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EARLY INDICATORS OF VERY LONG TERM VENTURE PERFORMANCE: A 20 YEAR PANEL STUDY

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EARLY INDICATORS OF VERY LONG TERM VENTURE PERFORMANCE: A 20 YEAR PANEL STUDY

ABSTRACT

This paper discovers early indicators of very long term performance of high technology new ventures (HTNVs). We tracked the progress of a sample of 142 HTNVs founded at the Israeli government's Technology Incubator Program (ITIP) in the 1990s through 2001, 2004, 2010 and 2018. The results demonstrate a surprisingly strong effect of early sales traction, signifying achievement of early product/market fit in a HTNV's earliest years, on long term (a decade) and very long term (two decades) survival, and also on survival-at-scale (i.e. relatively high sales levels). In our sample, HTNVs that made sales in each of their earliest years reduced the hazard of closure, over a 20 year period, by around ninety per cent compared with HTNVs who made no sales in their earliest years. It also significantly increased the chances of survival-at-scale among those HTNVs that survived over the long or very long term. In contrast, the effect of early external investment on survival was positive in the short to medium term but then faded over time. We propose an underlying mechanism that would explain the surprising finding of distal effects of early product/market fit, that builds on imprinting theory, resourcing theory and the concept of market-based assets.

Keywords: Founding conditions, long-term performance, new high technology ventures, early product/market fit.

JEL code M13, O32, O38

INTRODUCTION

Can we predict how sustainable a high technology new venture (HTNV) is likely to be over the long term: over decades, rather than years? This is an important question because, over the long term, failure rates of such ventures are quite high, their growth distribution is highly right skewed and growth rates of individual ventures can vary widely over time (Puri and Zarutske, 2012; Anyadike-Danes et al., 2015). Most entrepreneurial resources are therefore expended on failed experiments (Shane, 2009), and investors must spread their investments over a wide portfolio in order to capture gains from the few that are highly successful (Zider, 1998). Yet, ventures that persist and achieve scale in their operations punch above their weight as net contributors to wealth and job creation (Henrekson and Johansson, 2010; Criscuolo et al., 2017). This has led to vigorous debates on whether policy makers can and should "pick winners": firms that will survive and grow over the long term (Freel, 1998; Autio and Ranniko, 2016).

Early indicators of long term venture performance would be very valuable to entrepreneurs, early investors, designers and implementers of policies who aim to boost technology commercialization through entrepreneurship, and to entrepreneurship educators and trainers. As their own "first investor", entrepreneurs could use indicators to focus on what matters for long term sustainability and "fail fast" if the indicators are not positive. For entrepreneurs starting a business with a view to exit and capital gain, the purchasers of their shares will be interested in the long term and therefore the venture's long term prospects are likely to affect their capital gains. This also applies to other early equity investors, such as business angels, technology transfer offices, technology incubators and venture capitalists. Thus, early indicators of long term prospects could help early investors to identify high potential investment opportunities. Policymakers might find in such indicators a solution to the 'picking winners' dilemma (Freel, 1998; Shane, 2009). Educators could focus their efforts on the issues highlighted by the indicators. However, intuitively, it seems unlikely that such indicators could exist; if half of registered new ventures in developed economies typically disappear within just five years (Levie et al., 2011), then how plausible is it that we could find early indicators of survival and scale-up over decades and through successive economic cycles?

Empirically, the search for early indicators of long term venture performance has been hampered by a lack of longitudinal studies that are of sufficient length to truly test for possible indicators and that do not contain significant selection or survivor bias (Geroski et al., 2010; Colombo and Grilli, 2010; Grilli et al., 2018). Meanwhile, investors in HTNVs differ on what matters most, even for performance over shorter time horizons of less than ten years. For example, the father of venture capital, Georges Doriot, and an early investor in Apple, Arthur Rock, both argued that the quality of the entrepreneur matters more than the quality of their idea (Kirsner, 2008; Kaplan et al., 2009). Tom Perkins, founder of Kleiner Perkins Caulfield and Byers, looked for ventures with a technological advantage (Gompers and Lerner, 2001). Other investors see early sales traction as a critical indicator; as Marc Andreesen put it, “all that matters is product/market fit” (Andreesen, 2007). Another leading venture capitalist, Don Valentine, “considered whether the market was large and growing” (Kaplan et al., 2009: 76).

A tendency to rely on one’s assessment of founder rather than business characteristics, despite the more objective nature of the latter, is apparent in large scale empirical studies of HTNV investor behavior (Baum and Silverman, 2004; Bernstein et al., 2017; Gompers et al., 2020). For example, almost half (47%) of all new venture capital-invested U.S.-based new employer firms started between 1981 and 2005 had no commercial revenues in their first year, compared with only 9% in a matched sample of non-venture capital-backed employer firms (Puri and Zarutske, 2012). Clearly, half of investors in that study did not seek early product/market fit, Marc Andreesen's preferred (and readily measurable) indicator, before investing, despite research that suggests that sales in a venture's first year boost survival chances and revenues over the first three years of a venture's life, especially when the team is high quality (Wang et al. 2014).

One explanation for this apparent contradiction between choice of indicators and actual investment outcomes is that professional early-stage investors are not looking for "average" investments, and therefore what might be true for the average company does not hold for their picks. Another explanation, supported by empirical research, is that early-stage investors, like many experts, tend to over-estimate their ability to pick winners based on their assessment of the character of venture founders, and under-estimate the effect of more situational variables (Zacharakis and Shepherd, 2001; Baum and Silverman, 2004; Franke et al., 2006; Gimmon and Levie, 2011; Brooks et al., 2014). Thus, while the performance of HTNVs with external investors tends to be better than the performance of HTNVs without external investors (Puri and Zarutske, 2012; Kerr et al., 2014), investors' choices of early indicators may not be the best possible guides to future performance.

The purpose of this study, therefore, is to identify indicators, observable in a HTNV's earliest years, that could be used by entrepreneurs, policymakers and other stakeholders in the entrepreneurial ecosystems of the future to assess the likely long term viability of the venture. To do this, we tracked a random sample of 142 CEOs of HTNVs who entered the Israeli Technology Incubator Program (ITIP) between 1994 and 1999. The CEOs were interviewed in 2001 and the ventures were tracked until 2018, measuring survival and sales levels in 2001, 2004, 2010 and 2018 (representing short, medium, long and very long term periods from founding). This unique sample enabled us to measure the efficacy of a range of possible early indicators over two decades, while controlling for many aspects of founding context. This is much longer than typical longitudinal studies of HTNVs, and because we sampled all entrants rather than graduates of the program, we avoided survivor bias.

The novel finding of this research is that certain indicators do have significantly - and surprisingly - different effects on survival and survival-at-scale at different points over this long time period, and also that some indicators fade in effect while others increase in effect over time. Overall, the results suggest that while a focus on a combination of founder characteristics may be appropriate as one indicator of HTNV longevity, early product-market fit is a consistently strong indicator of both survival and survival-at-scale over the long and very long term.

To summarize, we ask: *Are there indicators, available in a HTNV's earliest years, that can predict venture performance, that is, survival and survival-at-scale over the very long term?* We answer this question by tracking a cohort of new ventures with varying founder characteristics, external funding, and early sales performance, but with an otherwise very similar founding environment. The remainder of the paper proceeds as follows. The next section reviews the literature on early indicators of future venture performance. This is followed by a description of the methodology, and then the main empirical results. Finally, we discuss our findings, propose explanations for our findings, draw implications of our analysis for policy, for HTNV founders, investors, and for entrepreneurship educators and trainers, note limitations and suggest opportunities for further research.

EARLY INDICATORS OF FUTURE VENTURE PERFORMANCE

Founder Characteristics

Many scholars have argued that founders' characteristics influence venture survival and scale (Colombo and Grilli, 2010; Erikson, 2002; Shaw et al, 2009). Founders set the tone for the venture and their human, social and financial capital determine many aspects of how the venture operates and with whom. Imprinting theory suggests that as the founders' cognitive scripts and resulting actions become routines that are replicated by other actors in the venture, they are in effect imprinted on the venture, and may become resistant to change. Thus founder characteristics such as tacit knowledge or even personality traits can become part of the culture of a venture, which is made, in a sense, in the image of its founder (Marquis and Tilcsik, 2013).

Previous research has found evidence of the medium term imprinting effects of founders' characteristics (e.g. Beckman and Burton, 2008; Ding, 2011; Geroski et al., 2010; Jones-Evans, 1997; Shane and Stuart, 2002). For example, Grilli et al. (2018) found that only founders' industry-specific human capital has a strong effect on venture performance. This imprinting effect becomes significant in years 2-3, peaks at years 4-5, and slowly dissipates over time afterwards. These researchers call for further exploration of other firm- and environmental-specific contingencies.

Some founder characteristics can be captured as legal instruments and held or used as resources by the venture. An important example for HTNVs is patents. Patents are descriptions of novel inventive steps which may have commercial application. They spring from the mind of an individual, but unlike most ideas they can be bought and sold under a government-sanctioned monopoly. Thus they are resources (in our case, of the venture founder) that have been alienated to increase their value. Patents enable the owner to not just sell products produced using a technique covered by a patent, but also to sell or rent the technique to others. Technology transfer can provide new ventures with a quick income without having to create a new value chain. One would expect that patents, as well as providing a measure of market protection, would act as a legitimacy signal to external resource providers (Audretsch et al., 2012). While in some new venture studies, patents appear to operate successfully as signals to attract equity providers (Nadeau, 2010; Hoenen at al., 2014), researchers have found mixed evidence of the effects of patents on venture survival and success. Shane and Stuart (2002) found that patent stock significantly reduces high-tech venture failure rate as well as increases the propensity to IPO. However, other authors have found direct effects to be elusive (see e.g. Lee and Lee, 2004; Gimmon and Levie, 2010).

External Resource Provision

HTNVs typically invest in product development, and traditional lending providers tend not to fund this high risk investment (Baum and Silverman, 2004). HTNVs can increase their short term survival chances and bridge the gap between founding resources and positive operational cash flow by attracting equity investors (Zider, 1998). Raising funds is one of the organizing activities at founding which may generate venture legitimacy and reduce disbanding hazard (Delmar and Shane 2004). First, funding may indirectly aid market acceptance by reducing the perceived risk of exchange relationships with a young venture in the eyes of other stakeholders such as suppliers or customers (Sørheim, 2005). Second, funders may bring sales and marketing expertise and contacts to the venture, directly aiding market acceptance (Ivanov and Xie, 2010; Pratch, 2005). In one study, venture capitalists were found to increase the probability of bringing a product to market by 79% (Hellmann and Puri, 2000). Third, the additional resources that external investment buys might enable a new venture to enter more than one market (Gruber, 2004), increasing its chances of acceptance of its products by the market. There is abundant evidence for the positive effect on short term survival of raising funds at early stage (e.g. Shane and Stuart, 2002). Access to funds has also been found to improve the likelihood of survival and growth in the medium term (Bertoni et al., 2011) and the likelihood of going public (Beckman and Burton, 2008). Typically, early equity investors expect to exit with capital gain in the medium term (Zider, 1998). While this may be their aim, one would expect them to seek investments with high potential in the longer term, since the buyers of their shares are likely to assign valuations based on their potential beyond the medium term.

Early Product/Market Fit

The search for markets is acknowledged as "one of the most important activities for technology ventures in nascent industries" (Wright and Clarysse, in press: 5). Surprisingly, the effect on venture performance of early and sustained acceptance by the market of a venture's products or services, dubbed "product/market fit" by Marc Andressen (2007), in subsequent performance has been little studied (Brush et al. 2008; Delmar and Shane 2004). Yet sales are the life blood of a business; while external funding may provide temporary infusions of cash, sustained sales are a necessary condition of long term survival, even for those endowed early with high levels of external funding (Mullins, 2014). Confirmation of an entrepreneur's hypothesis about the demand for their product or service is a highly symbolic milestone (Bird 1992; Wang et al. 2014), particularly for novice entrepreneurs, whose personal reputations are at stake, and HTNVs which require considerable effort and time to develop a technology before marketing has commenced. Early sales confirm operational capabilities, generate visibility in the market place and legitimize new ventures (Macmillan et al., 1985; Schoonhoven et al., 1990; Stuart et al., 1999; Wang et al., 2014).

Wang et al. (2014) highlighted the benefit of early sales for venture legitimacy in a large representative longitudinal sample of new firms in the US. They found that early customers positively affect subsequent short term firm performance, and also have the highest signaling effect on firm performance when the firm gains cognitive legitimacy from a capable founding team and regulative legitimacy. But no study exists that explores possible long term effects of early product/market fit. The legitimacy argument of Wang et al., which seems plausible for short term survival effects, seems inadequate as a longer term explanation.

Context: Local, Regional, and Temporal

Trettin and Welter (2011: 575) reviewed the entrepreneurship literature and concluded that “the entrepreneur’s socio-spatial contexts in which they operate on a daily basis are still absent from much of the entrepreneurship debate”. A core concept for the entrepreneurial context is resource munificence, defined as “the scarcity or abundance of critical resources needed by firms operating within an environment” (Castrogiovanni, 1991: 542). According to the resource munificence theory, if the environment is scarce, fewer resources will be available for entrepreneurs to experiment with growth-oriented strategies, while the reverse is the case in abundant environments (Castrogiovanni, 1991; Tushman and Anderson, 1986).

Local, regional or temporal differences in founding conditions can produce cohort effects, or common outcomes among a group of organizations with similar founding conditions. These differ from imprinting effects which involve the process of formation and subsequent stability of organization behaviors over time. For example, Geroski et al. (2010) asserted that contextual founding conditions contribute very significantly to explaining the observed variation in firm survival rates a few years after birth and later decreases as time goes by. They observed a very large sample of 118,000 Portuguese firms over ten years and found that although the effect of initial conditions is not permanent strictu sensu, many factors including entry rates and GDP growth seem to have relatively long-lived effects on survival. These researchers indicated they had to leave open the question how much longer these cohort effects last.

At a regional or less than regional level, agglomeration tends to cause an imbalance in resource accumulation such that resources become more abundant in central agglomerations than in the periphery (Schnell et al., 2017). Regional entrepreneurial ecosystems may also differ widely in the founding conditions they provide for new ventures (Spigel, 2017).

Because of the importance of contextual founding conditions, any panel study that sought to understand the long term effect of different types of founding conditions would need to carefully control for context. In the next section, we explain how we achieved this.

METHOD

Sample

We address the question of early indicators of long term HTNV performance with a longitudinal, repeated measures study of a sample of a population of high technology-based, export-oriented start-ups in Israel that had very similar starting conditions, and whose founding resources, early external funding and early sales record was known. In 2001, 196 randomly selected founders or chief executives out of all 643 (= 30.5%) technology incubatees that ever entered the Israeli Technology Incubators Program (ITIP) since 1991 were interviewed by two consultancy firms for the Chief Scientist of the Ministry of Industry and Trade. All non-survivors and survivors were included in the sample frame, eliminating survivor bias. Specifically, between September

2000 and December 2001, following a pilot survey of 47 founders selected at random from a list of all 643 technology incubatees entering the program since it had started in 1991, a further 149 randomly selected founders and/or chief executives of their ventures were interviewed face to face, using a structured questionnaire. Ten percent of selected founders/CEOs refused to be interviewed, and were replaced using the same random selection method. Of the 196 interviews, 193 contained sufficient data for initial analysis.

We conducted follow-up surveys of the survival status of these 193 HTNVs in January 2004 and January 2010. The 2010 follow-up survey was conducted from November 2009 through February 2010. The reported annual sales or sales intervals of surviving ventures (less than $1 million, less than $5 million, or higher) was collected through telephone interviews. $1 million is close to the official threshold that distinguished micro businesses from larger businesses in Israel in this period. (By comparison, the European Union used a cut-off of 2 million euros).

Only 33 HTNVs in our sample entered an ITIP incubator between 1991 and 1993 and another 18 HTNVs entered between the years 2000 and 2001. We excluded the former from our analysis to avoid firms that had time to mature (eight years is a common threshold for venture maturity, see e.g. Chrisman et al., 1998, and Reynolds and White, 1997) and in case these "guinea pigs" received special treatment or benefited from a Hawthorne effect. We also excluded the two earliest years of entry, 2000 and 2001, as we needed to measure early sales traction and early external funding over at least the first two years of the venture. This reduced the mean time from entering the incubator to the first survey from seven years to four years and the sample size to 142, with no material effect on the results. Of these 142, 24 were closed in 2001. By the 2004 follow-up, a total of 47 (33.1%) had closed. By the 2010 follow-up, a further 43 (30.3%) had closed, 18 (12.7%) were marginally surviving with no sales, 16 (11.3%) were surviving with annual sales of less than $1 million, and 18 (12.6%) were surviving at scale (annual sales of at least $1 million).

In 2018 we conducted another follow-up survey using the same methodology as in 2010. We found that 108 (76.1%) HTNVs had closed down, 5 (3.5%) were surviving marginally, 10 (7.0%) had annual sales of less than $1 million, and 19 (6.3%) had sales of at least $1 million. All those with sales of at least $1 million in 2010 were still in that category in 2018, and they were joined by one firm that had increased its sales level.

A small minority of HTNVs were acquired. We tracked these to check if they were still operating as identifiable economic entities under their new owner, for example as divisions or product lines. These were treated as survivors, because from an economic development perspective, the economic activity of these HTNVs had not ceased.

This longitudinal study was resource intensive, requiring performance of each firm to be measured in the short, medium, long and very long term. As time passes, the hazard of venture failure declines; hence to obtain meaningful numbers of failures between later intervals, longer interval times were chosen between succeeding follow-up surveys. Of course, we could not know what the survival curve would look like ex ante. Post ante we have approximately equal reductions of the surviving firms in the sample in each period. In hindsight (see Figure 4), our selection of years was not too far out; if we had selected in 2005, 2009 and 2017, rather than 2004, 2010 and 2018, we would have recorded at the end of each period almost exactly equal reductions of a third of surviving firms at the start of each time period.

Independent Variables

To measure the quality of the founder, which as outlined above is an important predictor of performance in the literature and a key criterion for HTNV investors, we used the following human capital attributes:

1. Founder is an engineer or scientist – This variable was coded 1 if the founder reported he is either engineer or scientist by education and coded 0 if not.

2. Founder has management experience – We coded 1 founders who had ever held P&L responsibility exercised by being a CEO or self-employed or project manager.

We also had data on founder's years of R&D experience and number of years of work experience but found that these correlated highly with founder age ($r = .742$ and $r = .887$ respectively) and with each other ($r = .796$). Founder age is recognized as an important general control variable for studies of new venture performance and invariably included in them (Kalleberg and Leicht, 1991; Lévesque and Minitti, 2006; Dencker and Gruber, 2015). It was important to avoid multicollinearity, and we therefore included founder age rather than these two variables after checking that, when we substituted either of them for founder age in our models, the results were virtually identical.

Because patents are known to attract investors to early stage ventures (Nadeau, 2010; Hoenen at al., 2014) and can be viewed as resources that can confer both technological advantage and legitimacy on a HTNV, we also measured the number of patents registered or applied for by the founder up to 2001.

As an indicator of early product/market fit (sales traction), we used the percentage of years in which sales were made from entrance to the incubator up to the time of the first interview (2001).

We also measured persistence of early external investment, indicated by the average number of fund rounds per year between entrance to the incubator and 2001. This measure of fund rounds frequency indicates sustained belief in the young venture on the part of external investors. Because we had six cohort years in the sample (i.e. year of entry varied from 1994 to 1999), we controlled for possible cohort effects (including stage in the economic cycle at founding) through cohort year (from 1 to 6). To control for regional context, we created a dummy variable that identified the incubator as located in either a core or a peripheral region following the classification suggested by Shefer and Frenkel (2002). We also checked to see if the founder's subjective incubator experience affected survival, using a founder rating variable from 1 to 10, rated in the year 2001 by the founder on the incubator from which the venture graduated. This variable had no effect in any model, and the variable distribution suggested the founder experience was reasonably uniform and positive (mean = 6.8, S.D.= 2.3, median = 7, mode = 8. However, an ANOVA test suggested that ratings were not random by incubator. This has implications for analysis (as discussed in the next section).

The 2001 survey had an industry sector variable with nine categories. Because of small numbers in some categories, we created a five category industry sector which comprised (1) electronics, computers, and communications together as an ICT category, (2) medical devices, (3) medicine/biotechnology, (4) chemistry/materials, and (5) machinery, agriculture, and others as the base category representing more traditional industry sectors.

Statistical analysis

Table 1 provides descriptive statistics for all variables and Table 2 shows a correlation matrix. Correlations between independent variables are low. To explore our data, we first employed probit regressions for each survey year in which the dependent variables were survival and, in the case of 2010 and 2018, high sales levels (at least $1 million). In each model, we tested for multi-collinearity by observing the variable inflation factors for each dependent variable. All were less than 2, and the condition index number was 22.32, suggesting that collinearity was not an issue (Hair et al., 1998). We checked the area under the ROC curve, and performed a linktest to check that each model was adequately specified. The pseudo Rsquare was satisfactory in every model and, in later years, noticeably higher in the models predicting high levels of sales (Table 3).

Insert Tables 1 and 2 about here

We then applied a further series of robustness checks. First, we clustered the data by incubator and reran the probit regressions to account for possible differences in incubator context (Table 4). This has the effect of adjusting standard errors of the estimated hazard ratios to account for the possible lack of independence of HTNVs within each of 25 incubators. We also conducted six logistic regressions which provided similar results.

The probit analyses on their own suggest different effects of some variables over time, but suffer from two weaknesses. The first is that the full potential of the panel data is not exploited. The second is that the regressions modelling survival-at-scale may hide selection issues: to survive at scale, a venture must first survive, and the factors that affect survival-at-scale, conditional on survival, may be different to those that affect survival. Therefore, we conducted non-parametric survival analysis (cox regression) using the stcox command in STATA16 after transforming the data into panel data form (i.e. with an entry for each case-survey year). We checked for independence of observations over time, and checked the proportional hazard assumption for every independent variable and overall model. This enabled us to identify two possible time-dependent covariates: fund rounds frequency and cohort year, which were indeed the two variables that changed in effect the most across the four years in the probit regressions. The patterns in the probit regressions for survival in Tables 3 and 4 suggested that these two variables had a curvilinear effect on survival over time: significant and positive at first and then losing significance. This suggested they could be modeled as polynomials of the form $y = x{*}t - x{*}t^2$ where t = time. We split the data by episode and conducted tests with alternative functional forms, which confirmed that this polynomial form did indeed model these variables' variation in effect across time the best, without violating the proportional hazard assumption.

We also identified that the hazard function varied across different industry sectors. We therefore stratified the model by industry sector. We used the Efron method for ties for a better approximation of the exact marginal log likelihood than the Breslow method, and, to account for possible differences in incubator context, we adjusted the standard errors of the estimated hazard ratios to account for the possible correlation by clustering by incubator.

We checked for interactions by plotting survival functions and found that the two founder expertise variables appeared to interact, and that the interaction term significantly added to the model. We included a time-varying covariate to check for significant effects of changes in the industry context over time. While our interest was in finding indicators, available in a HTNV's earliest years, that could accurately predict long and very long term performance, we needed to check that changes in the environment in subsequent years did not wash out the effect of these early indicators. To do that, we computed the annual average percentage change in industry employment growth in each period between performance measures drawing on data from Israel's

Central Bureau of Statistics. We found that the main results remained substantially the same when this time-varying covariate was added to the model (model 3, Table 5) and when we then clustered the data by incubator (model 4, Table 5).

Finally, we checked for possible effects of different time intervals between observations (Allison, 2010: 249), using the difference from the mean interval length in years. However, because the intervals between observations increased over time, the time interval correlated highly with time, and therefore with the variable cohort year interacted with time (though less so with fund round frequency interacted with time). In testing for the effect of time intervals, we therefore dropped cohort year from the model. Adding the time interval variable did not materially alter the results (model 5, Table 5).

For our survival-at-scale models, we conducted two-step probits (using the heckprob command in STATA16) to control for selection effects when isolating indicators of survival-at-scale (i.e. survival with relatively high sales levels). The choice of variables in the selection equation was the same as that for the probits for survival to 2010 or 2018 in Tables 3 and 4. The choice of variables in the main equation was guided by those variables that appeared to have a significant effect in the probits in Tables 3 and 4, and the need to minimize the number of variables, given the sample size of surviving ventures.

RESULTS

In Table 3 we report marginal effects based on probit regressions for each year in which performance was measured, and these show the change in probability of survival or survival-at-scale when the predictor or independent variable increases by one unit. Table 4 reports marginal effects when the data are clustered by incubator. Tables A1 and A2 in Appendix A show marginal effects when the continuous variables are standardized with a mean of zero and a standard deviation of one to facilitate comparison of effects. The pattern across the models is that ventures whose founders had prior management experience, and possibly technical expertise, were less likely to survive at scale. This latter result appears counter-intuitive at first sight, and we discuss it further in the next section. Number of patents had a positive effect on long term survival. Incubator location was marginally significant in the long term for survival-at-scale when the data was clustered by incubator. The effect of early product/market fit grew in strength over time from short through medium to long term, dipping slightly in the very long term, and also had a strong positive effect on survival-at-scale in the long and very long term. In the long and very long term, this variable made the largest contribution to the model (verified using likelihood ratio tests). We plotted the marginal effect of early product/market fit in quintile increments from 0 (no sales prior to 2001) to 1 (sales in each year prior to 2001) for the long term and very long term horizons and this suggested an approximately linear increase in effect across the range from no sales in any early year to sales in each early year (i.e. prior to 2001). Early external funding had a positive and significant short term effect on survival, and a stronger positive effect medium effect, but no long term or very long term effect.

Insert Tables 3 and 4 about here

Table 5 shows the results of a non-parametric survival analysis (cox regression). As explained in the previous section, this captures more information than the individual probits. Hazard ratios for each covariate are reported; these represent the estimated proportional change in the hazard function due to a unit change in a covariate. A hazard function greater than 1 denotes a higher hazard (in this case, of failure) relative to the base case, and a hazard function less than 1 denotes a lower hazard. For example, in model 4 the result for early product/market fit suggests that all other things equal, the hazard function for ventures that made sales in each year prior to 2001 is 0.079 times the hazard for ventures that made no sales at all. In other words, the hazard of failure for ventures who made no sales in their earliest years was 100*(.079–1)% or 92% higher than the hazard of failure for ventures that made sales in each of their earliest years. Compared with model 4, in model 5 the hazard of failure for ventures who made no sales in their earliest years is very slightly less higher (at 89%) than the hazard of failure for ventures that made sales in each of their earliest years. It is clear from Table 5 that early product/market fit is the strongest significant predictor in the model.

The next strongest variable is an interaction term for founders who had both a technical background and management experience. The reported hazard ratio is actually a ratio of ratios. In model 4, this combination of expertise “increases” the hazard function of each main effect by 0.351 times compared to ventures with founders with just one of these characteristics. For example, the hazard of failure of ventures whose founders had technical expertise and prior management experience was 0.65 (0.351*1.840) times the hazard of failure of ventures without prior management experience, while the hazard of founders who had prior management experience (but not technical expertise) was 1.84 times higher than the hazard of failure of founders without prior management experience (or technical expertise). For model 5, these hazards are only slightly less, at .7 times and 1.821 times respectively. We plotted the survivor functions for the four combinations and these confirmed that in the long run, ventures whose founders had just one form of expertise had lower survival rates than those with both – or, surprisingly, neither.

Figure 1 illustrates the effect of early product/market fit and combined founder expertise, separately and in combination, by plotting Kaplan-Meyer survivor functions. In this figure, a HTNV has high early product/market fit if they made sales at least every other year up to 2001, and high founder expertise if the founder had both technical expertise and prior management experience. It shows that over the very long term, while combined founder expertise does lift survival rates, the effect of product/market fit is much more compelling, and there is no evidence of an interaction between these two effects. In summary, models 4 and 5 of Table 5 share an overall pattern that product/market fit is a stronger potential indicator of survival than combined founder expertise.

Insert Table 5 and Figure 1 about here

Table 6 shows the results of a two-stage Heckman selection probit analysis for survival-at-scale conditional on survival to the years 2010 and 2018 respectively. For 2010, we also report results clustered by incubator; the results are almost identical. We do not report results with clustering for 2018, given the small number of ventures that survived this long. Remarkably, we see the estimates of the negative marginal effect of founder’s management experience and the positive marginal effect of early product/market fit are both slightly higher in 2018 than in 2010. We plot the combined effect of early product/market fit and prior management experience in Figures 2 (2010) and 3 (2018). These results suggest that founder’s lack of management experience has a significant positive effect on the probability that a firm surviving to 2010 or 2018 will survive at scale, in cases where early product/market fit is low. It has no significant effect on the probability of survival-at-scale when early product/market fit is high.

Because of small numbers in some cells, the model did not converge when the variable identifying a technologist was entered with other variables. However, entered on its own in the main equation it too had a significant negative marginal effect in 2010 (-.167, p=.012), mirroring the pattern in Table 4. Finally, we see a positive effect of number of early patents on the probability of survival-at-scale in both 2010 and 2018, conditional on survival. This is what we would expect to see, since the purpose of patents is to protect a market while the inventor builds out a market presence.

Insert Table 6 and Figures 2 and 3 about here

DISCUSSION & IMPLICATIONS

Three Surprising Findings

In our search for early indicators of long and very long term survival and survival-at-scale, we made three surprising findings. Perhaps our most surprising finding, given the lack of attention to this factor in the literature, is the strong effect of early product/market fit on survival and scale over the long term – between one and two decades after founding. While Wang et al. (2014) reported a short term positive effect of sales in the founding year on survival over the short term, they were unable to study effects over the long term because their panel was at most seven years in duration. Our panel, however, spans two decades and we found that the effect of early product/market fit strengthened from short to medium to long term.

Our second surprising finding is that if founders had management experience, their ventures were less likely to survive or survive-at-scale in the long and very long term than if they had no management experience. This negative effect was reversed for survival, but not for survival-at-scale, if the founder also had technical expertise. We also found that lack of management expertise appeared to compensate, to some extent, for lack of early product/market fit, which is very counter-intuitive if one takes these findings at face value.

Third, while we did find, as expected, evidence that early external funding raised the chances of survival in the short and medium term, this did not carry forward to the long term and very long term, either for survival or survival-at-scale. Survey evidence suggests that the HTNV founders themselves believed the opposite would be the case (Shefer and Frenkel, 2002: 44), and the emphasis on raising external funding within the incubator program strongly suggests that this was a working hypothesis of program managers, with raising management knowledge ranked second in importance (ibid: 46).

Eight HTNVs reached at least $5 million in 2010 and nine reached that level in 2018, representing half (47%) of all survivors at scale in 2018. This does suggest that, in this panel of technology ventures at least, the “rich” ventures get richer over time and the poor die off. There is no evidence in our data however that those with the highest sales in 2010 and 2018 were more likely to secure more fund rounds in the early years. While the number of cases with at least $5 million in the long and very long term is low, and therefore we err on the side of caution in not reporting the results in Table 6, when we used this high sales category as an outcome measure in our heckprobits, early product/market fit was the only significant predictor of sales of at least $5 million in 2010, conditional on survival to 2010, and also in 2018. We also reran these results with an indicator of VC funding. This was not significant, suggesting that VCs were no better than other equity investors at identifying high potential firms in this sample.

Theoretical Contributions

By tracking a cohort of HTNVs for two decades, which to our knowledge is much longer than similar previous studies, we found a vivid pattern in our data demonstrating a strong long-lasting effect of early product/market fit. We interpret this surprising finding as indicative of a feed-forward effect (Barabási, 2009; Crawford et al. 2015) through a "resourcing" (Feldman, 2004) process in which early product/market fit accelerates the development of what marketing theorists call "market-based assets" (Srivastava et al., 1998). Several theories have been employed to predict the future performance of new ventures. One of these is "imprinting". In this section, we suggest by abduction a theory and plausible mechanism by which this could happen: imprinting of routines that provide value to customers over the long term.

Founding conditions can be imprinted and provide a lasting legacy to organizations by influencing ways of operating that become routine as the organization matures (Stinchcombe, 1965; Boeker, 1989; Levinthal, 2003). Building on this idea, some authors assert that founding conditions significantly define the trajectory of an organization's future development and can continue to affect organizational performance for many years (Bryant 2014), while others argue that the effect of founding conditions diminishes over time (Bamford et al., 2000). Note that imprinting is different from path dependence; the former requires the persistence of organization behaviors that arise at a time early in the life of the organization when it is particularly sensitive to prevailing environmental conditions, while the latter requires the unfolding of a sequence of events. To date, scholars of organizational imprinting have focused mainly on founders' general and specific human capital and external funding as possible predictors of future performance (e.g. Beckman and Burton, 2008; Ding, 2011; Geroski et al., 2010; Jones-Evans, 1997; Shane and Stuart, 2002). These factors are seen as resources that determine the options the venture has to gain competitive advantage and thus survive and grow (Barney, 1991, 2001). A significant exception is the work of Gruber et al. (2013: 295), who used an imprinting approach to suggest that a pre-entry search for markets could “deeply imprint the nascent firm's trajectory”. However, theirs was a cross-sectional study of technology ventures with a mean age of 5 years.

What is less understood is whether and how this mechanism may have much longer effects. For example, one could speculate that early and intense interaction by a capable entrepreneur with a lead customer may lead to the discovery of a viable business model that generates new routines that generate more sales. This feed-forward mechanism, described by Barabási (2009) as a preferential attachment model, is a positive feedback mechanism focusing on networks, which explain how the rich get richer, based on differences in initial conditions. Crawford et al. (2015: 709) described preferential attachment as the driver of power laws: "for example, agents that start with slightly greater endowments (e.g., human, social, or financial capital) than others could be programmed to have a slightly higher probability of successfully capturing resources (e.g., bank or venture capital funding) in the environment". While this mechanism is plausible for short term effects, it seems a stretch to invoke it for long term effects in a dynamic environment, and the lack of suitable longitudinal databases has prevented scholars from exploring this possibility (Simsek et al., 2015). However, our results would support it.

Drawing on imprinting theory (Marquis and Tilcsik, 2013) and market-based assets theory (Srivastava et al., 1998), and the patterns in our data, we therefore propose that, in addition to operating as a signaling mechanism to potential customers (Wang et al., 2014), early and sustained acceptance by the market of a new venture’s products (which we call “early product/market fit”) has a profound shaping effect on the HTNV’s organizational routines. In doing so, it generates “market-based assets” such as customer relationships, channel relationships, partner relationships and branding (Ramaswami et al. 2009; Srivastava et al. 1998) that self-replicate and thus sustain the venture into the long term – in effect, an imprinting mechanism that helps the venture to survive and to scale up.

We think that this imprinting may be particularly strong in our sample of HTNVs because of the lack of prior new venture experience among the founders. Not only is the venture a “blank slate”, but the founder is experiencing first customer feedback for the first time. This experience is likely to have a profound effect on the development of schemas (i.e. norms or rules of thumb) for dealing with customers and the institutionalization of these schemas into more formal sales routines and, through enactment of these routines, the creation of customer relationships, channel relationships, partner relationships and branding. It provides a clearly delineated “sensitive period” that is an essential requirement for imprinting (Marquis and Tilcsik, 2013: 199).

The second requirement for imprinting is that a “focal entity develops characteristics that reflect prominent features of the environment” (ibid.). In our case, the new venture is the focal entity, that is being shaped by feedback from customers. The final requirement is that “these characteristics continue to persist despite significant environmental changes in subsequent periods” (ibid.). Our finding that the effect of early product/market fit increases and then persists over time even after controlling for time-varying industry-level activity rates and several economic cycles suggests a persistence of characteristics in the venture.

Taking this combined imprinting/market-based assets approach, we can see how early engagement with customers and sales traction might create virtuous, or “ampliative” (Feldman, 2011) cycles of growth in market-based assets, and thus in sales income. To Feldman (2004: 296), resourcing is “the creation in practice of assets such as people, time, money, knowledge, or skill; and qualities of relationships such as trust, authority, or complementarity such that they enable actors to enact schemas". In the case of HTNVs, prior research shows that early customer relationships contribute not just income but knowledge about what customers want and about how to engage with them for mutual benefit (Roberts, 1991, 1992; Boussouara and Deakins, 1999). These schemas get laid down as more formal routines that enable the venture to scale up sales. In turn, these virtuous cycles attract new talent and more funding to scale up even further. Thus we see early sales from the venture's perspective not only as economic outputs but as a learning resource that enables specific routines to be developed that sustain the venture through successive sales cycles (Block and Macmillan 1985; LeBrasseur et al. 2003). These routines may include new value chains, the production of products with more highly valued bundles of benefits, and the conduct of transactional relationships.

While the notion of market-based assets seems far-fetched at first – perhaps a stretch too far for the resource-based view (Barney 1991, 2001) – if we switch from a view of resources as artifacts to resourcing as a process (Feldman, 2004; Feldman and Worline, 2011), we can see the emergence of customer relationships, channel relationships, partner relationships and branding, where none of these valuable things previous existed, as acts of resourcing. The outcome of this process is market-based assets, resources that are just as valuable to the venture (if not more so) than human capital, a topic to which we now turn.

We interpret our second surprising finding, a negative effect of prior management experience, as follows. The incubator environment was designed for first time technology entrepreneurs who would not, on their own, be able to attract external investment. Those without prior management experience would have been connected with experienced managers to round out the venture team; founders who were more experienced managers with technical expertise would likely have been under less pressure to build a high quality team. The individuals joining the less experienced entrepreneurs would likely be uninterested in joining lifestyle ventures: they would have wanted to grow the pie so that their slice of it would become substantial. This is one of the reasons why ventures with larger teams tend to be more growth oriented (Mayer-Haug et al., 2013; Czarnitzki et al., 2014). The relative pressure on inexperienced incubatees to develop an experienced team, especially if they were struggling to gain sales traction, and the growth imperative of experienced new team members is therefore a plausible mechanism for this counter-intuitive finding.

In support of this plausible explanation, fully half of HTNVs that achieved survival-at-scale in 2018 were founded by researchers, a subset of those with a technological background. Of all occupations, these were probably least likely to have any relevant business or management experience. These founders had a success (i.e. survival at scale) rate of 38%, compared with a success rate of 9% for founders whose former occupation was CEO. This raises the provocative possibility that this team-building function of technology incubators is more important than their role (much praised by both founders and external commentators) in facilitating venture capital investment for incubatees (Shefer and Frenkel, 2002: 43; Frenkel et al., 2008). Furthermore, this type of sponsorship activity does not fall neatly into either buffering or bridging activities that are the foundation of organization sponsorship theory (Amezcua et al., 2013). We suggest that “building” activity could be added as a third sponsorship activity and would represent this type of sponsorship more accurately.

In summary, drawing on imprinting theory (Marquis and Tilscik, 2013) and market-based assets theory (Srivastava et al., 1998), and a vivid pattern in our data demonstrating a strong long-term effect of early product/market fit, we abducted that sustained early acceptance by the market of a new venture's products (early product/market fit) has a profound imprinting effect on the venture's organizational routines and generates market-based assets that self-replicate and thus sustain the venture into the long term and enable scale up. We now turn to possible practical implications of our findings.

Practical Implications

If validated in other longitudinal panel studies, the key role of early product/market fit in building sustainable and scalable high technology new ventures would have clear implications for entrepreneurs, potential investors, policymakers and entrepreneurship educators. Our results suggest that in order to achieve better longevity and higher scale, entrepreneurs and their investors should focus on business models that gain market traction and build market-based assets early. Technology entrepreneurs need to be aware that early product/market fit is not a fortuitous event, or a case of "build the perfect product and they will come", but a process of early and deep engagement with their customers' world to understand and satisfy their needs. This way they will learn how to serve their customers and embed the routines that deliver these while the venture is at its most pliable and susceptible to environmental signals.

Early equity investors, such as business angels, technology transfer offices, technology incubators and even venture capitalists who pursue exit strategies and returns in the short or medium term should take note of this indicator, because the buyers of their shares will likely value the venture based on long term potential. As earlier referenced, empirical studies suggest that early investors may place too much emphasis on their assessment of founder characteristics and not enough on situational variables. In this light, while we would not go as far as Marc

Andreesen that “all that matters is product/market fit”, our research suggests he has a point and that other early investors should take note.

Policy makers and managers could encourage and prioritize training in founder selling as an entrepreneurial skill that is distinct from professional sales. Our findings fit very well with the emphasis by Lean Startup movement (Ries, 2011) on early product/market fit. They also corroborate recent structured programs of training for entrepreneurs that emphasize engaging with customers and making sales (e.g. Aulet, 2013). We think that these movements and programs reflect a specific human capital weakness in many new technology ventures that are founded by technologists: customer development skills, and suspect that our results related to survival-at-scale in part reflect this weakness. Our results could also be seen to endorse government policies or programs that facilitate early sales, such as the SBIR program or small business procurement, where the government acts as a first customer rather than as a source of grants, provided that these engender routines that are relevant for other customers also.

In this light, our findings support the conclusions of Autio et al. (2007) and Autio and Ranniko (2016) that policy interventions emphasizing retention over selection might be a solution to the “picking winners” dilemma facing policymakers (Freel, 1998; Shane, 2009). In other words, initial selection criteria might be relatively loose, given that conventional pre-start indicators are poor and, for human capital, possibly misleading long term predictors of long term performance, but criteria could become more restrictive post-start, as early product/market fit - an objective criterion not subject to cognitive bias - is or is not demonstrated. In the startup phase, training and assistance in customer development is likely to be a significant aid in helping HTNVs to achieve early product/market fit, and as Autio and Ranniko (2016) suggest, further training interventions may therefore play a role in retaining winners through capacity boosting of firms that have demonstrated early product/market fit. Rounding out the management team with experienced managers is likely to increase desire for growth. These interventions could raise the proportion of HTNVs producing new economic activity that is sustainable over the long term.

This policy perspective is different to that of other entrepreneurial ecosystem stakeholders such as venture capitalists, who accept high failure rates in expectation that a small number in their portfolio will attract high valuations in the medium term. The goal for policymakers is to facilitate the emergence of economic activity of the future. HTNVs can be an important source of this activity. However, it would be naïve of policymakers to assume (or worse, require) long term legal independence of HTNVs, especially those that are funded by early external equity providers or by first time founders. The former will require an exit in the medium term, and the latter may require to diversify their asset base before taking on significant scaling risks. Our data suggests that early product/market fit predicts long term survival and survival-at-scale of the economic activity created by the HTNV, whether or not it is subsequently acquired.

Limitations and Future Research

Clearly, our study is potentially limited in its generalizability by the fact that it is based on a homogeneous cohort of HTNVs graduated from technology incubators in Israel. There is a selection bias, because entry to the ITIP was competitive. However, the ITIP program also sought projects that might not attract resources without prior incubation; for example, lack of prior venture experience and lack of a fully formed venture team was a requirement for entry to the ITIP. It is perhaps not surprising therefore that, according to Avnimelech et al. (2007), between 1991 and 2004, 46% of ITIP graduates went out of business, compared with 36% of all Israeli HTNVs. This could mean that our sample did not include (or measure) important founder experience effects. For example, serial founders might bring with them previously formed customer development schemas, but it is difficult to know ex ante whether these would generate positive or negative effects. Nuscheler et al. (2019) suggest that startup experience may indeed help transform HTNV product introductions into growth. However, Nielsen and Sarasvathy (2016) report that Type I and Type II errors are prevalent in serial entrepreneurship, suggesting that individuals often draw incorrect conclusions from their prior entrepreneurial experience. Thus the "founder experience" argument may over-estimate the effect of personal characteristics and under-estimate situational variables.

More work could be done to eliminate possible sources of endogeneity. For example unmeasured factors which entered the scene after 2001 and which are not accounted for in our time-varying covariates could be responsible for the continued success of a limited number of ventures. But the mechanisms underlying our conjecture are general and we think our findings may have wider applicability to first-time technology entrepreneurs without prior customer development experience. The fact that movements like Lean Startup have been enthusiastically adopted worldwide also gives some face validity to our findings.

Observing the pattern of effects across different founding conditions over time, our findings suggest that customer development behaviors lay down strong or robust routines that can generate highly sustainable cycles of economic activity within growing ventures, in ways that founder characteristics and external funding do not. This is well worth exploring further, both theoretically, and empirically. From the theory side, more work is needed that connects the generation of market-based assets to the laying down of robust routines that facilitate long-term survival and scaling up. Empirical work could include using qualitative methods that track down why people in ventures that last do things the way they do. For example, researchers could explore how new ventures accumulate market-based assets, and document the rewards of a proactive approach to market development, such as how early customer development activity may affect other venture activities including product or service features and performance (Srivastava et al. 1998; Ulwick, 2002; Newbert et al., 2007; Schindehutte et al., 2008; Ramaswami et al., 2009; Aulet, 2013).

Conclusion

The mortality rate of HTNVs in our sample is about the same as that for the global human population in 1960 (Roser et al., 2019). By 2001, a little over 80% of our HTNVs were still operating. By 2018, less than a quarter were still operating, either autonomously or as acquired activities within a larger business. This is a high rate of attrition. While we would not wish to stretch this analogy too far, human society has pushed the 5 year child survival rate globally to 96% by using modern health practices, and the average life expectancy has risen to 70 years globally from around 30 years in the pre-modern era. We know that malnutrition in the earliest years contribute to infant mortality: a sickly child is vulnerable to external shocks like disease or famine. Again, without pushing the analogy too far, lest it become absurd, we can think of early product/market fit as a marker of HTNV life expectancy, one that drastically improves the chances of long term survival and also of scaling beyond the size of a lifestyle venture. Modern techniques of entrepreneurial practice, such as Lean Startup, are designed precisely to find early product/market fit. To our knowledge, our results are the first to demonstrate the effect this important element of the Lean Startup approach has on long term survival and scale up. We expect, therefore, that as such practices become widespread, the longevity of HTNVs could rise in the coming decades.

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TABLE 1
Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Survived to 2001	142	0.83	0.38	0	1
Survived to 2004	142	0.67	0.47	0	1
Survived to 2010	142	0.37	0.48	0	1
At least $1 million sales in 2010	142	0.13	0.33	0	1
Survived to 2018	142	0.24	0.43	0	1
At least $1 million sales in 2018	142	0.13	0.34	0	1
Founder age	142	53.27	10.50	28	76
Founder is an engineer or scientist	142	0.72	0.45	0	1
Founder has management experience	142	0.39	0.49	0	1
Number of patents	142	1.64	1.47	0	6
Cohort year (1994 = 1)	142	3.94	1.69	1	6
New Industry sector	142	3.32	1.51	1	5
HTNV is in central location	142	0.44	0.50	0	1
Early product/market fit level	142	0.10	0.23	0	1
Average fund rounds per year to 2001	142	0.17	0.22	0	1

TABLE 2
Correlation matrix of independent variables[a]

		1	2	3	4	5	6	7	8
1	Founder age	1.00							
2	Founder is an engineer or scientist (only)	0.07	1.00						
3	Founder has management experience (only)	-0.05	-0.21 *	1.00					
4	Number of patents	-0.16	0.13	0.02	1.00				
5	Cohort year	-0.16	0.13	0.13	0.15	1.00			
6	New Industry sector	0.27 *	0.16	-0.02	0.05	-0.07	1.00		
7	HTNV is in central location	-0.04	-0.05	0.12	0.16	0.13	-0.16	1.00	
8	Early product/market fit level	-0.25 *	-0.01	0.16	-0.03	-0.17 *	0.07	-0.14	1.00
9	Average fund rounds per year to 2001	-0.20 *	0.00	0.17 *	0.21 *	-0.10	-0.11	0.10	0.30 *

[a] *p<.05

TABLE 3
Probit analysis: Marginal effects of 2001 variables on survival and survival with high sales to 2001, 2004, 2010 and 2018[a]

VARIABLES (all as of 2001)	Short term survival to 2001 Marginal Effects	Medium term survival to 2004 Marginal Effects	Long term survival to 2010 Marginal Effects	Sales at least $1 million in 2010 Marginal Effects	Very long term survival to 2018 Marginal Effects	Sales at least $1 million in 2018 Marginal Effects
Founder Age	0.00	0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Founder is an	-0.02	0.06	0.08	-0.12	0.03	-0.13
engineer or scientist only	(0.04)	(0.10)	(0.11)	(0.08)	(0.09)	(0.09)
Founder has management	0.01	0.04	0.06	-0.12*	0.04	-0.13**
experience only	(0.05)	(0.09)	(0.10)	(0.05)	(0.09)	(0.05)
Number of patents	0.01	-0.01	0.07*	0.02	0.03	0.02
	(0.02)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)
Cohort year	0.07**	0.07**	0.02	-0.01	-0.01	-0.01
	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)
Industry: ICT	-0.11	-0.10	-0.06	-0.00	0.05	-0.01
	(0.11)	(0.14)	(0.14)	(0.04)	(0.12)	(0.04)
Industry: Medical Devices	0.00	-0.07	-0.18	0.08	0.01	0.07
	(0.05)	(0.13)	(0.12)	(0.08)	(0.11)	(0.08)
Industry: Medicine/Biotech	-0.02	-0.11	0.04	0.03	0.16	0.02
	(0.06)	(0.13)	(0.14)	(0.06)	(0.13)	(0.06)
Industry: Chemistry/	-0.00	-0.03	-0.01	0.06	0.06	0.11
Materials	(0.05)	(0.12)	(0.13)	(0.07)	(0.11)	(0.09)
Incubator is in central	0.07	0.02	0.02	-0.06	-0.07	-0.06
location	(0.05)	(0.08)	(0.09)	(0.04)	(0.08)	(0.05)
Early product/market fit	0.16	0.57*	0.75**	0.35**	0.59**	0.35**
	(0.13)	(0.29)	(0.23)	(0.12)	(0.19)	(0.12)
Average fund rounds per	0.30*	0.62**	-0.03	0.05	0.02	0.04
year to 2001	(0.14)	(0.24)	(0.21)	(0.10)	(0.18)	(0.11)
Chi-square (global LR test)	49.79**	26.18**	24.84*	35.02**	21.04*	36.18**
Pseudo-Rsquare	.39	.15	.13	.32	.14	.32
Observations	142	142	142	142	142	142

[a] Standard errors in parentheses † p<0.1, * p<0.05, ** p<0.01 NOTE: All predictors at their mean value

TABLE 4
Probit analysis: Marginal effects of 2001 variables on survival and survival with high sales to 2001, 2004, 2010 and 2018, clustered by incubator[a]

VARIABLES (all as of 2001)	Short term survival to 2001 Marginal Effects	Medium term survival to 2004 Marginal Effects	Long term survival to 2010 Marginal Effects	Sales at least $1 million in 2010 Marginal Effects	Very long term survival to 2018 Marginal Effects	Sales at least $1 million in 2018 Marginal Effects
Founder Age	0.00	0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Founder is an engineer or scientist only	-0.02	0.06	0.08	-0.12†	0.03	-0.13†
	(0.04)	(0.09)	(0.11)	(0.07)	(0.08)	(0.08)
Founder has management experience only	0.01	0.04	0.06	-0.12**	0.04	-0.13**
	(0.03)	(0.07)	(0.08)	(0.04)	(0.08)	(0.04)
Number of patents	0.01	-0.01	0.07*	0.02	0.03	0.02
	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)	(0.01)
Cohort year	0.07**	0.07**	0.02	-0.01	-0.01	-0.01
	(0.02)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)
Industry: ICT	-0.11	-0.10	-0.06	-0.00	0.05	-0.01
	(0.07)	(0.15)	(0.12)	(0.04)	(0.09)	(0.03)
Industry: Medical Devices	0.00	-0.07	-0.18	0.08	0.01	0.07
	(0.03)	(0.11)	(0.13)	(0.07)	(0.11)	(0.07)
Industry: Medicine/Biotech	-0.02	-0.11	0.04	0.03	0.16	0.02
	(0.07)	(0.17)	(0.17)	(0.06)	(0.13)	(0.06)
Industry: Chemistry/ Materials	-0.00	-0.03	-0.01	0.06	0.06	0.11
	(0.03)	(0.12)	(0.14)	(0.06)	(0.13)	(0.10)
Incubator is in central location	0.07	0.02	0.02	-0.06†	-0.07	-0.06†
	(0.05)	(0.09)	(0.06)	(0.03)	(0.08)	(0.03)
Early product/market fit	0.16†	0.57*	0.75**	0.35**	0.59**	0.35**
	(0.08)	(0.22)	(0.18)	(0.11)	(0.15)	(0.11)
Average fund rounds per year to 2001	0.30**	0.62**	-0.03	0.05	0.02	0.04
	(0.10)	(0.18)	(0.22)	(0.08)	(0.19)	(0.09)
Chi-square (global Wald test)	76.91**	112.82**	46.44**	46.35**	39.68**	49.03**
Pseudo-Rsquare	.39	.15	.13	.32	.14	.32
Observations	142	142	142	142	142	142

[a] Robust standard errors in parentheses † p<0.1 * p<0.05, ** p<0.01, NOTE: All predictors at their mean value

TABLE 5
Non-parametric survival analysis (cox regression)[a]

VARIABLES	Model 1 Hazard ratio (95% C.I.)	Model 2 Hazard ratio (95% C.I.)	Model 3 Hazard ratio (95% C.I.)	Model 4 Hazard ratio (95% C.I.)	Model 5 Hazard ratio (95% C.I.)
Founder Age	0.99	1.00	1.00	1.00	0.99
	(.98 – 1.01)	(0.98 - 1.01)	(0.98- 1.01)	(0.98 - 1.02)	(0.97 – 1.02)
Founder is an engineer or scientist	0.77	1.18	1.21	1.21	1.21
	(0.48 – 1.24)	(0.63 - 2.23)	(0.65 - 2.24)	(0.64 - 2.29)	(0.68 – 2.17)
Founder has management experience	0.95	1.88	1.84†	1.84*	1.82*
	(0.62 – 1.44)	(0.98 - 3.59)	(0.97 – 3.49)	(1.05 – 3.23)	(1.05 – 3.17)
Number of patents	0.89†	0.90	0.90†	0.90†	0.93
	(0.78 – 1.02)	(0.79 - 1.02)	(0.79 - 1.02)	(0.78 - 1.03)	(0.81 – 1.08)
Cohort year times t	0.94**	0.94**	0.94**	0.94**	
	(0.90 – 0.98)	(0.90 – 0.98)	(0.90 – 0.98)	(0.90 – 0.97)	
Cohort year times t^2	1.01**	1.01**	1.01**	1.01**	
	(1.00 – 1.01)	(1.00 – 1.01)	1.00 – 1.01	(1.00 – 1.01)	
Average fund rounds times t	0.79†	0.79†	0.78†	0.78*	0.72*
	(0.61 – 1.02)	(0.61 - 1.02)	(0.61 - 1.01)	(0.62 – 1.00)	(0.56 – 0.94)
Average fund rounds times t^2	1.02*	1.02*	1.02*	1.02*	1.02**
	(1.00 – 1.03)	(1.00 - 1.03)	(1.00 - 1.03)	(1.00 - 1.03)	(1.01 – 1.04)
Incubator is in central location	0.94	0.99	0.98	0.98	0.88
	(0.65 – 1.37)	(0.68 - 1.45)	(0.67 - 1.42)	(0.71 - 1.35)	(0.62 – 1.24)
Early product/market fit	0.09**	0.08**	0.08**	0.08**	0.11**
	(0.02 – 0.39)	(0.02 - 0.33)	(0.02 - 0.33)	(0.02 - 0.26)	(0.02 – 0.51)
Interaction of Founder engineer or scientist and management experience		0.35*	0.35*	0.35**	0.38*
		(0.15 - 0.80)	(0.15 - 0.80)	(0.17 - 0.74)	(0.18 – 0.83)
Industry Employment growth (time varying covariate)			1.41	1.41	2.10
			(0.88 – 2.27)	(0.92 - 2.16)	(0.64 – 6.89)
Time interval between observations (time-varying covariate)					1.46*
					(1.01 – 2.10)
Stratified by Industry sector	yes	yes	yes	yes	yes
Clustered by incubator	no	no	no	yes	yes
Chi-square	25.98**	33.70**	37.17**	55.36**	30.45**
Global PH test (p value)	0.61	0.64	0.74	0.73	0.92

[a] 1,469 observations, 142 subjects, 108 failures. 95% confidence intervals in parentheses † $p<0.1$ * $p<0.05$, ** $p<0.01$

TABLE 6
Two-stage Heckman selection probit analysis: Marginal effects of 2001 variables on survival with high sales conditional on survival to 2010 and 2018, with and without clustering by incubator[a]

VARIABLES (all as of 2001)	Sales at least $1 million in 2010 Marginal Effects	Sales at least $1 million in 2010 Marginal Effects	Sales at least $1 million in 2018 Marginal Effects
Survival-at-scale, conditional on survival			
Founder has management experience	-0.103**	-0.103**	-0.151*
	(0.0396)	(0.0380)	(0.0663)
Early product/market fit	0.440**	0.440**	0.561**
	(0.109)	(0.106)	(0.155)
Number of patents	0.0282*	0.0282*	0.0620*
	(0.0123)	(0.0114)	(0.0297)
Variables included in selection equation (survival)			
Founder age	yes	yes	yes
Founder is an engineer or scientist only	yes	yes	yes
Founder has management experience only	yes	yes	yes
Cohort year	yes	yes	yes
Industry sector (5 categories)	yes	yes	yes
Incubator is in central location	yes	yes	yes
Early product/market fit	yes	yes	yes
Average fund rounds per year to 2001	yes	yes	yes
Clustered by incubator	no	yes	no
Wald chi	29.21**	57.75**	13.62**
LR test of independent equations	4.53*		5.89*
Wald test of independent equations		337.41**	
Observations	142	142	142

[a] Standard errors in parentheses † p<0.1 * p<0.05, ** p<0.01, NOTE: All predictors at their mean value

FIGURE 1
Kaplan–Meier survivor function (years after entry to incubator) for combinations of low and high early product-market fit and low and high founder expertise

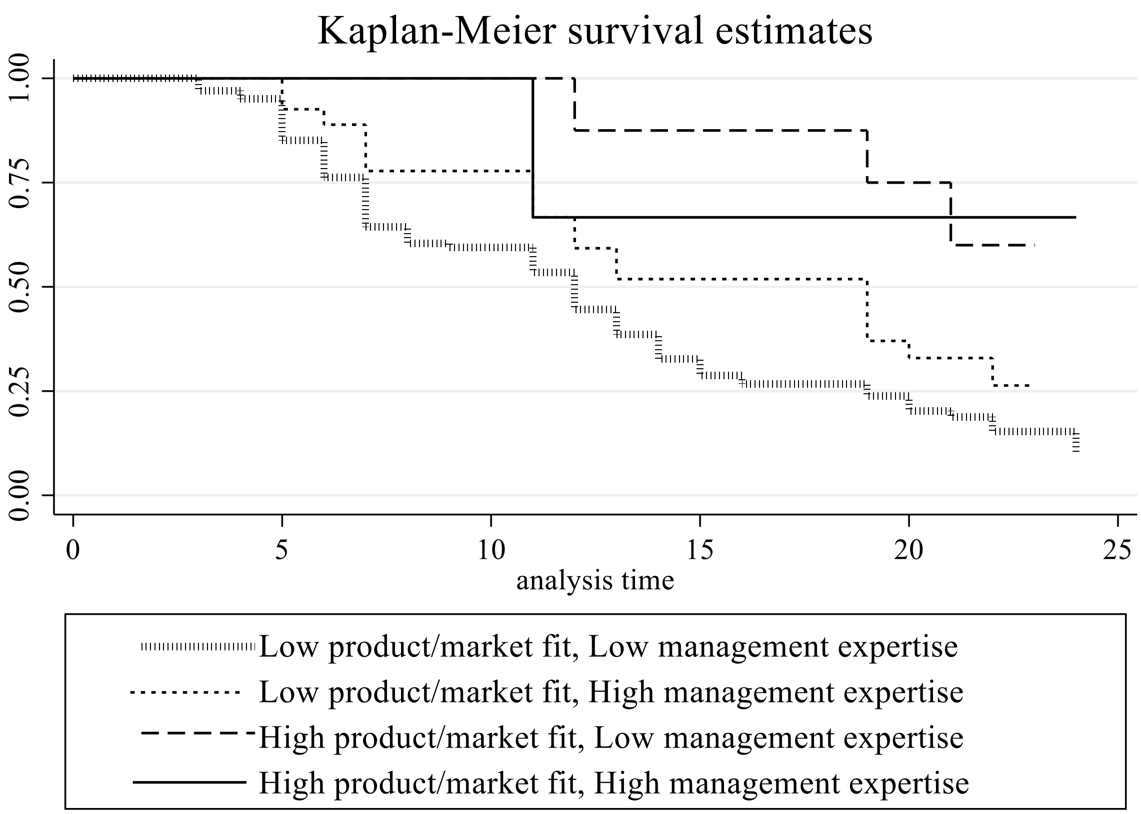


FIGURE 2
Probability of survival-at-scale conditional on survival to 2010, by level of founder's management experience and early product/market fit

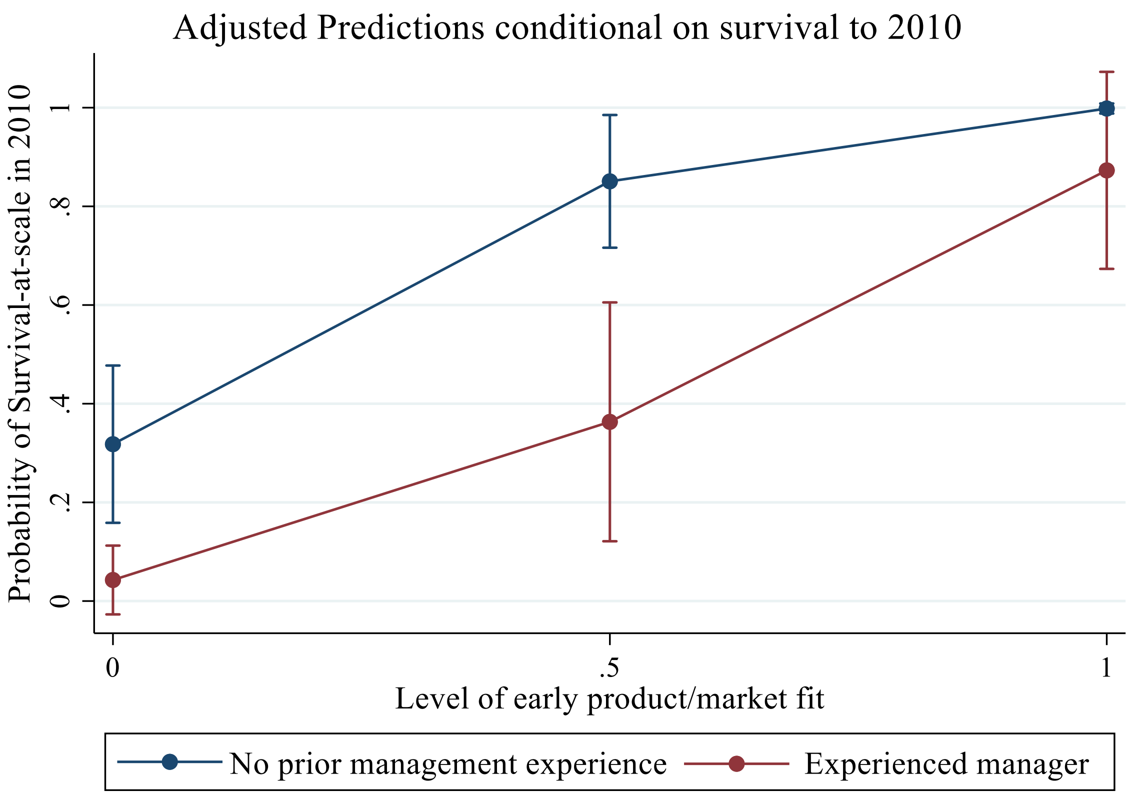


FIGURE 3
Probability of survival-at-scale conditional on survival to 2018, by level of founder's management experience and early product/market fit

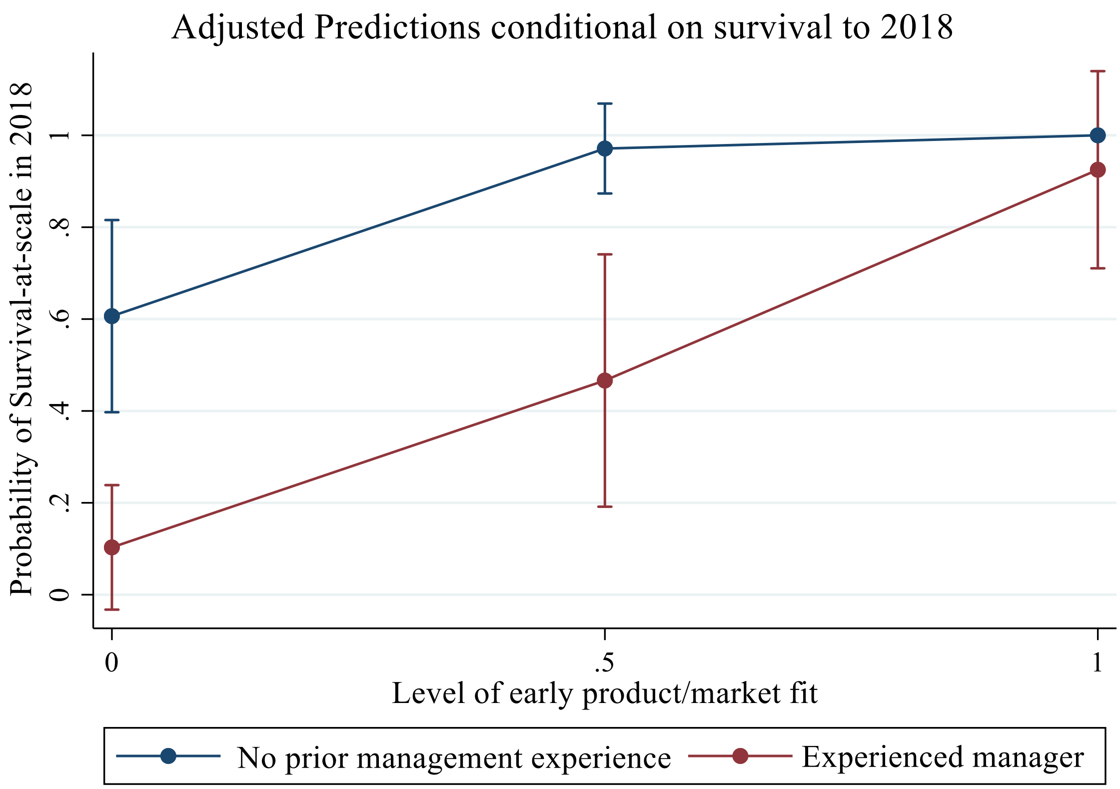
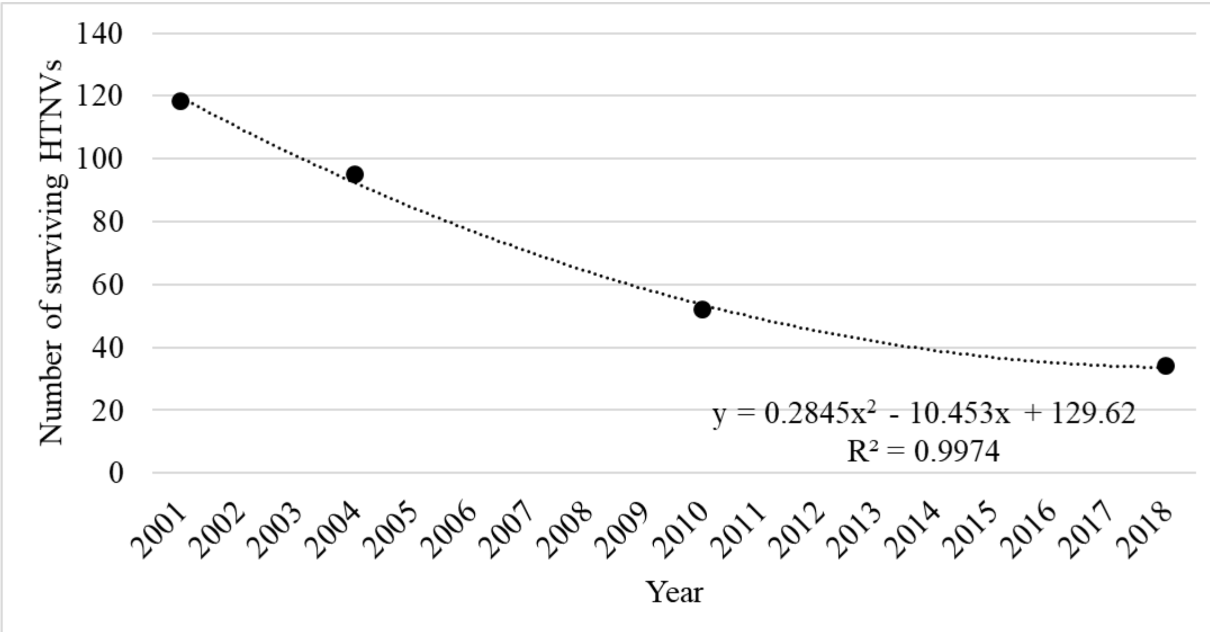


FIGURE 4
Reduction in number of surviving firms in sample across four surveys



APPENDIX A

TABLE A1
Probit analysis: Marginal effects of 2001 variables on survival and survival with high sales to 2001, 2004, 2010 and 2018; continuous variables are standardized[a]

VARIABLES (all as of 2001)	Short term survival to 2001 Marginal Effects	Medium term survival to 2004 Marginal Effects	Long term survival to 2010 Marginal Effects	Sales at least $1 million in 2010 Marginal Effects	Very long term survival to 2018 Marginal Effects	Sales at least $1 million in 2018 Marginal Effects
Founder Age	0.04	0.04	0.03	-0.01	0.01	-0.03
	(0.03)	(0.05)	(0.05)	(0.02)	(0.04)	(0.02)
Founder is an	-0.02	0.06	0.08	-0.12	0.03	-0.13
engineer or scientist only	(0.04)	(0.10)	(0.11)	(0.08)	(0.09)	(0.09)
Founder has management	0.01	0.04	0.06	-0.12*	0.04	-0.13**
experience only	(0.05)	(0.09)	(0.10)	(0.05)	(0.09)	(0.05)
Number of patents	0.02	-0.01	0.10*	0.03	0.04	0.03
	(0.03)	(0.05)	(0.05)	(0.02)	(0.04)	(0.02)
Cohort year	0.12**	0.12**	0.03	-0.01	-0.02	-0.01
	(0.04)	(0.04)	(0.05)	(0.02)	(0.04)	(0.02)
Industry: ICT	-0.11	-0.10	-0.06	-0.00	0.05	-0.01
	(0.11)	(0.14)	(0.14)	(0.04)	(0.12)	(0.04)
Industry: Medical Devices	0.00	-0.07	-0.18	0.08	0.01	0.07
	(0.05)	(0.13)	(0.12)	(0.08)	(0.11)	(0.08)
Industry: Medicine/Biotech	-0.02	-0.11	0.04	0.03	0.16	0.02
	(0.06)	(0.13)	(0.14)	(0.06)	(0.13)	(0.06)
Industry: Chemistry/	-0.00	-0.03	-0.01	0.06	0.06	0.11
Materials	(0.05)	(0.12)	(0.13)	(0.07)	(0.11)	(0.09)
Incubator is in central	0.07	0.02	0.02	-0.06	-0.07	-0.06
location	(0.05)	(0.08)	(0.09)	(0.04)	(0.08)	(0.05)
Early product/market fit	0.04	0.13*	0.17**	0.08**	0.13**	0.08**
	(0.03)	(0.07)	(0.05)	(0.03)	(0.04)	(0.03)
Average fund rounds per	0.07*	0.14**	-0.01	0.01	0.00	0.01
year to 2001	(0.03)	(0.05)	(0.05)	(0.02)	(0.04)	(0.02)
Pseudo-Rsquare	.39	.15	.13	.32	.14	.32
Observations	142	142	142	142	142	142

[a] Standard errors in parentheses † $p<0.1$ * $p<0.05$, ** $p<0.01$, NOTE: All predictors at their mean value

TABLE A2
Probit analysis: Marginal effects of 2001 variables on survival and survival with high sales to 2001, 2004, 2010 and 2018, clustered by incubator; continuous variables are standardized[a]

VARIABLES (all as of 2001)	Short term survival to 2001 Marginal Effects	Medium term survival to 2004 Marginal Effects	Long term survival to 2010 Marginal Effects	Sales at least $1 million in 2010 Marginal Effects	Very long term survival to 2018 Marginal Effects	Sales at least $1 million in 2018 Marginal Effects
Founder Age	0.04	0.04	0.03	-0.01	0.01	-0.03
	(0.02)	(0.04)	(0.05)	(0.02)	(0.05)	(0.03)
Founder is an	-0.02	0.06	0.08	-0.12†	0.03	-0.13†
engineer or scientist only	(0.04)	(0.09)	(0.11)	(0.07)	(0.08)	(0.08)
Founder has management	0.01	0.04	0.06	-0.12**	0.04	-0.13**
experience only	(0.03)	(0.07)	(0.08)	(0.04)	(0.08)	(0.04)
Number of patents	0.02	-0.01	0.10*	0.03	0.04	0.03
	(0.02)	(0.05)	(0.05)	(0.02)	(0.04)	(0.02)
Cohort year	0.12**	0.12**	0.03	-0.01	-0.02	-0.01
	(0.04)	(0.05)	(0.04)	(0.02)	(0.04)	(0.02)
Industry: ICT	-0.11	-0.10	-0.06	-0.00	0.05	-0.01
	(0.07)	(0.15)	(0.12)	(0.04)	(0.09)	(0.03)
Industry: Medical Devices	0.00	-0.07	-0.18	0.08	0.01	0.07
	(0.03)	(0.11)	(0.13)	(0.07)	(0.11)	(0.07)
Industry:	-0.02	-0.11	0.04	0.03	0.16	0.02
Medicine/Biotech	(0.07)	(0.17)	(0.17)	(0.06)	(0.13)	(0.06)
Industry: Chemistry/	-0.00	-0.03	-0.01	0.06	0.06	0.11
Materials	(0.03)	(0.12)	(0.14)	(0.06)	(0.13)	(0.01)
Incubator is in central	0.07	0.02	0.02	-0.06†	-0.07	-0.06†
location	(0.05)	(0.09)	(0.06)	(0.03)	(0.08)	(0.03)
Early product/market fit	0.04†	0.13*	0.17**	0.08**	0.13**	0.08**
	(0.02)	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)
Average fund rounds per	0.07**	0.14**	-0.01	0.01	0.00	0.01
year to 2001	(0.02)	(0.04)	(0.05)	(0.02)	(0.04)	(0.02)
Pseudo-Rsquare	.39	.15	.13	.32	.14	.32
Observations	142	142	142	142	142	142

[a] Robust standard errors in parentheses † p<0.1 * p<0.05, ** p<0.01, NOTE: All predictors at their mean value

BIOGRAPHIES

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