting the sales revenues threshold of $5,000, and still active in 2008 are spelled out in Table 4. "Workers," in the regression exercises include paid employees as well as owners who worked in the firm. We include firm fixed effects in the worker growth regressions to capture unobserved heterogeneity across industries and years. Regression results are reported separately for the three overlapping firm groups of interest: high-tech, financial-capital-intensive, and human-capital-intensive firms. Owner age is included as a control variable in the reported regression exercises, as is a binary variable delineating nonminority white from minority owners.

There was simply too much heterogeneity in these samples of very young firms to generate interesting regression findings, absent application of select thresholds to delete firms that may not actually be operating businesses. Furthermore, we are not really interested in understanding the "average" firm in the overall population of young firms. Our goal is to understand growth dynamics among growing firms. We proceed initially imposing revenue cutoff values of $5,000, thus deleting firms having only trivial sales revenues – presumed nascent firms – and by dropping firms having negative growth. Our attention is thereby focused on explaining growth among firms generating some positive growth in worker numbers (Table 4 regression exercises). Later (Table 5), we impose an additional cutoff, dropping firms having no owners working at least 20 hours per week in the business; our intent is to cut out nascents as well as casual ventures (Table 5). We next explore growth dynamics by examining solely those firms with nontrivial sales, owners working at least 20 hours per week, *and* generating at least five-fold growth in worker numbers by yearend 2008 (Table 6).

This final exercise permits us to observe whether ventures experiencing substantial growth are impacted by growth constraints similar to those impacting the broader firm population, as opposed to specific constraints that may apply most heavily to rapidly growing business ventures. Thus, we can test whether potentially limiting factors like low firm credit scores or limited owner human capital have an increasing and/or particularly noticeable relevance as growth becomes rapid.

Before our discussion of regression analysis outcomes is presented, several details require clarification. Many firms have more than one owner, and traits such as owner age and educational background can obviously vary across owners. We employ the concept of a "dominant" owner, defined as the owner with the largest ownership stake in the venture; in cases where owners have identical ownership shares, we define the dominant owner as the one working the most hours in the firm. Thus, such dependent variables as owner demographics and educational background reflect the characteristics of the dominant owner.

Our final hypothesized source of firm growth is the owner's orientation (or lack of) toward actively pursuing venture growth. We have no direct measure of this orientation and rely, instead, upon a proxy measure – setting up a home-based business. This imperfect measure assumes that the owner decision to operate the firm out of one's personal residence is often rooted in the desire to pursue venture operation simultaneously with the pursuit of another objective – raising one's children is one common example. We are not implying that firms operating out of personal residences are necessarily less growth-oriented than others. Rather, the home-based business decision is simply positively correlated to owner inclinations to place less emphasis on venture growth, relative to those owners not operating out of the home; thus, it is a proxy measure of owner growth orientation.

Scanning the regression analysis findings explaining growth in worker numbers among firms exceeding the $5,000 sales revenues threshold, the frequent presence of part-time businesses is noteworthy, manifesting itself in multiple ways. First, young part-time business ventures are disproportionately home-based firms, and women owners are disproportionately the owners of both part-time and home businesses. Both traits – women owners (high-tech and financial-capital-intensive subgroups) and home-based firms (human- and financial-capital-intensive subgroups) – are statistically significant negative predictors of venture growth. Higher amounts of hours worked by owners, likewise, are a strong positive predictor of growth (financial- and human-capital-intensive subgroups). Owner human-capital traits are less prominent as explanations of growth patterns: among financial-capital-intensive ventures, teams of three or more owners as well as prior startup experience of owners are positive, statistically significant determinants of growth in worker numbers (Table 4). Interestingly, higher levels of state-wide unemployment predicted higher growth among high-tech firms, suggesting that these businesses might possibly be benefitting from their improved ability to hire skilled workers in conditions of rising unemployment reflecting an increased supply of job seekers.

Strength in venture finances positively predicted growth in several instances: statistically significant determinants of firm growth included higher levels of financial capital investment (high tech and financial-capital-intensive subgroups), although the latter subgroup may be negatively impacted by high levels of outside indebtedness (largely bank loans); stronger credit scores had a similar impact on human-capital-intensive firms (Table 4). The robustness of these findings is tested below by revisiting performance of these growth determinants in regression models based upon differing assumptions: some are robust and some are not. It is noteworthy, finally, that high-tech firms – holding other factors constant – grew faster than other firms in the financial-capital-intensive subgroup.

Table 4: Regression Analysis of KFS Data: Growth in Worker Numbers (firms exceeding revenues threshold value only)

Variables	**Regression coeffients**		
	High-tech firms	**Financial-capital-intensive firms**	**Human-capital-intensive firms**
Minority	.157	.201	.210
	(.458)	(.280)	(.481)
Owner Age	-.067	.0208	-.270
	(.128)	(.053)	(.240)
Age Squared	.001	-.000	.002
	(.001)	(.001)	(.002)
College Degree Plus	.489	.127	-.484
	(.428)	(.166)	(.494)
Hours Worked (week)	.031	.014**	.022**
	(.023)	(.005)	(.009)
Work Experience in this Field	-.025	-0.003	.007
	(.041)	(.009)	(.013)
Prior Startup Experience	.172	.511*	.687
	(.450)	(.182)	(.531)
Gender (Female=1)	-.791*	-.396*	-.186
	(.447)	(.134)	(.347)
Team (3 or more owners)	.656	.882*	1.514
	(.817)	(.326)	(1.001)
Intellectual Property	-.246	.385	.971
	(.720)	(.236)	(.841)
Product Offering	.996*	-.165	-.801*
	(.545)	(.189)	(.476)
Home-based Firm	-.608	-.886*	-1.712*
	(.526)	(.172)	(.401)
High Tech	–	.565*	-.093
		(.294)	(.409)
Credit Score	.016	-.000	.016*
	(.010)	(.003)	(.007)
Financial Capital Injections ($000)	.004*	.001*	.000
	(.002)	(.000)	(.000)
Outside Debt Ratio	-.660	-.468*	-.267
	(.753)	(.199)	(.516)
Unemployment Rate Level	.465*	.065	.056
	(.232)	(.082)	(.120)
Constant	-1.309	.140	8.880
	(3.806)	(1.364)	(6.318)
Observations	742	2620	2110
R-squared	.168	.066	.039

Note: Standard errors in parentheses. * $p<0.05$

Findings emerging from the Table 4 regression analyses of growth in worker numbers, while provocative, are, by themselves, not very impressive. A possible explanation for our limited ability to explain growth is the fact that the very young ventures being analyzed are in their “learning” phase, in which various push and pull factors are pushing some firms forward and pulling others back in complex ways. Consider the finding that greater owner hours worked often predicts greater firm growth. We already know that rapidly growing financial-capital-intensive and high-tech firms were losing money in 2008 (see Tables 1 and 2). Quite possibly, firm owners having very strong human-capital traits often have to retain their salaried jobs in order to finance firm growth (and survival). Dividing one’s time between salaried work and operating one’s growing small business, of course, may detract from the performance of the young business venture. We attempt to test this hypothesis, which is one of the tasks undertaken in the regression exercises in Table 5.

In addition to imposing a threshold value of sales revenues to filter out nascent firms, we next proceed by dropping all firms whose owners are devoting less than 20 hours per week to working in their young business ventures. In the case of multiple-owner firms, we dropped those where none of the owners met the 20-hours-worked threshold; if one did and others did not, the fact that at least one owner was working in the venture at least 20 hours per week was deemed sufficient. Re-estimation of Table 4’s regression equations for surviving firms meeting the owner-hours-worked threshold produced somewhat different empirical findings. Imposing these additional restrictions reduced sample sizes – as firms with owners working few hours were dropped – but the slight improvement in regression exercise performance was not impressive.

Table 5: Regression Analysis of KFS Data: Growth in Worker Numbers (firms exceeding the owner-hours-worked threshold only)

Variables	**Regression coeffients**		
	High-tech firms	**Financial-capital-intensive firms**	**Human-capital-intensive firms**
Minority	.139	.069	.100
	(.507)	(.301)	(.529)
Owner Age	-.0935	.0396	-.301
	(.156)	(.068)	(.282)
Age Squared	.001	-.000	.003
	(.002)	(.001)	(.002)
College Degree Plus	.442	.173	-.549
	(.430)	(.188)	(.578)
Hours Worked (week)	.0415	.0121	.021
	(.031)	(.009)	(.015)
Work Experience in this Field	-.030	-.006	.004
	(.047)	(.011)	(.015)
Prior Startup Experience	.101	.589*	.947
	(.497)	(.225)	(.650)
Gender (Female=1)	.730	-.441*	-.146
	(.463)	(.168)	(.388)
Team (3 or more owners)	.581	.992*	1.855*
	(.935)	(.368)	(1.123)
Intellectual Property	-.273	.462*	1.141
	(.766)	(.270)	(.981)
Product Offering	1.037	-.194	-.853
	(.592)	(.213)	(.554)
Home-based Firm	-.651	-.937*	-1.858*
	(.642)	(.203)	(.468)
High Tech	–	.590*	-.129
		(.342)	(.477)
Credit Score	.0179	-.001	-.016*
	(.0121)	(.004)	(.008)
Financial Capital Injections ($000)	.004*	.001*	.000
	(.002)	(.000)	(.001)
Outside Debt Ratio	-.643	-.506*	-.425
	(.794)	(.225)	(.590)
Unemployment Rate Level	.500*	.0804	.123
	(.258)	(.105)	(.172)
Constant	-1.509	-.174	9.465
	(4.896)	(1.67)	(6.905)
Observations	637	2171	1714
R-squared	.164	.060	.038

Note: Standard errors in parentheses. * $p<0.05$

We have only two statistically significant predictors of high-tech firm growth, while eight explanatory variables predict growth of financial-capital-intensive firms and three are significant for human-capital-intensive ventures (Table 5). The amount of financial capital invested into firms continues to be positively related to growth for high-tech and financial-capital-intensive ventures, a relationship that is statistically significant. Higher unemployment in the state in which a high-tech firm operates continues to be a positive determinant of venture growth. The fact that owner hours worked ceases to be a strong positive predictor of growth is rooted in our deletion of firms with owners working in their businesses on only a part-time basis.

Home-based businesses continue to lag growth-wise for both the financial- and human-capital-intensive firms – a finding that replicates patterns observed in Table 4's regression findings. We conclude that basing a firm in one's home and the subsequent pattern of significantly lower venture growth is a reflection of more than simply a desire of owners for part-time work. This finding is consistent with our hypothesis that owners of home-based firms are often less inclined to pursue venture growth than otherwise identical owners choosing to locate their businesses outside the home.

Other statistically significant determinants of venture growth emerging from Table 5's regression exercises replicate Table 4 findings, suggesting robustness in the strength of their relationships to growth patterns in numbers of workers over time. Firms experiencing higher levels of new financial capital injections continue to outgrow their counterparts in both the hi tech and financial-capital-intensive subfields (Table 5), although the latter group continues to be impacted negatively by high levels of outside indebtedness. Team ownership once again explains higher growth among businesses in the human- and financial-capital-intensive subgroups, while prior startup experience among owners positively predicts higher growth among the latter. For the financial-capital-intensive ventures, finally, the high-tech firms continue to grow faster than otherwise identical businesses. This recurrence of certain patterns across the econometric modeling exercises reported in Tables 4 and 5 is encouraging. Finally, it is noteworthy that ownership of intellectual property is a positive, statistically significant growth determinant among the financial-capital-intensive firms.

On balance, outcomes of regression exercises explaining growth patterns were weakest in the human-capital-intensive firm subgroup (Table 5). Indeed, team ownership (three or more owners) is the only human-capital trait that stands out as a significant and positive predictor of growth. Does this mean that strong owner educational background and relevant work experience are unimportant in the context of understanding venture growth? We doubt that.

Owners having particularly strong human-capital endowments are often pulled away from their entrepreneurial pursuits because of opportunity-cost considerations. Those with graduate degrees and applicable work experience are the specific subset of entrepreneurial candidates likely to have the most attractive opportunities to pursue salaried employment. When they do launch startups, they are hypothesized to pursue the “toe-in-the-water” approach quite often. Stated differently, they often start out very small to get a sense of what the prospects of their business startup may be, but they retain an “option value” of expanding once their learning phase of venture operation is completed (Caves, 1998). Exactly how this option-value phenomenon may be expressing itself in Table 5's regression findings and how we might test whether option-value considerations are at work here is spelled out further in section 5 below.

Table 1 summary statistics suggested that rapidly growing high-tech and financial-capital-intensive firms faced stress created by attempting to maintain venture growth while operating unprofitably in an environment, in 2007 and 2008, of tightening credit availability. Yet, the very real challenges involved in financing growth while they were generating such operating losses are not clearly reflected in Table 5's regression analysis outcomes. Obviously, the better capitalized among the growing high-tech ventures should have more success in sustaining growth than their undercapitalized counterparts. The expected strong, direct relationship between larger financial capital and greater firm growth rooted in the need for adequate capitalization to sustain growth is further explored below in regression analyses summarized in Table 6.

Calendar year 2008 was characterized by a cyclical economic downturn; more importantly, this downturn was rooted in severe credit-market instability and contraction. The weaker small-business loan applicants, in 2008 circumstances, were likely to experience loan denial and reduction of their lines of credit. For the unprofitable yet rapidly growing firms, these conditions were possibly deadly not only for sustaining growth but for maintaining even steady-state status. Furthermore, states where high-tech firms most often concentrate – California for example – were harder hit in 2008 by the recession and credit crisis than firms in other parts of the nation. A comparison with the human-capital-intensive firms in the credit-crisis context is revealing. The rapid growth firms in this subgroup, in stark contrast, to their high-tech counterparts, were highly profitable in 2008, reporting mean net profits of $97,471 (Table 2). They were therefore less vulnerable to the 2008 drop in credit access.

Regression analysis findings described in Table 6 apply solely to high-growth firms, specifically those generating at least five-fold growth in worker numbers, and surpassing threshold values of 20 hours worked per week by owners and $5,000 in annual sales revenues. Explanatory variables directly related to venture financing stood out as statistically significant determinants of firm growth patterns. Higher levels of venture financing, once again, positively explained growth for financial-capital-intensive and high-tech businesses; among the latter, the regression coefficient attached to the “financial capital injection” variable doubled in size (Table 6) in comparison with the corresponding coefficient value in Table 5. Firms actually investing new capital into their ventures are consistently the higher growth businesses. Furthermore, hi tech and financial-capital-intensive firms with higher credit scores achieved greater growth than otherwise identical businesses, and this relationship was statistically significant in a one-tailed test.

Table 6: Regression Analysis of KFS Data: Growth in Worker Numbers in High-Growth Firms (5X Growth)

Variables	Regression coeffients		
	High-tech firms	Financial-capital-intensive firms	Human-capital-intensive firms
Minority	-1.314	1.262	2.532
	(1.307)	(1.883)	(2.555)
Owner Age	-.852	.469	.023
	(.494)	(.364)	(1.260)
Age Squared	.013*	-.004	-.001
	(.005)	(.004)	(.011)
College Degree +	.655	.225	1.483
	(.923)	(.899)	(3.031)
Hours Worked (week)	.172*	.006	-.019
	(.072)	(.043)	(.060)
Work Experience in this Field	-.168	-.110*	-.027
	(.160)	(.049)	(.077)
Prior Startup Experience	1.077	1.430	2.370
	(1.458)	(.897)	(3.384)
Gender (female=1)	-2.022	-1.985*	-.954
	(2.360)	(0.974)	(2.028)
Team (3 or more Owners)	1.545	.366	3.181
	(1.799)	(.830)	(2.601)
Intellectual Property	-0.452	-.242	-.963
	(1.419)	(.812)	(3.842)
Product Offering	-.321	-.896	-2.119
	(1.477)	(.825)	(3.666)
Home-based Firm	-.992	-1.767	-2.368
	(1.578)	(1.083)	(1.741)
High Tech	–	.334	-.965
	(0)	(.929)	(1.803)
Credit Score	.058*	.040*	-.033
	(.035)	(.018)	(.033)
Outside Debt Ratio	-3.712*	-3.149*	-1.866
	(2.051)	(1.005)	(2.531)
Financial Capital Injections ($000)	.008*	.003*	.000
	(.003)	(.001)	(.002)
Unemployment Rate Level	-.375	-.007	-.345
	(.787)	(.288)	(.898)
Constant	7.760	-8.256	4.373
	(12.37)	(7.134)	(28.23)
Observations	177	435	287
R-squared	0.363	0.115	0.053

Note: Standard errors in parentheses. * p<0.05

Credit constraints were clearly impacting many of these firms. Most directly, the combination of rapid growth without profits was predictably causing difficulties in meeting debt repayment obligations for some firms, a fact reflected in the negative, statistically significant relationship (one-tail test) between venture outside debt ratios and growth in worker numbers. Too much bank debt is obviously a particular problem for high-growth firms generating negative profits in an environment of tightening credit market conditions. Indeed, this combination can threaten venture survival. This fact is reflected as well in the complementary finding that credit scores significantly impacted growth; the down side of this is that low credit scores were constraining venture growth, a predictable outcome since borrowers of marginal quality are the ones most often impacted by tight credit.

5. Two-stage Model of Growth

Particularly in promising new ventures recently started by owners possessing advanced degrees and abundant valuable work experience, there is often an option value of waiting before making substantial commitments to the young business in such forms as expanded owner work hours, additional hiring, and further investments in equipment, inventory, and the like (Caves, 1998). Thus, new ventures having the potential to become large-scale employers often begin operations at a small scale and their owners choose to exercise their expansion option *only* if firm performance is judged to be proceeding favorably. Arrival of a significant macroeconomic downturn and credit crisis is the type of contingency that would encourage owners of potentially significant ventures not to exercise those expansion options. Among those retaining ties to salaried employment while they operate very young small-firm ventures, the macro environment in 2008 would encourage some to maintain their employee status at the expense of expanding their businesses. Thus, the unfortunate fact that the KFS time-series data began in 2004 and ended at yearend 2008 amidst recession and credit contraction makes it ideal for investigating impacts of credit restriction but less than ideal for investigating long-term firm growth dynamics.

The sharp 2008 economic downturn is not a problem that can be adequately controlled for with proxy measures like state-specific unemployment rates when one's objective is to explain how important owner and firm traits, strategic choices, and environmental factors predict growth among successful startups. Owner decisions about whether to exercise the kinds of option values identified above are heavily shaped by an entrepreneur's expectations of business prospects in future years. Thus, owners in states like California and Florida may be reining in growth plans because of the reality of recessionary conditions and restricted credit availability; they may be postponing expansion plans even if credit needs are slight if they feel that future business prospects are diminishing.

5a. Learning Phase and Growth Phase

Recessionary conditions in 2008 notwithstanding, it may nonetheless be useful to define venture growth as a two-stage process: 1) the learning phase, and 2) the growth phase. The learning phase is expected to exhibit substantial uncertainty regarding venture prospects (see, for example, Jovanovic, 1982) as owners assess both their own managerial acumen and the performance of their very young ventures, and choose one of three paths: 1) exercise their expansion options, 2) maintain a steady course of small-scale operation, or, alternatively, 3) abandon entrepreneurship altogether. Since those facing the highest entrepreneurship opportunity costs are expected to be those with the strongest human capital, they may disproportionately choose not to exercise their expansion options. Thus, potentially powerful determinants of firm growth potential – strong owner human-capital characteristics – may be latent during both the learning and growth phases of the venture life cycle, and thus unobservable in regression exercises explaining growth patterns.

Once the firm learning stage ends, ventures with significant growth potential and positive learning-phase experiences should be willing to exercise their expansion options, since learning-phase lessons have given owners the necessary confidence to invest in business expansion, hire more employees, drop their salaried employment in favor of a full-time entrepreneurial work commitment, and the like. This outcome, of course, may be hard to observe in an environment of recession and credit constraint. If it is true that venture growth dynamics differ across the learning and growth stages of its life cycle, then regression exercises like the ones summarized in Tables 4 and 5 may come up short in terms of explanatory power since they are modeling two distinct stages of firm development – learning and growth – as though they were one and the same stage.

If the above characterization of owner uncertainty and option values is correct, then econometric estimates of firm growth while venture owners are in the learning phase should be messy, possibly resulting in poor explanatory power. Econometric estimates of firm growth determinants in the post-learning growth stage may yield clearer, more potent findings of venture growth prospects. How long does the learning phase last? While this varies from firm to firm, we do know that firm startups are particularly prone to close down during years one and two of their operations (Bates, 1990).

Table 7: Regression Analysis of KFS Data: Growth in Worker Numbers in Years One and Two of Operations

Variables	All firms Regression coefficients
Minority	.689
	(.626)
Owner age	.031
	(.101)
Age squared	-.000
	(.001)
College degree plus	-.020
	(.253)
Hours worked (week)	.031*
	(.009)
Work experience in this field	-.002
	(.011)
Prior startup experience	.341
	(.301)
Owner gender (female=1)	-.402
	(.257)
Team (3 or more owners)	.674
	(.596)
Intellectual property	.170
	(.290)
Product offering	-.140
	(.234)
Home-based firm	-.839*
	(.204)
High tech	.847
	(.569)
Credit score	.003
	(.005)
Outside debt ratio	-.109
	(.237)
Startup capital ($000)	.002*
	(.001)
Unemployment rate level	.178
	(.109)
Constant	-2.246
	(2.684)
Observations	1837
R squared	.096

Note: Standard errors in parentheses. * p<0.05

Table 8: Regression Analysis of KFS Data: Growth in Worker Numbers From Year Three of Operations to Yearend 2008

Variables	Regression coeffients		
	High-tech firms	Financial-capital-intensive firms	Human-capital-intensive firms
Minority	.462	.466	.529
	(.577)	(.582)	(.857)
Owner age	.116	.114	.082
	(.112)	(.111)	(.162)
Age squared	-.001	-.001	-.001
	(.001)	(.002)	(.002)
College degree plus	.265	.270	-.164
	(.203)	(.203)	(.527)
Hours worked (week)	-.008	-.008	-.029
	(.015)	(.016)	(.021)
Work experience in this field	-.001	-.001	.033
	(.015)	(.015)	(.031)
Prior startup experience	.325	.314	-.527
	(.313)	(.313)	(.570)
Gender (female=1)	-.470*	-.453*	.427
	(.233)	(.238)	(.909)
Team (3 or more owners)	1.523*	1.534*	3.623
	(.505)	(.500)	(2.284)
Intellectual property	.612*	.598*	.262
	(.307)	(.310)	(.433)
Product offering	-.349	-.357	-.877*
	(.277)	(.276)	(.441)
Home-based firm	-.846*	-.852*	-2.038*
	(.228)	(.236)	(.570)
High tech	.626	.619	-.377
	(.346)	(.375)	(.477)
Credit score	.000	.000	-.033*
	(.005)	(.005)	(.017)
Financial capital injections ($000) Moving ave.	.001*	.001*	.001*
	(.000)	(.000)	(.000)
Outside debt ratio	-.571	-.549	1.330
	(.423)	(.441)	(1.068)
Unemployment rate level	-0.195	-.191	4.891
	(2.204)	(2.199)	(3.816)
Constant	-.195	-.191	4.891
	(2.204)	(2.199)	(3.816)
Observations	915	910	637
R-squared	.059	.059	.055

Note: Standard errors in parentheses. * $p<0.05$

The alternative to estimating a single regression model explaining growth for KFS firms of all ages is to model the growth stage of firm development separately from the entrepreneurial learning stage. Thus, a logical approach is to model firm growth for years one and two separately from latter years to see if cleaner econometric estimates of growth dynamics emerge. By assumption, many ventures experiencing negative outcomes during their learning stage of operations would have exited already, leaving a survivor group of firms dominated by those whose learning-stage experiences were positive. If we assume a two-year learning stage, the growth stage would be analyzed by explaining growth only for those firms that did not close down – those still active in year three of the venture's active, post-nascent life.

Venture growth during the first two years of life for small firms is examined in Table 7's regression exercise explaining growth in worker numbers. The firms under consideration in all cases met minimum threshold values regarding owner hours worked and sales revenues. Growth is measured simply by the unlogged change in worker numbers in year two (as opposed to year one) of operation. Regression findings are presented in Table 7 for firms in all industries, since separate analysis of industry subgroups revealed that determinants of growth patterns during the learning stage did not differ across industries. Two explanatory variables were positive, statistically significant predictors of venture growth and one variable negatively explained growth patterns. All three of these variables have been recurring important determinants of growth differentials throughout this study. The firms experiencing higher growth than their peers were those beginning operations with higher levels of startup capital and those having owners who worked longer hours per week. Home-based firms, finally, generated significantly less growth than businesses operating outside of the home. None of the qualitative measures of owner human capital were important determinants of venture growth, nor was the explanatory power of Table 7's regression exercise impressive.

Small firm growth in numbers of workers from year three of operation through yearend 2008 is examined in Table 8's regression analysis. By year three, high-tech firms available for growth phase analysis had declined in number to such an extent that their overlap with financial-capital-intensive firms was quite substantial. We therefore combined these two firm subgroups in the regression exercises. Because venture growth in the "growth" phase of the firm life cycle is in part measured by comparing year-four and year-three worker numbers, Table 8 regression exercises include only those firms with actual year-four operations. Many high-tech firms had not been in operation for four years because they had not been counted as active firms in 2004 and 2005 – they had not yet attained sufficient sales revenues to meet the $5,000 sales threshold. These firms are excluded from Table 8's analysis not because of firm closure but because of their late arrival into the population of small businesses beyond the nascent stage of development.

Among the high-tech and financial-capital-intensive firms, five traits were statistically significant regarding explaining growth patterns. Being home-based or women-owned were the traits negatively predicting growth, while traits positively explaining firm growth in worker numbers were team ownership, financial capital injections, and possession of intellectual property. This last finding – ownership of intellectual property – is interesting and consistent with the hypothesis that such ownership enhances venture growth prospects; the fact that it emerges as statistically significant only during the growth phase of small-business operations is noteworthy.

Unfortunately, this was the only noteworthy new finding emerging from our calculation for distinct regression models to explain growth in worker numbers separately for the learning and growth stages of the life cycle of small firms.

The explanatory power of the overall regression models (R-squared) described in Table 8, furthermore, was unimpressive. It may indeed require additional years of time-series data to illuminate key differences in venture growth dynamics at different stage of the small-business life cycle. Fortunately, KFS data will be supplemented in coming months with additional rounds of survey data describing these firms and their owners, as well as venture outcomes, in 2009 and 2010. We address our limited and somewhat disappointing findings emerging from regression models described in Tables four through eight by asking the question – what determines venture growth dynamics – in a fundamentally different way in regression models that explain a very different measure of small-business growth. This new approach and the outcomes it has produced are spelled out in the next section.

6. Competing Risk Model of Venture Growth

While it is not entirely clear why the regression results summarized above yielded so few concrete findings, the theoretical insights of Jovanovic (1982) and others do offer real clues. Jovanovic (1982), as previously noted, stresses that many entrepreneurs running new firms are initially unaware of their own abilities. However, they learn about their managerial abilities from their annual performance realizations, which are nevertheless to some extent (possibly a large extent) determined by random events beyond their control. An implication of this model is that short-term growth rates of new ventures will be characterized by a high degree of unobserved heterogeneity.

Consequently, the commonly used dependent variable of annual growth rates may simply have intrinsically limited usefulness as a measure of firm performance for new firms. Of course, this is broadly what our own findings, discussed above, confirmed.

Fortunately, Jovanovic's theory furnishes alternative performance metrics for the empirical researcher. One implication of Jovanovic's theory, and also that of subsequent models such as Ericsson and Pakes (1995), is that entrepreneurs need time to learn about their abilities, a fact that often encourages them to start out on a small scale (Caves, 1998). Another important implication is that, conditional on satisfactory venture performance and the interrelated fact of their expected abilities being high enough, entrepreneurs eventually start committing increasing amounts of costly investment to their ventures. As a result, deterministic aspects of performance outcomes (survival with growth, survival without growth, and exit) eventually begin to clarify and take shape. Notice the gap between the new venture performance outcomes envisioned by this body of theoretical work on one hand, and the empirical practice of using fine-grained annual growth measures on the other. We believe that one gets closer to the theory by utilizing more coarse-grained performance outcomes, after several years have elapsed, such as whether firms survive, and if so, whether they can achieve appreciable earnings growth.

There is a second fundamental reason why the Tables 4 through 8 regression models were only moderately successful at identifying venture growth dynamics. New and very young small business ventures cannot grow unless they remain in operation. Particularly in periods of credit-market contraction and recessionary conditions in the aggregate economy, an alternative to not growing is simply to close down one's firm, to go out of business entirely. An alternative approach to modeling venture growth is to predict growth subject to the constraint that the business must remain in operation. Thus, an attractive econometric model would be one capable of simultaneously identifying factors predicting venture growth and small-firm closure. The "competing-risk" model (below) undertakes this task.

In recognition of the above points, the next step of our empirical investigation operationalized two coarse-grained measures which are broadly consistent with the theoretical perspectives outlined above. These measures capture whether, after three years have elapsed, (a) entrants have gone out of business; or (b) entrants have progressed beyond mere survival to "survive and prosper." Briefly stated, our intent is to understand determinants of venture growth – conditioned on venture survival – during the growth phase (as opposed to the learning phase) of small-business operations. In this sense, the survive and prosper model is an analytical alternative to the growth phase regression exercises shown in Table 8 and described previously. Hereafter, the term "prospering" is taken to mean attaining or surpassing some minimum rate of growth or net profit threshold. Our empirical strategy first established the status of entrants in 2008 in terms of this dichotomy, and then analyzed the determinants of their status using event history analysis. Specifically, we used a competing risk survival model, where the competing risk (i.e. alternative) to "surviving and prospering" is either surviving without prospering or closing; and where the competing risk for "closing" is surviving, either with or without prospering.

To operationalize such a model, it is necessary to determine appropriate performance thresholds associated with "prospering." There is no need to fix these thresholds absolutely and dogmatically; a practical alternative approach, which we chose to adopt, is to define performance in a relative fashion, i.e., in terms of percentile performance. For instance, we might set a "prospering" threshold at the sample median (50^{th} percentile) of the observed four-year growth rates. Alternatively, a prospering threshold might be set below the median (e.g. at 10^{th} and 25^{th} percentiles) or above it (e.g. at 75^{th} and 90^{th} percentiles). These percentiles correspond to the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of growth after year three of operation. In the end, we chose to consider all five of these thresholds, and estimated competing risk models for each of them. These five thresholds are identified in Tables 9 and 10. An advantage of analyzing the determinants of these events for both outcome measures and for multiple thresholds is that one can immediately assess the robustness of results to different choices of performance measure and threshold. Another advantage is that this analysis reveals whether the same determinants of performance affect different outcome measures, and also performance at low thresholds versus high ones for any given measure. The competing-risk model assumes firms operate in an environment where they are at risk of failure while they grow. At any time they might close (closure outcome) or they might reach a moderate or high level of growth (prosper outcome). These are Cox regression models (Tables 9 and 10) where a positive coefficient raises the probability of prospering (Table 9) or closing (Table 10) and negative coefficients do the opposite.

Our results point to several interesting findings, which were disguised by our earlier regression analyses. First, consider the survive-and-prosper outcomes (Table 9). Regardless of the growth percentile at which the threshold was set, possession of undergraduate degrees as well as graduate or professional training was found to have a significant positive impact on the likelihood that a given entrant survives and prospers after three or more years of being in business. The magnitude of this effect increases with the height of the threshold, with a fivefold increase in the impact of advanced educational credentials at 90th percentile growth performance, relative to 10th percentile growth performance. At each threshold level, the competing risk (Cox) regression model generates two sets of coefficients, one reflecting the probability of prospering while the other reflects the likelihood of firm closure. Outcomes of the likelihood of prospering are presented in Table 9, closure in Table 10.

A good credit score significantly increases the likelihood of prosperous survival, a fact that may be impacted by tightening credit market conditions in 2007 and 2008. One reason might be the fact that lenders simply refuse credit to loan applicants with poor credit scores, regardless of their growth potential; and undercapitalized ventures are most susceptible to low growth and/or failure. This effect is found across all but the highest threshold and is fairly uniform across the thresholds (Table 9). This outcome suggests that highly profitable firms may be able to sustain venture growth by self-financing when necessary, limiting the necessity to maintain a high credit score. Among firms meeting the lower growth thresholds, amount of financial capital invested in the firm increases the likelihood of prosperous survival. Other variables were found to significantly impact the likelihood of survive-and-prosper outcomes either at high levels of threshold performance (not running a home-based business), or at low levels of performance (female gender and initial employee numbers). In short, these findings seem to uncover some of the hidden structure behind the heterogeneity which dominated our earlier regression results.

Table 9: Competing Risk Analysis: Survive and Prosper Model (Cox regression)

Variables	cox_1 **10% threshold**	cox_2 **25% threshold**	cox_3 **50% threshold**	cox_4 **75% threshold**	cox_5 **90% threshold**
Minority	-.075	.040	-.005	-.057	.001
	(.058)	(.068)	(.085)	(.122)	(.157)
Owner age	.007	.004	-.001	.013	.000
	(.015)	(.018)	(.021)	(.028)	(.038)
Age squared	-.000	-.000	-.000	-.000	-.000
	(.000)	(.000)	(.000)	(.000)	(.000)
College degree +	.099*	.135*	.187*	.311*	.371*
	(.047)	(.060)	(.073)	(.101)	(.131)
Hours worked (week)	-.001	.000	.003	.004	-.000
	(.001)	(.002)	(.002)	(.003)	(.004)
Work experience in this field	.001	.002	.004	.003	.009
	(.002)	(.003)	(.003)	(.005)	(.006)
Prior startup experience	-.015	-.029	.051	.059	.040
	(.044)	(.055)	(.069)	(.091)	(.120)
Gender (female=1)	.138*	.167*	.161	-.036	.027
	(.049)	(.066)	(.087)	(.126)	(.161)
Team (3 or more owners)	-.001	-.070	.017	-.083	-.024
	(.089)	(.109)	(.112)	(.155)	(.181)
Intellectual prop.	.030	-.045	.007	-.067	.102
	(.057)	(.075)	(.087)	(.116)	(.148)
Product offering	-.002	-.095	-.078	-.022	.055
	(.051)	(.068)	(.080)	(.104)	(.137)
Home-based firm	-.036	-.089	-.169*	-.385*	-.392*
	(.050)	(.067)	(.088)	(.123)	(.161)
High tech	-.062	.020	.026	.050	.147
	(.086)	(.096)	(.100)	(.128)	(.175)
Credit score	.003*	.004*	.004*	.004*	.002
	(.001)	(.001)	(.001)	(.002)	(.002)
Outside debt ratio	.235	.141	-.298	-1.032*	-1.402*
	(.204)	(.242)	(.240)	(.301)	(.346)
Financial capital injections ($000)	.008*	.008*	.000	-.003	-.002
	(.003)	(.004)	(.004)	(.005)	(.005)
Initial employment	.012*	-.008	-.007	.001	.006
	(.004)	(.004)	(.004)	(.004)	(.004)
Unemployment rate level	.010	.001	-.003	.034	.017
	(.029)	(.036)	(.042)	(.055)	(.072)
Observations	1,950	1,950	1,950	1,950	1,950

Note: Standard errors in parentheses. * p<0.05

The determinants of the closure outcome, in contrast, differ markedly from those affecting the survive-and-prosper outcome. As shown in Table 10, an entrepreneur's credit score had a larger absolute negative impact on the likelihood of closure, across all growth rate thresholds, than it had a positive impact on surviving and prospering. This result is consistent with the preceding discussion. But financial capital, work hours, college education and having a home-based business had no significant impact on the likelihood of closure. This suggests that survival is risky for all entrepreneurs regardless of factor endowments such as high levels of education and firm capitalization – whereas it seems that these endowments are definitely needed to survive and prosper. In addition, minority firm ownership was found to have significant positive effects on the likelihood of closure: these effects applied at the 10, 25, and 50 percent performance thresholds but were strongest for the slowest growers. This suggests that for some minority entrepreneurs, survival is a key challenge, especially for those operating the lowest growth businesses. Among women-owned businesses, furthermore, survival was most challenging among the highest growth firm group. Finally, possession of unique product offerings was found to reduce closure prospects among the growth performer groupings, except those in the 10th percentile of growth performance.

Table 10: Competing Risk Model: Closure Model (Cox regression)

Variables	cox_1 **10% threshold**	cox_2 **25% threshold**	cox_3 **50% threshold**	cox_4 **75% threshold**	cox_5 **90% threshold**
Minority	.725*	.475*	.320*	.133	.166
	(.183)	(.192)	(.181)	(.172)	(.163)
Owner age	-.015	-.011	.006	-.017	-.033
	(.049)	(.049)	(.048)	(.039)	(.037)
Age squared	.000	.000	-.000	.000	.000
	(.001)	(.001)	(.001)	(.000)	(.000)
College degree +	-.020	.013	-.095	-.060	-.123
	(.180)	(.170)	(.165)	(.148)	(.141)
Hours worked (week)	.004	.007	.007	.004	.004
	(.005)	(.005)	(.005)	(.005)	(.004)
Work experience in this field	-.007	-.012	-.008	-.006	-.007
	(.008)	(.009)	(.008)	(.007)	(.007)
Prior startup Experience	-.272	-.187	-.215	-.260*	-.116
	(.186)	(.179)	(.163)	(.149)	(.137)
Gender(female=1)	-.048	.179	.212	.217	.318*
	(.270)	(.225)	(.196)	(.166)	(.154)
Team (3 or more owners)	-.280	-.405	-.206	-.198	-.274
	(.399)	(.365)	(.333)	(.286)	(.281)
Intellectual property	-.281	-.223	-.130	-.147	-.092
	(.260)	(.238)	(.213)	(.190)	(.180)
	(.227)	(.215)	(.195)	(.171)	(.164)
Home-based firm	.019	.118	.146	.184	.203
	(.215)	(.216)	(.191)	(.171)	(.160)
High tech	.291	.366	.221	-.009	-.191
	(.432)	(.386)	(.372)	(.324)	(.318)
Credit Score	-.015*	-.012*	-.011*	-.011*	-.011*
	(.003)	(.003)	(.003)	(.002)	(.002)
Outside Debt Ratio	.454	-.232	-.542	-.537	-.655
	(.907)	(.758)	(.699)	(.721)	(.705)
Financial capital injections ($000)	-.202	-.127	-.076	-.054	-.107
	(.211)	(.153)	(.139)	(.129)	(.147)
Initial employment	.000	.003	.005	.007	.007
	(.005)	(.005)	(.005)	(.005)	(.005)
Unemployment rate level	.151	.117	.115	.079	.039
	(.109)	(.103)	(.099)	(.087)	(.082)
Observations	1,950	1,950	1,950	1,950	1,950

Note: Standard errors in parentheses. * $p<0.05$

To summarize, the findings from our earlier regression analysis stimulated us to think about alternative ways of modeling and explaining growth among new ventures. The competing risk methodology we eventually adopted, which focuses on relatively coarse-grained performance outcomes, is, we believe, consistent with well-established economic theories of firm growth and survival. At the same time, our approach generates several novel findings that were concealed by the use of fine-grained regression analysis that have been so popular in prior work. In particular, we believe that our findings relating to credit scores, financial capitalization, advanced educational credentials, and other factor endowments, gender and owner minority status all carry important implications for practitioners and policymakers tasked with promoting sustainable entrepreneurship. Avoiding closure appears to be a greater challenge for minority business owners, relative to others. In contrast, women business owners are significantly more likely to survive and achieve low to median growth performance than they are either to close or to survive and achieve high relative growth performance. This in turn suggests that the current policy emphasis on barriers to entry among women entrepreneurs might need to be supplemented with an analysis of their barriers to achieving above-average growth rates (Klapper and Parker, forthcoming).

D. Concluding Statements

Our econometric analysis sought to identify determinants of venture growth. Although our findings hardly constitute a thorough explanation of small-business growth dynamics, they yield valuable insights about explaining growth and understanding how the KFS data may facilitate future investigations of firm growth dynamics. In the sense of being able to examine a diverse collection of new ventures at the point of startup and sort the gold nuggets from the dross, our efforts were unsuccessful. We cannot, with precision, distinguish the likely winners from the growth laggards simply by examining firm and owner traits and strategic choices at the point of venture startup. On the positive side, we enhanced our understanding of the traits of firms and their owners that actually do successfully explain growth patterns among very young small businesses.

Small business startups likely to endure, operate profitably, and expand have certain common traits. Key ingredients of viable venture creation, operation, and growth, broadly speaking, include 1) involvement of capable entrepreneurs possessing appropriate human capital for operating the business and 2) assembly of, and access to, sufficient financial capital to achieve efficient scale and to exploit opportunities (Bates, 2011). Our findings support this conventional wisdom regarding the building blocks of venture viability. Certain factors stand out repeatedly in our analytical efforts to isolate firm and owner traits that explain growth patterns among very young small businesses. On the positive side, firms with groups of three or more owners often experience higher growth, other factors being equal, than businesses with fewer owners. This finding supports our hypothesis that larger teams of owners provide a greater depth of experience and expertise, relative to firms with fewer owners, and this larger talent pool enhances growth. Next, we hypothesized that greater investment of financial capital into young business ventures translates into a higher likelihood of growth than lower investment and weaker capitalization; our empirical findings support this hypothesis. On the negative side, we hypothesized that ventures whose owners were less growth motivated would indeed experience less actual firm growth than others, and our proxy measure of owner growth orientation was basing the businesses in one's home; our findings, once again, were consistent with this hypothesis.

Other hypothesized determinants of strong venture growth receiving empirical support included firm ownership of intellectual property, which predicted enhanced growth. In our regression analysis of growth beyond year three of operation, ownership of intellectual property indeed predicted higher growth for high-tech and financial-capital-intensive firms, other factors being equal. Firm credit score, a measure of credit market access, was hypothesized to impact access to capital and this, in turn, shapes firm growth. In most of our regression exercises, higher credit scores did in fact successfully explain higher venture growth, and vice versa for low scores.

Highly educated owners, furthermore, were expected to generate positive growth for their firms – relative to the less educated – yet we found strong, positive, statistically significant relationships between the college-graduate (or higher) education trait and enhanced growth only in our competing risk model (Table 9), where growth was conditioned on avoidance of firm closure. We interpret this to mean that highly educated owners of very young ventures often choose to keep their businesses in operation only when initial operational outcomes are encouraging and future prospects appear to be positive. Absent these traits, their high opportunity costs of pursuing firm ownership on a full-time basis encourages owners to cut their losses.

Other factors emerging as statistically significant determinants of growth outcomes included the firm's ratio of outside debt (bank loans primarily) to total financial capital injections. Because the years analyzed in this study included periods of severe credit-market contraction, we interpret this finding as evidence that many firms caught by heavy bank indebtedness burdens were harmed by this credit crunch and suffered, as a consequence, lower growth than their counterparts less burdened by outside debt. In normal credit-market conditions, this outcome of reduced growth most likely would not have arisen. Female-owned firms, finally, were often found to be achieving lower growth rates than otherwise identical male-owned small businesses, a relationship that was frequently statistically significant. We did not hypothesize a relationship between venture growth and owner gender, but this finding suggests that this relationship merits further examination.

Certain noteworthy inter-group differences, particularly regarding young high-tech firms, underlie these broad relationships between venture growth patterns, owner and firm characteristics, and strategies actually employed. Over the 2004-2008 time period, growing high-tech firms faced particularly daunting challenges. Levels of educational attainment among high-tech owners of firms achieving at least four-fold growth in worker numbers were higher than those of any of the other firm/owner subset analyzed in this study. These firms, furthermore, exhibited the highest incidence of team ownership and their owners, on average, worked longer hours per week, relative to their cohorts outside of high-tech. Ownership of intellectual property, finally, was much higher in high-tech than in other industry groups (Tables 1, 2, and 3). Yet the obvious stress under which many of these high-tech firms were operating is most clearly reflected in their poor performances, as measured by average 2008 profits. Among the high-tech firms achieving at least four-fold growth in employee numbers through yearend 2008, average profits were in the minus $90,000 range, even though the owners of these ventures were noteworthy for both their strong levels of educational attainment and their particularly long hours of work per week (Table 1). The common observation that one has to be crazy to launch a high-tech startup is seemingly supported by these empirical facts.

The venture growth patterns analyzed in this study, importantly, overlapped with a time period noteworthy for both a downturn in the U.S. economy and a tightening of credit availability. Small-firm growth dynamics certainly may differ in more normal times when credit market ease and robust growth prevail in the aggregate economy. Small businesses, regardless of macroeconomic conditions, are started by owners driven by differing motivations, ranging from lifestyle choices not emphasizing venture growth to the desire to build cutting-edge technology giants capable of competing effectively in export markets. From the perspective of understanding the drivers of venture growth, startups that represent lifestyle choices (in ways inconsistent with making small-business growth a high priority) appear to have the lowest prospects for achieving rapid growth of their firms. We cannot determine whether the tentative entrepreneur group – the toe-in-the water owner subset – is more likely than others to achieve substantial venture growth over the life cycle of their small businesses. This is one of many interesting issues concerning venture growth dynamics in need of clarification. As additional years of data reflecting venture operations in 2009 and 2010 are added to the KFS data, such issues will be further explored and clarified.

References

Bates, T. (1990). Entrepreneurial human capital inputs and small business longevity. *Review of Economics and Statistics.* 72: 551-59.

Bates, T. (1997.) *Race, self-employment and upward mobility*. Baltimore, Md.: Johns Hopkins University Press.

Bates, T. (2011). Minority entrepreneurship. *Foundations and Trends in Entrepreneurship,* 7, 151-311.

Caves, R. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature.* 96: 1947-82.

Chapple, K., A. Markesun, G. Schrock, and D. Yamamoto. (2004). Guaging metropolitan high-tech and I-tech activity. *Economic Development Quarterly.* 18: 10-29.

Davidsson, P. (2006). Nascent entrepreneurship: Empirical studies and developments, *Foundations and Trends in Entrepreneurship.* 2: 1-76.

Ericson, R., and A. Pakes. (1995). Markov-perfect industry dynamics: A framework for empirical analysis. *Review of Economic Studies.* 62: 53-82.

Hadlock, P., D. Heckler, and J. Gannon. (1991). High-tech employment: Another view. *Monthly Labor Review,* 26-30.

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica,* 50: 649-70.

Klapper, L.F. and S.C. Parker, forthcoming. Gender and the business environment for new firm creation, *World Bank Research Observer*.

Lofstrom, M. and T. Bates. forthcoming. African-Americans' pursuit of self-employment. *Small Business Economics*.

Parker, S. (2009). *The Economics of Entrepreneurship*. Cambridge, England: Cambridge University Press.

Robb, A. (2000). *The Role of Race, Gender, and Discrimination in Business Survival.* doctoral dissertation.

Robb, A., J. Ballou, D. DesRoches, F. Potter, and and Z. Zhao. (2009). *Overview of the Kauffman Firm Survey.* Kansas City, Mo.: E. M. Kauffman Foundation.

Appendix A: The Kauffman Firm Survey Database

The target population for the Kauffman Firm Survey (KFS) was all new businesses that were started in the 2004 calendar year in the United States. This population excludes any branch or subsidiary owned by an existing business or a business inherited from someone else. A business start was defined as such based on indicators of business operations, such as having an Employer Identification Number (EIN), Schedule C income, a legal form, or payment of state unemployment insurance or federal Social Security taxes. For the study population, a business started in 2004 was defined as a new, independent business that was created by a single person or a team of people, the purchase of an existing business, or the purchase of a franchise. Businesses were excluded if they had an EIN, Schedule C income, or a legal form or had paid state unemployment insurance or federal Social Security taxes prior to or after 2004.

The KFS database was explicitly designed to facilitate efforts of researchers seeking to analyze small-firm growth dynamics from the point of startup through 2011. The KFS collected information on 4,928 firms that began operations in 2004 (as defined above) and surveyed them annually. In addition to the 2004 baseline year data, we make use of four years of follow up data (2005-2008). The full survey will eventually cover the period 2004-2011. Detailed information on the surveyed firms includes industry, physical location, employment, profits, intellectual property, and financial capital (equity and debt) used at start-up and over time. For more information about the KFS survey design and methodology, please see Robb et. al (2009). A public use dataset is available for download from the Kauffman Foundation's website and a more detailed confidential dataset is available to researchers through a data enclave provided by the National

Opinion Research Center (NORC). For more details about how to access these data, please see www.kauffman.org/kfs.

The sampling frame for the KFS is based on the Dun & Bradstreet (D&B) database and restricted to businesses (or enterprises) that D&B reported started in 2004. The D&B database is a compilation of data from various sources, including credit bureaus, state offices that register some new businesses, and companies (e.g., credit card and shipping companies) that are likely to be used by all businesses. The frame was partitioned into sampling strata defined by industrial technology categories (based on industry designation). The high and medium technology strata were defined based on categorization developed by Hadlock et al. (1991), which took into account the industry's percentage of R&D employment and classified the businesses into technology groups based on their Standard Industrialization Classification (SIC) codes. High technology businesses were oversampled. Specifically, the original sampling design called for 2,000 interviews to be completed among businesses in two categories of high-technology businesses and 3,000 interviews to be completed among businesses in all other industrial classifications.

Six-digit NAICS codes are used to identify high tech firms using more current definitions in the KFS. We classify subsets of firms in high technology industries in two ways. Following Chapple et al. (2004), we identify industries that are considered technology employers, that is, industries where employment of these occupations exceeds three times the national averages of 3.33%, or 9.98%. In addition, we identify industries that are generators of technology, which are defined by the NSF's Survey of Industrial Research and Development as industries that exceed the U.S. average for both research and development expenditures for employee ($11,972) and the proportion of full-time-equivalent R&D scientists and engineers in the industry workforce (5.9%). We classify firms as high-tech if they fall into at least one of these two categories.

Firms analyzed in the study were often organized into specific industry subgroups and there is some overlap across the different industry classifications. Firm numbers listed below are not consistent with numbers of observations noted in Tables 4 through 8. This is because the regression exercises reported in those Tables 1) typically count one firm multiple times since each year of venture operation is treated as a distinct observation for regression analysis purposes, and 2) impose various threshold conditions leading to the exclusion of firms which fail to meet certain criteria.

Number of Firms in Each Classification Group

Human Capital Intensive	1,876
Financial Capital Intensive	2,186
High Tech	593
Firms that are both Human Capital Intensive and Financial Capital Intensive	1,447
Firms that are both Human Capital Intensive and High Tech	383
Firms that are both Financial Capital Intensive and High Tech	588
Full Sample	3,978

Appendix B: KFS Database: Explanatory Variable Definitions

Intellectual property: Dummy variable indicating that the firm has any intellectual property (patents, trademarks, and/or copyrights.

Product offering: Dummy variable indicating that the firm sells some kind of product (as opposed to offering a service).

Home-based firm: Dummy indicating the firm is based in the owner's home.

High tech: Dummy variable indicating the firm is in an industry considered to be high tech.

Credit score: Dun & Bradstreet credit score.

Financial capital injections: Three year moving average for new financial injections over three years, incl. current year.

Outside debt ratio: Ratio of formal bank financing to total financial capital invested.

Unemployment rate: Rate in the state where the firm is located.

Minority: Dummy indicating the primary owner of the firm is black, Asian, other, or Hispanic.

Owner age: Primary owner's age in 2004.

Age squared: Owner's age squared.

College degree plus: Dummy indicating primary owner has at least a bachelor's degree.

Hours worked: Variable indicating the average number of hours worked by the primary owner in a given week.

Previous industry experience: Years of previous work experience in the industry in which the current firm operates.

Prior startup experience: Dummy variable indicating primary owner has previous startup experience in other business ventures.

Female: Dummy variable indicating primary owner is female.

Team: Dummy variable indicating three or more owners.

Appendix C: Can the KFS Database Be Improved?

1. Pragmatic Treatment of Nascent Firms

Pursuing entrepreneurship seriously often entails quitting one's salaried job, and the combination of lost earnings and uncertainty of success creates hesitancy. Stated differently, the opportunity costs of serious pursuit of new-firm creation are often high. This reality can encourage gradual entry, i.e., undertaking preliminary business operations abbreviated in scope, as entrepreneurs "test the waters" before incurring the risks of quitting salaried employment and jeopardizing their personal assets by entering entrepreneurship (Caves, 1998). Dabbling in entrepreneurship and deferring a costly switch until the returns from self employment become clarified – or sunk cost barriers become sufficiently modest – is often pragmatic strategically. This often gives rise to nascent firms run by owners who are considering pursuing business ownership seriously.

Such nascents often decide, after testing the waters, not to proceed, having chosen salaried work as more appealing than the uncertain prospects offered by owning a small firm (Davidsson, 2006). Very young firms reporting small revenues are numerous, yet many are nascents that will disappear, sometimes quickly and sometimes after lingering for years. The utility of including nascents in small-business databases at all is highly problematic and the preferred strategy appears to be to study them by creating databases specifically designed to include nascents only, the prominent example of which is the Panel Study of Entrepreneurial Dynamics (PSED) database.

The innovative Kauffman Firm Survey (KFS) illustrates risks of including nascents. Among the 4,928 KFS firms started in 2004, roughly half reported zero sales revenues that year and about a quarter had zero operating expenses. In Kauffman's write-up summarizing early results of KFS data analysis, over 900 of the original 4,928 startups were excluded because attempts to collect follow-up data were unsuccessful, leaving us wondering what became of them (Robb et al., 2010). Since their owners could not be contacted nor induced to respond to queries, even when offered monetary incentives, we simply do not know their outcomes. Past experience tracking nonrespondents suggests that closure is a common outcome (Robb, 2000). An educated guess is that most of the mystery firms were nascent operations whose owners decided not to proceed, yet the fact that only 4,022 of the 2004 startups could be tracked reveals one of the many risks in treating nascents as small businesses. Predictable results are depressed survey response rates and noise in the database.

Actual sales revenues and expenses generated by KFS firms at two points in time – 2004 and 2008 – reveal that young firms generating low or no sales revenues were common not only in 2004 but also in 2008, four years beyond startup (Robb et al., 2010). Note that those figures included only 4,022 of the firms included in the original KFS sampling frame; the 906 non-respondents were excluded. Over 46 percent of responding firms reported 2004 sales of zero as did 30.2 percent reporting sales for 2008. Firms generating neither sales nor incurring expenses were numerous years after their 2004 startup date.

Empirical studies of small businesses seek to identify firm and owner traits and strategies that accurately predict venture outcomes reflecting successful firm performance. Thus, firms generating jobs and operating profitably are typically judged successful, while those closing down and, or generating losses or minimal profits are unsuccessful (Bates, 2011; Fairlie and Robb, 2008). Yet these success measures are really not applicable to nascents, since owner decisions to shut down and, or not to hire employees are typically rooted in pragmatic assessment of the opportunity costs of entrepreneurship entry in the face of limited prospects for venture success. Judged from the standpoint of researchers attempting to explain business performance, outcomes of ventures never proceeding beyond the nascent stage are irrelevant. Since the internal logic of whether or not to remain in operation differs for nascents, versus businesses whose owners actually do choose to create new firms, it is unclear what we would learn even if all nascents responded to KFS followup surveys.

The challenge facing the Kauffman Foundation, the Census Bureau, and others creating and maintaining small-firm databases is to generate data that is simultaneously useful for expanding our understanding of small-firm dynamics and cost effective. Including numerous nascents muddles the process of analyzing small-business behavior, while simultaneously raising the costs of data collection and database creation. The problem, of course, is that no widely accepted protocol for delineating nascents from genuine firms (post-nascents) has emerged and the challenge going forward is to create a consensus on how this is to be done. The likely payoff – more powerful small-business databases generated at lower costs – suggests that undertaking this exercise should be a high priority.

2. Asking Surveyed Firms the Right Questions

By design, the KFS database seeks to promote understanding of small-firm growth dynamics. Viewing high-tech firms as a particularly interesting type of small firm from the venture growth perspective, the designers of the KFS database chose to oversample this type of business. With hindsight, we observe that growing firms – particularly those in the overlapping high-tech and financial-capital-intensive subgroups – with larger capital resources and greater access to financial capital experienced higher growth in worker numbers than less capitalized ventures (Tables 4 through 8). It is also apparent in hindsight that rapidly growing high-tech firms, unprofitable and quite often cash-flow negative (Table 1), are frequently likely to be capital constrained.

In light of the clear relevance of venture capitalization as a subsequent venture growth determinant , it would be useful to collect additional firm-specific information that enhances our understanding of relationships between small-business capital structure and growth performance. Because the KFS collected only data on gross capital flows of debt and equity in its firm-specific surveys subsequent to 2004, we have no direct measure of their net capitalization beyond 2004. Particularly for growing cash-flow-negative young firms in high-tech fields, gross flows provide only rough proxies for measuring actual venture capitalization after 2004. One can simply add up the gross flows year by year to approximate capital, but this method will often overestimate actual venture capitalization, since large leakages clearly typify cash-flow-negative ventures, and the potential for mis-estimation rises annually as the collected KFS survey data get farther beyond the 2004 base year. Even among cash-flow-positive firms relying on short-term debt sources like credit cards and working capital loans, net capital flows are likely to diverge significantly from gross flows. Ideally, we need to understand not only gross capital flows but net flows as well.

Although some young firms do not in fact measure their net capitalization annually, proxy measures are readily available to identify the cash-flow-strapped ventures most likely to hold capital well below the stock estimated by summing gross flows; growing cash-flow-negative firms are quite likely to face difficulty paying their bills on a timely basis. Simply asking the owners whether timely payment of outstanding obligations poses a major operating problem flags the financially constrained venture subset, and this insight would, in conjunction with currently available data on capitalization, help to explain firm growth patterns.

Beyond capital investment and access, another factor in need of elaboration in the KFS database is owner human capital, particularly educational background. Among high-tech firm owners, for example, we currently can identify owners with graduate or professional training. Yet the owner with a Ph.D in engineering cannot be delineated from one whose graduate training entailed working for a year toward a master's degree in education. Additional detail allowing researchers to delineate Ph.D recipient owners from those receiving masters or professional degrees would be useful, particularly if accompanied by sufficient detail to distinguish holders of engineering degrees (and business fields) from others. These suggestions are illustrative rather than exhaustive.