VENTURE CAPITAL FIRM EXPERIENCE AND COMPANY GROWTH

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ABSTRACT

Academics argue that growth studies should be longitudinal, because organizational growth is inherently a dynamic measure of change over time. The goal of this paper is (a) to gain an insight into the temporal pattern of growth within venture capital backed companies and (b) to study the impact of differences in venture capital firm (VCF) experience on this growth pattern. For this purpose, a unique longitudinal database is used, related to a sample of 100 venture capital backed companies that are followed from the year of VCF participation up to five years after VCF participation. It is shown how Linear Mixed Models (LMMs) can be used to examine dynamic issues in growth studies. Contrary to prior studies (implicitly) assuming a constant growth rate across time, which is in line with Gibrat’s law, I present evidence of non-linearities in growth trajectories. Results further indicate that ventures backed by VCFs with high overall or industry deal experience grow significantly faster in terms of total assets compared to ventures backed by VCFs with low overall or industry deal experience.

INTRODUCTION

It is well established in the literature that only a small percentage of firms are responsible for a disproportionate share in employment generation, value creation and innovation in any economy. Research by Storey (1994) indicates that some 50% of the jobs created by all startups in the U.K. can be attributed to only 4% of these startups. Similarly, Birch (1997) shows that 3% of U.S. companies are responsible for more than 70% of employment creation between 1992 and 1996. This makes that research into the antecedents of entrepreneurial growth is a central area of research in entrepreneurship and a major policy concern.

Despite the large amount of academic studies on venture growth, several academics claim that the lack of longitudinal growth studies is problematic (Delmar, 2006; Davidsson & Wiklund, 1999; Weinzimmer et al., 1998). Research on venture growth should be longitudinal, because of the dynamic nature of growth (Weinzimmer et al., 1998). However, prior studies typically use only first and last years sizes and consequently do not fully capture the growth of ventures, because they ignore development in-between (and outside of) these two time points (Delmar et al., 2003; Weinzimmer et al., 1998). Nevertheless, it is necessary to first have an insight into the temporal pattern of growth, before one can start answering questions about the impact of particular company or industry characteristics on company growth (Delmar 2006; Weiss, 2005).

Venture capital backed companies are a special type of entrepreneurial companies with high growth ambitions. Prior growth studies make (often implicit) assumptions about the temporal pattern of growth. Some research using the growth formula underlying Gibrat’s law of proportionate growth assumes an exponential growth curve. Other studies assume that growth occurs as one large quantum size leap over the period studied. The first goal of this paper is to study unconditional change within venture capital backed companies.

After modeling the temporal nature of growth, it becomes possible to study the impact of
particular company and/or industry characteristics on the growth curve of companies. Research only recently started to study the consequences of venture capital firm heterogeneity. Not all venture capital is the same and from whom a company receives venture capital financing may be far more important than the amount of financing or how much the entrepreneur pays for it (Bygrave & Timmons, 1992). Hsu (2004) indicates that US VCFs with high experience and high past performance acquire start-up equity at a 10%-14% discount. Hence, it is important to understand whether this discount is worthwhile. The second goal of this paper is to study conditional change, which involves examining the impact of overall and industry deal experience differences between VCFs on the growth trajectories of entrepreneurial companies.

Prior research on the consequences of VCF heterogeneity has almost exclusively relied on performance from the perspective of the VCF (see Sorensen, 2007; Hochberg et al., 2007; Dimov & Shepherd, 2005). These studies relate differences in VCF experience to differences in the relative amount of exits, such as Initial Public Offerings (IPOs) and Mergers and Acquisitions (M&As). This approach has two main drawbacks. First, for VCFs to be able to exit from promising ventures through an IPO, an active stock market is required, which is not the case in most Continental European countries (Black and Gilson, 1998). Additionally, M&As represent a more common exit route both for very promising ventures and less promising ones in Continental Europe. Hence, M&As do not distinguish between successful and unsuccessful ventures (Schwienbacher, 2002). Second, what is considered a successful exit from the fund’s perspective may not always be considered successful from the portfolio company’s perspective. Exits by VCFs also bear risks for entrepreneurs, like losing control and major changes in board composition (Schwienbacher, 2002). VCFs may even have perverse incentives and act in their self interest. Gompers (1996), for example, shows how young VCFs bring IPOs to the market prematurely, thereby not optimizing the value of the IPO. This paper is distinctive in that it studies the growth of venture capital backed companies from the company’s perspective.

The paper starts with a discussion of the theoretical background and development of hypotheses. Next, we discuss the data set, measures and method of analysis. Thereafter, we present our research findings, followed by a conclusion and avenues for future research.

**LITERATURE REVIEW AND DEVELOPMENT OF HYPOTHESES**

**The temporal growth pattern of venture capital backed companies**

There is an emerging consensus among both scholars and practitioners that companies which succeed in attracting venture capital will on average show significant growth across time and this at a rate significantly higher than that of comparable non-venture capital backed companies. The positive effect of venture capital is driven by two distinct processes. First, VCFs select those companies that are of higher quality and have more growth opportunities (Zacharakis and Meyer, 2000). Venture capital backed companies have to move through a lengthy pre-investment process consisting of multiple hurdles, such as due diligence, valuation and contracting, which only a handful of companies will successfully overcome (Fried & Hisrich, 1994). Second, VCFs influence company development post-investment. VCFs play an important role in monitoring the management and progress of their portfolio companies (Fried et al., 1998). Additionally, VCFs help their portfolio companies with professionalizing (Hellmann & Puri, 2002). Finally, when investing in informationally opaque ventures, VCFs with their reputation may offer a credible signal to other key stakeholders about the quality of the venture (Meggison & Weiss, 1991).

Despite this consensus, we know little about the temporal pattern of change across time within
venture capital-backed companies. The lack of insight into the growth pattern of organizations is a neglected issue even outside the venture capital literature and characterizes most organizational growth studies (Weinzimmer et al., 1998). Most studies calculate growth as the difference between two time points and ignore development between these two time points (Delmar et al., 2003; Weinzimmer et al., 1998). However, without a good understanding of the temporal nature of growth, it is difficult to start asking questions about what the effect of particular company and industry characteristics on the growth trajectory are (Delmar et al., 2006). Hence, I start to study unconditional change, which involves modeling the mean trajectories of change in specific growth concepts (such as employment, total assets, and sales) for the population as a whole (Weiss, 2005).

Gibrat's law has implicitly or explicitly been a basic ingredient in most models used in growth studies (see Audretsch et al., 2004 for an overview). Gibrat’s law of proportionate growth is a proposition regarding the process of firm growth and indicates that companies draw growth rates from a distribution that is the same for all companies (within an industry) regardless of their current size or prior size history (Mansfield, 1962). It implies that the expected value of change in company size for each period is proportional to the current size of the firm (Sutton, 1997). Mathematically, the expression is:

\[ S_{t1} = S_{t0} (1+g)^{(t1-t0)} \]  

where \( S_{t0} \) refers to the size at the start of the period, \( S_{t1} \) refers to the size at the end of the period, and \( g \) refers to the annual growth rate. In this model, growth is assumed to be spread over all years of the period and the growth rate is constant. This entails that the growth curve has an exponential shape (Davidsson & Wiklund, 1999).

**Hypothesis 1:** A constant growth rate is sufficient to model unconditional growth within venture capital backed companies.

The impact of experience differences between VCFs on the change trajectories of their portfolio companies

Recent research has challenged the uniform treatment of venture capital investors as if all investors are the same (Hsu, 2004). Dimov and Shepherd (2005) find that the portfolio companies of VCFs with more specific human capital (including law and finance experience) exhibit a lower probability of failure, but find no evidence for a positive relationship with the probability of going public. Sorensen (2007) finds that companies funded by more experienced VCFs are more likely to go public. However, both of these studies focus on performance from the perspective of the VCF. In contrast to most prior research, I study the impact of experience differences between VCFs on company growth from the company’s perspective.

Particularly highly experienced VCFs are expected to be the type of VCFs that can produce better ex-post results for their portfolio companies. The experience that VCFs accumulate across time will alter their investment behavior. VCFs are likely to learn through prior investments and develop routines based on past experiences (Nelson and Winter, 1982). The routines that will become part of a VCFs repertoire are those that previously produced favorable outcomes (Levinthal & March, 1993). Furthermore, the application of routines will increase their efficiency and hence the likelihood of a desirable outcome (Levitt & March, 1988). Hence, we might reasonably expect that experienced VCFs will be better at selecting the most promising ventures and offering value-adding services compared to their less experienced counterparts. This is expected to ultimately benefit the growth of companies backed by these more experienced...
inventors.

_Hypothesis 2: Ventures backed by more experienced VCFs will exhibit higher growth rates compared to ventures backed by less experienced VCFs._

**METHOD**

**Sample and Data**

I use a list of venture capital backed deals closed between 1999 and 2003 from the Belgian Venture Capital & Private Equity Association. Deals are selected until 2003 in order to have at least 3-year financial figures for the ventures selected at the end of this timeframe. In this way, 100 ventures are selected offering 477 data points.

For each portfolio company in the sample I collect detailed financial statement data. All Belgian limited liability companies, irrespective of their size, are required to file yearly financial statement data with the National Bank. The sample includes start-ups and more mature companies. The average age at baseline (i.e. year of venture capital firm investment) equals 5, with a minimum of 0 and maximum of 45 years. At baseline, the average company employs 19.45 people, has 5,580,770 euro of assets and creates over 995,000 euro of added value. On average cash flow is negative in these firms with –32,950 euro. Some 60% of the sample firms are active in 4 sectors, namely computer and related activities (23%), manufacturing (17%), research and development (11%) and wholesale (11%).

In order to collect data on the VCFs, I use Zephyr, a database of private equity deals with a special focus on pan-European transactions dating back to 1997. Data from Zephyr is supplemented with data from the Belgian Venture Capital & Private Equity Association and allows me to construct measures of VCF experience. I study the _initial investments_ made by 20 different _lead investors_. First, the decision to focus the analysis on the initial investment is in line with Sorensen (2007). Including later financing rounds would complicate the analysis, because separating company growth over the different financing rounds is difficult. It is unclear, for example, if growth in later rounds should be attributed to the initial investors’ ability to attract other investors or the later stage investors’ selection and value adding skills. Second, although it is common for VCFs to invest in a syndicate, I decided to focus the analyses on the lead investor. It is the lead investor who is typically responsible for the main contacts with the portfolio company.

The 20 different VCFs providing initial financing range from small VCFs with only 6 million euro of assets under management to VCF with more than 1 billion euro of assets under management. The majority of lead VCFs in Belgian companies are local investors. Only 2 firms received initial financing from an international fund.

**Measures**

Prior organizational growth research is often criticized because it does not take into account the multidimensional nature of growth. The classification of a company as a high growth company depends on the growth concept and growth formula used (Delmar et al., 2003). We take into account the multidimensional nature of growth by using two different growth concepts, namely employees and total assets. The use of different concepts gives richer information and is therefore better than the use of a single indicator (Weinzimmer et al., 1998). We decided to focus on the
absolute growth. Relative growth is not as suitable in our context since many variables may have a value equal or close to zero during the early stages of VCF involvement.

Researchers argue that growth studies should be longitudinal because of the dynamic nature of growth (Davidsson & Wiklund, 1999; Weinzimmer et al., 1998). Prior studies using only first and last-year sizes do not fully capture the dynamic nature of company growth, because they do not identify behaviors of a company during the middle periods of the study (Delmar et al., 2003; Weinzimmer et al., 1998). I study the dynamics of growth from the year of VCF participation up to 5 years after the initial investment. This is important as the typical lifespan of a venture capital investment is around three to five years (Zarutskie, 2007). Furthermore, a five-year period has been the time frame most widely used in prior organizational growth studies (Weinzimmer et al., 1998).

The key independent variables are correlates of VCF experience measured at baseline. Prior experience by VCFs should affect their ability to select more promising ventures and/or add value to their portfolio companies due to knowledge accumulation. **OVERALL DEAL EXPERIENCE**, is operationalized as the total number of investments made by the VCF prior to the current investment (Gompers et al., 2008; Sorensen, 2007), while **INDUSTRY DEAL EXPERIENCE**, is constructed similarly, but only examines investments in the same industry (2-digit industry code) as the company (Gompers et al., 2008; Sorensen & Stuart, 2001).

Prior studies have advanced important company and industry characteristics associated with firm growth. Age effects cause differences in growth patterns, which is consistent with the prediction of life-cycle models (Jovanovic, 1982). Therefore, **COMPANY AGE** at baseline is included as a control variable and is measured as the difference between the year of initial investment and company founding year. Firms situated in high technology sectors have also been shown to grow more than other firms (Harhoff et al., 1990). Hence, a **HIGH TECH DUMMY** variable is included which is equal to 1 when the venture operates in a high tech sector, zero otherwise. The classification of an industry as a high tech industry is based on a classification scheme provided by the Belgian government and is based on 2 digit industry codes. It includes industries, such as research and development and computer and related activities. Finally, it is necessary to control for size differences between VCFs, as there are multiple reasons why larger VCFs may have fast growing ventures in their portfolio (Sorensen & Stuart, 2001). **VCF SIZE** at baseline is measured as the natural logarithm of capital under management.

**Method of Analysis**

Linear Mixed Models (LMMs) for repeated measures are used to study change in employment and total assets (Fitzmaurice et al., 2004). First, models for unconditional change in employment and total assets are developed. An unconditional model does not have any static covariates of change. Therefore, an unconditional model focuses on the mean change of the entire group of venture capital backed companies over time. A neglected issue in most growth studies is the issue of regularity of growth (Delmar et al., 2003). Prior empirical studies typically model growth (implicitly) as a quantum size leap at some time during the period studied or the growth rate of companies is assumed to remain constant across time (Davidsson & Wiklund, 1999; Weinzimmer et al., 1998). Hence, while growth is considered inherently dynamic, most empirical studies ignore this dynamism (Delmar et al., 2003). I use the empirical data at hand to gain an understanding of the temporal pattern of growth, which is critical in order to be able to start answering questions about what the effects of particular covariates are (Weiss, 2005).
It is conceptually convenient to depict LMMs as multilevel models. The multilevel perspective is most useful if one assumes that companies randomly vary in terms of their initial size and change trajectory. This assumption characterizes a random effects model and seems reasonable for many applications in organizational studies. Individual profile plots (not presented) confirm significant heterogeneity in where companies start and how they evolve over time. For this purpose, I discuss two levels of equations.

The first-level in the hierarchy is the individual-level model, which specifies the nature of change for each individual company. The simplest model of individual company change is the following straight-line (linear) change model:

\[ Y_{ij} = \beta_{1i} + \beta_{2i} t_{ij} + e_{ij} \]  \hspace{1cm} (2)

where \( Y_{ij} \) is the \( i \)th company’s employment or total assets at the \( j \)th time point. \( t_{ij} \) is the linear time coding used to fit a linear trend to the \( i \)th company’s data across time. \( \beta_{1i} \) and \( \beta_{2i} \) are the company specific intercept and linear coefficient, respectively. The values of the \( \beta \)s can vary among the companies. The \( e_{ij} \) are the residuals, assumed to be normally distributed with mean zero and variance-covariance matrix \( R_i \). Equation (2) illustrates the flexibility of LMMs. Companies can have different number of time points, they may be measured at different times and each company can have a different trajectory (Fitzmaurice et al., 2004). LMMs can also accommodate non-linear change. The simplest non-linear model is a polynomial model (i.e. quadratic model), which is specified by adding \( \beta_{3i} t_{ij}^2 \) to equation (2):

\[ Y_{ij} = \beta_{1i} + \beta_{2i} t_{ij} + \beta_{3i} t_{ij}^2 + e_{ij} \]  \hspace{1cm} (3)

The second-level in the hierarchy are the group-level models. Though individual regression equations are informative, researchers are usually interested in group effects. Conceptually, the random change parameters from the individual-level model (e.g. \( \beta_{1i} \) and \( \beta_{2i} \)) are treated as response variables in a second set of models. Considering the equation (2) linear individual change model, the group level equations are:

\[ \beta_{1i} = \beta_1 + b_{1i} \]  \hspace{1cm} (4)

\[ \beta_{2i} = \beta_2 + b_{2i} \]  \hspace{1cm} (5)

\( \beta_1 \) and \( \beta_2 \) are the fixed intercepts in the level 2 equations and thus the averages of the individual-level parameters. \( \beta_1 \) and \( \beta_2 \) indicate the nature of change for the group as a whole, where \( \beta_1 \) is the group mean intercept or mean initial size and \( \beta_2 \) is the group mean linear slope. These \( \beta \)s are known as fixed effects, because they do not vary among companies. \( b_{1i} \) and \( b_{2i} \) are the level 2 residual terms reflecting individual company differences from the fixed effects.

An extension of the unconditional model discussed above is to incorporate one or more static covariates. A static covariate of change is a predictor of change that itself does not vary over the course of the study. The key covariates in this paper are overall deal experience and industry deal experience by the VCFs measured at baseline. That is, I examine whether the individual change parameters (e.g. \( \beta_{1i} \) and \( \beta_{2i} \)) vary as a function of the overall and industry deal experience of the investor backing the company. Overall and industry deal experience of the lead investor are measured at baseline and consequently do not vary across time. Hence, they are incorporated in
the group-level equations. Consider the individual-level linear model (2) above. The group level equations become:

\[ \beta_{i1} = \beta_1 + \beta_3 d_{ei} + b_{i1} \]  
\[ \beta_{i2} = \beta_2 + \beta_4 d_{ei} + b_{i2} \]

where \( d_{ei} \) is the value of overall or industry deal experience of the lead investor measured at baseline for the \( i \)th company. \( \beta_3 \) is the relationship between deal experience and intercept (initial size) and \( \beta_4 \) is the relationship between deal experience and slope. \( \beta_3 \) is also known as the intercept by deal experience interaction, as it indicates how the mean initial size of companies is dependent on investor experience. \( \beta_4 \) is also known as the trend by experience interaction, as it indicates how the mean trend is dependent on investor experience.

RESULTS

Table 1 shows descriptive information on employment and total assets. It reports unconditional means for employment and total assets across time. Furthermore, it reports the means conditional on median-split overall and industry deal experience across time. The median-split for overall and industry deal experience is only used for graphing and descriptive purposes, while the full range variables are used in the statistical analysis.

The bottom of Table 1 shows the sample sizes at each time point. The sample size decreases at the end of the time frame for multiple reasons. First, some companies are too young to have 4 or 5-year observations. Second, when a venture capital firm exits, it is difficult to contribute the growth after the exit to the VCF. Hence, the years after the exit are excluded from the analysis. Finally, contrary to prior research studying the impact of venture capital on firm growth, survivorship bias is limited, by including the failing companies in the analysis for the years they operated. This information is typically unavailable to other researchers (see Cassar (2004) for a discussion on survivorship bias when examining startup financing). In September 2007, 10 out of 100 ventures were registered as failed. Half of them were backed by investors with high overall deal experience, the others were backed by investors with low overall deal experience. Only one venture backed by high industry deal experience is registered as failed, while nine are registered as failed in the low industry experience group.

The LMM methodology used in this paper assumes that the response variable is normally distributed. We check the conditional and unconditional distributions of the raw employment and total assets values using longitudinal box plots (see Weiss, 2005). These show that employment and total assets are positively skewed (results not presented here). Therefore, the natural log of employment and the natural log of total assets are used as normalizing transformations for all subsequent analyses.

Unconditional LMMs

This paper first focuses on modeling the mean change of the entire group of venture capital backed companies across time (i.e. modeling unconditional change). A basic ingredient of much mathematical modeling in growth studies is Gibrat’s Law, which assumes an exponential growth curve (Davidsson & Wiklund, 1999). Given that measures of firm size are positively skewed, researchers often use the natural log of size as a normalizing transformation. A linear relationship in the log transformed model implies an exponential growth function in the non-transformed
model (Delmar, 2006), which is in line with Gibrat’s law of proportionate change. Hence, we study whether it is sufficient to model change as a linear function in the log transformed model. The linear model will be the comparison model against which we will compare non-linear models.

In accord with Royston and Altman (1994), fractional polynomials are used rather than polynomial models (such as equation (3), also known as quadratic change model) in order to model potential non-linear growth trends. Fractional polynomials have two main advantages. First, they enable the researcher to fit non-linear models with fewer parameters than polynomial models. Hence, fractional polynomial models are more parsimonious models. Second, fractional polynomials are often better than polynomials at producing plausible predicted values including plausible extrapolation.

The results of the unconditional analyses are shown in Table 3. Panel A reports the linear model. The mean initial value of log_e employment equals 1.6825 and the positive linear coefficient (0.1973) indicates the means steadily increased across time. The mean initial value of log_e total assets equals 7.3767 and the positive linear coefficient (0.1047) indicates the means increased across time. Panel B reports the non linear model. In the non-linear models, the following time transformation was used \( l_{ij} = \log_e (t_{ij}) \). The non-linear models lead to similar conclusions in that both indicate that venture capital backed companies grow across time. The non-linear models, however, put nuance to this finding and indicate the existence of curvature. Log_e employment and log_e total assets increase, but this at a decreasing rate.

Royston and Altman (1994) suggest a test that can be performed with the full maximum likelihood solution to compare models. The comparison statistic is \(-2 \text{ Log Likelihood (LL)}\) of the linear model minus \(-2 \text{LL}\) of the alternative model (i.e. the fractional polynomial). Positive values indicate better fit. The difference is approximately distributed as chi-squared with df =1. Since \(\chi^2(1, \alpha=0.05) = 3.84\), models with a difference greater than 3.84 perform significantly better than the linear model. For log_e employment and log_e total assets the comparison statistic equals 30.0 (i.e. 757.5-727.5) and 7.2 (i.e. 962.0-954.8 ) respectively. It indicates the non-linear models fit the data significantly better and linear change is not sufficient to model change in the log transformed models. Hence, we reject hypothesis 1 that a constant growth rate is sufficient to model growth within venture capital backed companies.

**Conditional LMMs**

The LMMs conditional on VCF experience were tested using the fractional polynomial models (taking into account individual company differences in initial size and non-linear change trajectory). The results of the conditional analyses are presented in Table 3. Panel A shows the LMMs conditional on overall deal experience by the lead VCF. The omnibus null hypothesis of no overall deal experience effect could not be rejected for log_e employment, but was rejected for log_e total assets. Table 3. Panel B shows the LMMs conditional on industry deal experience by the lead VCF. The omnibus null hypothesis of no industry deal experience effect could not be rejected for log_e employment, but was rejected for log_e total assets. Hence, we find no support that overall deal experience or industry deal experience influence the employment growth pattern of venture capital backed companies. However, we find support that overall deal experience and industry deal experience influence growth in total assets within venture capital backed companies.

Turning our attention to growth in total assets, the specific tests indicate that there is an overall deal experience by trend interaction (Table 3, Panel A). Companies backed by VCFs with high overall deal experience exhibit a steeper growth trajectory compared to companies backed by
VCFs with low overall deal experience. The overall deal experience by intercept interaction is not significant, indicating that there are no differences in the initial size between companies backed by investors with high or low overall deal experience. Table 3, Panel B shows there is a significant industry deal experience by trend interaction, but an insignificant industry deal experience by intercept interaction. This indicates that companies backed by VCFs with high or low industry deal experience are similar in size at baseline, but that the companies backed by VCFs with high industry deal experience have steeper growth curves compared to the companies backed by VCFs with low industry deal experience. In summary, our results support hypothesis 2 for growth in total assets, but we find no support for employment growth.

DISCUSSION AND CONCLUSIONS

The goal of this paper is to gain an insight into the temporal growth pattern of venture capital backed companies and study how differences in investor experience influence this growth pattern. For this purpose, I use a longitudinal dataset of 100 Belgian venture capital backed companies. The database includes companies, which eventually fail and thereby limits survivorship bias. It is shown how LMMs can be used to examine important and often ignored aspects of change.

The first part of this study was concerned with modeling unconditional growth, which is important as it is critical to gain an insight into the temporal pattern of growth, before one can start asking questions about how particular company or industry characteristics influence this growth pattern. Prior growth research is characterized by often implicit assumptions about the growth trajectories of companies. We reject the hypothesis rooted in Gibrat’s Law which indicates that a constant growth rate will be sufficient to model growth. This finding corresponds with other studies indicating that Gibrat’s Law generally fails to hold (Audretsch et al., 2004). I demonstrate how LMMs can be used in organizational growth studies to model unconditional growth with much flexibility (e.g. by allowing each company to have a different non-linear growth trajectory).

The second part of this study focuses on conditional change and studies the impact of investor experience on the growth trajectory of venture capital backed companies. I find no evidence of initial differences in employment level nor differences in employment growth between companies backed by investors with high overall or industry deal experience and companies backed by investor with low overall or industry deal experience. I did find evidence of significant differences in total asset growth between companies backed by investors with high overall or industry deal experience and companies backed by investor with low overall or industry deal experience. It is unlikely that these results are driven by survivorship bias.

This study is important for academics. Current organizational growth studies typically only focus on first and last year sizes and ignore development in between or the studies are characterized by simplistic assumptions about the temporal pattern of growth across time. I demonstrate how LMMs can be used in organizational growth studies to discuss issues related to unconditional change and conditional change, explicitly taking into account a number problems typically encountered in growth studies. LMMs allow missing data on the response variable (under the assumption of missing at random). LMMs can accommodate datasets in which the number and/or timing of observations is different for companies. Finally, LMMs allow that each company can have a different (non-linear) growth trajectory.

Results are also informative for entrepreneurs. Entrepreneurs typically have to balance the pressure of running out of cash and the time needed to search for suitable sources of financing. This study indicates that the decision from which investor to attract financing may have a long-
term impact, besides the provision of cash at the time of the investment. Although companies backed by investor with high (overall or industry) deal experience are similar in size at the time of VCF participation, compared to companies backed by investors with low deal experience, the former show a steeper growth curve for total assets in the years after VCF participation.

As with most studies, this research has limitations. First, this paper focuses on growth in employment and total asset and ignores other important growth concepts such as revenues, value added and cash flow. Second, with the current research design it is impossible to determine if ventures backed by investors with high deal experience grow faster in terms of total assets, because of superior selection or superior value-adding (such as help in attracting follow-on financing) by the highly experienced lead investor.

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NOTES

1. I thank Sophie Manigart for helpful comments. The financial support of the Intercollegiate Center for Management Science (I.C.M.) is gratefully acknowledged.

2. Other more stringent (and often implicit) assumptions have been made about the temporal growth pattern of companies. A very common assumption in organizational growth studies, for example, is that growth occurs as one large quantum size leap during the period studied (Davidsson & Wiklund, 1999).

3. (34 companies with 6 data points) + (32 companies with 5 data points) + (15 companies with 4 data points) + (15 companies with 3 data points) + (4 companies with 2 data points) gives 477 data points in total.

4. In order to keep the algebra of the LMMs simple and concise covariates that are a priori known to be important, such as company age, high tech dummy and VCF size are not described in the algebra of the models below, but are included in the empirical models.

REFERENCES


Table 1: Descriptive Statistics for Employment and Total Assets

<table>
<thead>
<tr>
<th>Measure^a</th>
<th>Baseline</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entire sample means (SDs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>19.45 (47.48)</td>
<td>19.33 (46.37)</td>
<td>21.90 (51.04)</td>
<td>23.49 (55.13)</td>
<td>25.92 (57.59)</td>
<td>29.38 (65.59)</td>
</tr>
<tr>
<td>Total Assets</td>
<td>5,581 (10,138)</td>
<td>5,118 (8,611)</td>
<td>5,505 (8,702)</td>
<td>6,566 (8,702)</td>
<td>8,166 (10,747)</td>
<td>7,351 (12,847)</td>
</tr>
</tbody>
</table>

High overall deal experience^b means (SDs)

| Employment | 29.12 (67.31) | 24.28 (60.73) | 27.66 (67.34) | 31.43 (71.30) | 38.84 (81.72) | 58.38 (107.86) |
| Total Assets | 6,892 (12,534) | 5,526 (9,013) | 5,865 (9,193) | 7,824 (12,667) | 13,245 (25,201) | 16,129 (20,741) |

Low overall deal experience means (SDs)

| Employment | 11.05 (14.17) | 13.78 (20.38) | 16.27 (26.69) | 15.15 (28.78) | 17.19 (31.20) | 17.59 (33.27) |
| Total Assets | 4,525 (7,701) | 4,741 (8,296) | 5,179 (8,312) | 5,334 (8,423) | 4,821 (5,991) | 3,840 (4,910) |

High industry deal experience^c means (SDs)

| Employment | 10.88 (13.30) | 8.85 (12.50) | 9.29 (10.42) | 11.63 (11.21) | 16.50 (17.37) | 17.60 (18.72) |
| Total assets | 2,582 (2,987) | 3,296 (5,183) | 3,627 (5,310) | 6,495 (12,364) | 11,956.24 (28,566) | 9,197 (14,609) |

Low industry deal experience means (SDs)

| Employment | 22.02 (53.54) | 24.05 (54.71) | 27.69 (60.53) | 29.31 (66.29) | 29.20 (65.97) | 32.74 (73.63) |
| Total Assets | 6,916 (11,476) | 5,883 (9,628) | 6,305 (9,723) | 6,599 (10,010) | 6,902 (10,697) | 6,878 (12,521) |

N (% Missing)

| Employment | 69 (6.76) | 87 (11.22) | 89 (8.25) | 82 (9.89) | 62 (8.82) | 45 (8.16) |
| Total Assets | 74 (0.00) | 98 (0.00) | 97 (0.00) | 91 (0.00) | 68 (0.00) | 49 (0.00) |

^a Employment is in full time equivalents and total assets in 1,000EUR.

^b Median overall deal experience at baseline equals 9 (minimum 1; maximum 90).

^c Median Industry deal experience at baseline equals 2 (minimum 1; maximum 26).

Note: SD = standard deviation.
Table 2: Unconditional Analysis for Employment and Total Assets

<table>
<thead>
<tr>
<th>Panel A: Linear change</th>
<th>Response</th>
<th>Omnibus χ²</th>
<th>Intercept (SD)</th>
<th>Linear Trend (SD)</th>
<th>-2LL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>logₑ employment</td>
<td>50.61 ***</td>
<td>1.6825 ***</td>
<td>0.1973 ***</td>
<td>757.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.1405)</td>
<td>(0.0277)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>logₑ total assets</td>
<td>10.52 ***</td>
<td>7.3767 ***</td>
<td>0.1047 ***</td>
<td>962.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.1559)</td>
<td>(0.0032)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Non-linear change logₑ employment and logₑ total assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Omnibus χ²</td>
</tr>
<tr>
<td>logₑ employment</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>logₑ total assets</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01.
### Table 3: Conditional Analysis on Overall and Industry Deal Experience Investor for Employment and Total Assets

<table>
<thead>
<tr>
<th>Response</th>
<th>Main Effects</th>
<th></th>
<th>Overall Deal Experience Interactions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Omnibus $\chi^2$</td>
<td>Intercept (SD)</td>
<td>Non-Linear Trend (SD)</td>
<td>Intercept (SD)</td>
</tr>
<tr>
<td>$\log_e$ employment</td>
<td>0.71</td>
<td>1.5602*** (0.1793)</td>
<td>0.4954*** (0.0933)</td>
<td>-0.0165 (0.0147)</td>
</tr>
<tr>
<td>$\log_e$ total assets</td>
<td>3.28** (0.4196)</td>
<td>8.2016*** (0.1114)</td>
<td>0.3164*** (0.0187)</td>
<td>-0.0094 (0.0095)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Response</th>
<th>Main Effects</th>
<th></th>
<th>Industry Deal Experience Interactions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Omnibus $\chi^2$</td>
<td>Intercept (SD)</td>
<td>Non-Linear Trend (SD)</td>
<td>Intercept (SD)</td>
</tr>
<tr>
<td>$\log_e$ employment</td>
<td>0.23</td>
<td>1.5707*** (0.1820)</td>
<td>0.4943*** (0.0943)</td>
<td>-0.024 (0.0470)</td>
</tr>
<tr>
<td>$\log_e$ total assets</td>
<td>3.61** (0.3980)</td>
<td>8.1937*** (0.1125)</td>
<td>0.3288*** (0.0567)</td>
<td>-0.0110 (0.0304)</td>
</tr>
</tbody>
</table>

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*aThe models include a priori covariates, company age at baseline, a high tech dummy and VCF size. *p < 0.1, **p < 0.05, ***p < 0.01.*