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Endogenous growth through knowledge spillovers in entrepreneurship: An empirical test *

Frédéric Delmar[a]

Karl Wennberg[b]

Karin Hellerstedt[c]

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[a]delmar@em-lyon.com, Center for Research in New Venture Creation and Growth, EMLYON Business School, 23 avenue Guy de Collongue, BP 174, 69132 ECULLY Cedex FRANCE and Research Institute of Industrial Economics, P.O. Box 55665, SE-102 15 Stockholm SWEDEN
[b]Karl.Wennberg@hhs.se, Stockholm School of Economics, P.O. Box 6501, 11383 Stockholm, Sweden Tel: +46-705-10 53 66 and
The Ratio Institute, P.O. Box 3203, SE-103 64 Stockholm, Sweden
[c]karin.hellerstedt@ihh.hj.se, Jönköping International Business School, PO Box 1026, SE-551 11 Jönköping, Sweden

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ABSTRACT

Endogenous growth theory is based on the notion that technological knowledge stimulates growth, yet the micro foundations of this process are rarely investigated and remain obscure. Knowledge spillover theory posits that growth is contingent on the technology dependence of industries, forming the landscape for technology entrepreneurs to launch and grow new ventures. We investigate these theoretical contingencies of endogenous growth with two research questions at two levels of analysis: First, do industries with a greater need for new technology-based entrepreneurship grow disproportionately faster than other industries? Second, do the knowledge spillover effects foster the growth of new technology based firms contingent on certain industry structures? These questions are examined empirically, using a comprehensive employee-employer data set on the science and technology labor force in Sweden from 1995 to 2002.

KEYWORDS*:* Endogenous Growth, Entrepreneurship, Industry Evolution

JEL-CODES: M13; L26; L11; D24

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INTRODUCTION

Endogenous growth theory rests on the assumption that technology-based growth is driven by investments in new knowledge (Romer, 1990). While this view of economic growth is relatively unchallenged in contemporary work, the precise theoretical mechanisms by which knowledge sources are exploited for commercial use have yet to be investigated empirically, and little is known about whether micro-level processes of endogenous growth differ across industries. Models of endogenous growth traditionally assume proportional expansions of industries (Metcalfe, 2003). This averages away the uneven incidence of growth across industries, concealing specific institutional and industrial contingencies that underpin growth (Pasinetti, 2003). In this paper we begin to fill this void in the literature by outlining and testing an endogenous model of industry-level and firm-level growth inspired by knowledge spillover theory.

The knowledge spillover theory of entrepreneurship posits that entrepreneurial opportunities emerge from a society's investment in human capital, research and development (Audretsch et al., 2006). These investments generate knowledge that "spill over" and is used by other economic actors, stimulating economic vitality through the birth and growth of new firms (Agarwal et al., 2007; Eliasson, 1996). The strategic management, industrial economics and geography literatures provide evidence of knowledge spillovers. Still, the questions of whether knowledge spillovers generated by skilled employees launching new firms eventually generate economic growth, and if such firms have differential impact depending on the technology dependence of the industry (Winter, 1984) have yet to be answered.

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In this paper we argue entrepreneurship among individuals trained in science and technology (the science and technology labor force, STLF) might well represent the missing link between new sources of technological knowledge and its commercial applications. We investigate whether ST entrepreneurship may function as a catalyst for economic growth on both the meso and micro levels of analyses. We try to provide solid empirical evidence of this causal mechanism, its direction and relative impact across industries, i.e. whether entrepreneurial activities stimulate economic growth or whether entrepreneurship is a response to growth from some other sources. We do this by analyzing in which industries ST entrepreneurship is most likely to generate growth. Methodologically, our challenge is to isolate the effect of entrepreneurial activity on economic growth in order to address the endogenous nature of entrepreneurship (Audretsch et al., 2006). We therefore focus our investigation on the contingencies of the theoretical mechanisms that enable technology driven entrepreneurship to facilitate growth at both the industry and the firm level. Our paper represents a novel contribution in this respect.

Since we are interested in the role of knowledge spillovers as a contingent force in endogenous growth, we need (i) to find a way to control for the technology dependence of an industry and (ii) to investigate these mechanisms at two different levels of analysis: industry growth and firm performance (growth and survival). We draw on knowledge spillover theory and research in evolutionary economics to posit a string of theoretical variables allowing us to investigate industry and firm patterns in growth. Two empirical tests are constructed to test this model using a unique longitudinal data set of all Swedish firms in the knowledge intensive sectors between 1995 and 2002. First, along the lines of Rajan and Zingales (1998) who tested the effects of financial development on growth, we identify industries' need for technology entrepreneurship using proxies derived from US data and from externally and theoretically validated measures of industries' technological regimes. We examine whether industries that are more dependent on technology driven entrepreneurship grow relatively faster. Second, since industry growth can be decomposed both into growth in the number of firms and growth in the average size of existing firms (Metcalfe, 2003), we investigate how the same contingencies affect firm-level growth among new firms. The second test allows us to gauge the extent to which new entrepreneurial firms in technology-intensive industries are able to expand their firms. If few ST firms succeed to grow, there is a clear risk that over time this type of entrepreneurship will shrink if and when potential entrepreneurs judge it too difficult or too costly to capture the economic value generated by their efforts.

Empirically, we find that firms started by ST entrepreneurs have a positive impact on growth at the industry level, but this is contingent on the technological regimes of industries. This suggests that while ST entrepreneurship represents a link between new knowledge and growth, whether this link will lead to realized growth or not depends on the prevailing technological needs of an industry. At the firm level, our results indicate that while ST startups enjoy higher rates of survival, they do not in general exhibit disproportional growth. This suggests that (i) ST entrepreneurs are not automatically able to fully capture the value of the new technologies they exploit, and/or (ii) the cost of experimentation is too high.

Theoretically, our paper contributes to the literature on entrepreneurship and economic growth by advancing solutions to the endogeneity problem of technology dependence which has hampered research progress in this vein (Braunerhjelm et al., 2010; Carree & Thurik, 2008). Specifically, the paper substantiates the presence of a causal link between new knowledge and economic growth, and furthermore contextualizes this by showing that whether or not this link will lead to realized growth depends on the technological regime of industries. Our findings here are perhaps the first in the literature following Nelson and Winter's (1982) seminal work that sought to provide simulations of these processes.

Methodologically, we contribute to the growth literature in two respects: First, our model looks for evidence of contingent mechanisms enabling technology entrepreneurship to drive growth, providing a stronger test for causality. Second, since the model is tested both at the industry and firm levels, we can investigate the reasonableness of microeconomic assumptions and hence offer some underpinnings for macroeconomic models of growth.

THEORY AND TWO EMPIRICAL TESTS

The following three statements represent the corner stones of our model of differentiated endogenous growth based on the activities of ST entrepreneurs:

- *Growth is an inherently endogenous process* based on the creation, dissemination and commercial use of new technological knowledge. Technological spillover is a central feature of this process. If one seeks to model the effect of one theoretical variable for subsequent growth, the correlation between this variable and an unobservable theoretical construct must be purged by means of some exogenous proxy variable.
- *ST entrepreneurship is posited as a link by which new sources of technological knowledge become exploited by new firms,* facilitating economic growth.
- *The effect of ST entrepreneurship on growth is contingent on the technology dependence* within a prevailing industry, sometimes facilitating growth and others not. Following Nelson and Winter (1982) we define technology dependence as the difference between industries in their tendency to adopt new knowledge as a way for firms to build competitive advantages. Consequently, growth processes are not symmetrical across industries as routinely assumed in macro models of endogenous growth (Metcalfe, 2003); to the contrary, they are rather uneven across industries since they differ in terms of the relationship between new technology, commercial outcomes and eventual growth (Audretsch & Fritsch, 2002; Bercovitz & Feldman, 2007; Klevorick et al., 2005).

These arguments are developed in the following three sections focusing on the key notion that *industry context* will moderate the effect of technological knowledge on both industry and new firm performance. We describe a test that allows us to take into account both the endogenous nature of our theory and the need for a better understanding of the causal structure governing the relationship between growth, ST entrepreneurship and industries' technology dependence.

Endogenous Growth and Knowledge Spillovers

Endogenous growth theory allows for several mechanisms for new knowledge and technologies to be transformed into economic growth. However, it does *not* explain how knowledge filters through from publicly available knowledge to knowledge that might be commercialized, and thus possibly spur economic growth. This is discussed by Acs and colleagues (2004) who specifically identify entrepreneurship as "the missing link" between publicly available and economically relevant knowledge.

Technological change has always represented a major determinant of entrepreneurial opportunities (Schumpeter, 1934). Yet, large enterprises whose R&D activities produce new knowledge do not automatically exploit the implied economic opportunities; in fact they are less likely to do so than new firms (Acs & Audretsch, 1988). New knowledge often brings about opportunities in large firms that are left unexploited due to the uncertainty of their potential value, information asymmetries between employees and managers, the bureaucratic structure of incumbent firms, or gaps between new ideas and the perceived core competence of incumbents (Acs & Varga, 2005; Audretsch et al., 2006; Klepper & Sleeper, 2005). These unexploited knowledge sources present possibilities for agents possessing the necessary knowledge – such as researchers and skilled employees – to start a new firm in an attempt to appropriate the new knowledge. In this respect, knowledge is a non-rival good (Acs, 2002).

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When opportunities springing from knowledge generated in incumbent firms lead to the formation of new firms based on this knowledge, the knowledge is said to 'spill over' (Agarwal et al., 2007). Such processes have been traced extensively on the micro level, showing how R&D efforts in incumbent firms often lead to new firms emerging in geographic proximity (Audretsch & Feldman, 1986), how knowledge sources more peripheral to an incumbent firm are more likely to become exploited (Klepper & Sleeper, 2005), and that such knowledge enhances the survival of new firms (Agarwal et al., 2004). While making progress on unearthing the micro processes of knowledge spillovers, research efforts to date have not been able to document if and when these micro-level processes of knowledge spillovers facilitate economic growth on the meso- or macro-level. This highlights the importance of better research design that bridges different levels of analyses necessary to further our knowledge of the functions and outcomes of knowledge spillovers. Macro level efforts, on the other hand, have focused on discerning whether the correlation between technology entrepreneurship and growth is causal or not in nature. Braunerhjelm et al. (2010) tested an endogenous growth model using OECD data for 17 countries between 1981 and 2002, revealing a positive relationship between self-employment in the non-agriculture sectors and GDP growth. Carree and Thurik (2008) emphasize the role of technology driven entrepreneurship in growth, but used general business ownership as a proxy for entrepreneurship. While these studies are valuable, especially in terms of examining the lag structure of entrepreneurship on economic growth, they have limitations because they cannot distinguish between technology-driven and other types of entrepreneurship. Moreover, the endogeneity problem of new technology dependence in industries is not addressed, nor do they investigate whether industry structure affects the importance of technology driven entrepreneurship.

Why Science and Technology (ST) Entrepreneurship is Important

Science and Technology entrepreneurs are important because they are likely to have access to technological knowledge or information different than other entrepreneurs. As Hayek (1945) points out, information is not equally distributed and valued. A central feature of a market economy is the division of knowledge among individuals, so that no two individuals share the same amount of knowledge or information. Only certain individuals will know about new technological knowledge that is not being exploited in the optimal way. It is this particular knowledge, emanating from an individual knowledge base and social and institutional context, that forms the belief that the individual has discovered a valuable opportunity that can be exploited commercially (Acs, 2002; Shane & Venkataraman, 2000).

Further, the possibility to transform this new information into commercial value and to appropriate that value is not equally distributed. Different groups have access to different knowledge. Educational background is a distinctive requisite and determinant of such differences in technological knowledge. Second, because industries (and firms) invest differently in new technologies, employees with the same level of education will vary in terms of their access to new and valuable knowledge. Hence, we will observe that between and within groups, returns to human capital increase in a situation where technological change is an important source to construct competitive advantages. Because different educational groups have access to different forms of technological knowledge, we also expect such groups to differ in their ability to develop successful firms. This is further moderated by the industry context, and more specifically its' dominating technological regime (Nelson & Winter, 1982). The unequal distribution of information among individuals who do not share the same interpretations, experiences or observations has two important implications (Acs, 2002). First, entrepreneurship is enabled because people do not have the same access to information, and thus differ in terms of what they believe are valuable opportunities for exploitation. Second, industry contexts differ not only in the kind of new technologies that are available for commercial use, but as well in the likelihood of successful commercial application of this new knowledge by new entrepreneurial firms.

We believe there are four theoretical arguments suggesting why ST entrepreneurship may be particularly important for economic growth, and why this activity is best measured by the entry and development of new firms. First, ST individuals are likely to have a good understanding of the possible economic value of opportunities based on new knowledge (Hellman, 2007; Shane, 2000). This makes it more likely they will identify opportunities with high potential than other groups in society. Second, because their opportunity costs are high, ST individuals are more likely to exploit valuable opportunities (Amit et al., 1995). Third, the entrepreneurial activities of this labor force represent a mechanism for spillovers of firm-specific tacit knowledge (Agarwal et al., 2007; Eliasson, 1996; 2000). This tacit knowledge resides within human capital and is derived from the training and labor market experience of individuals. It will spill over to other firms only if individuals leave their current employment (Hellman, 2007). Fourth, new firms are more likely to become carriers of Schumpeterian mark I opportunities (Schumpeter, 1934) because incumbent firms are less likely to develop technologies that challenge their core competencies (Klepper & Sleeper, 2005).

Why the Effect of ST Entrepreneurship is Contingent on Industry Technology Dependence

A central part of knowledge spillover theory is that the creation of innovative opportunities is endogenous to prevailing industries' structures. Industries differ in their disposition to adopt new knowledge as a way for firms to build competitive advantages (Malerba & Orsenigo, 1993). The consequence is that growth processes are not symmetrical across industries as traditionally assumed in endogenous growth, but rather uneven across industries depending on their technological regimes (Metcalfe, 2003; Nelson & Winter, 1982). Industries differ in terms of the relationship between new technology, commercial outcomes and economic growth (Audretsch & Fritsch, 2002; Bercovitz & Feldman, 2007; Klevorick et al, 2005; Metcalfe 1994). This is the starting point of Eckhardt and Shane's (2010) investigation of 201 US industries over 15 years, finding that the proportion of scientists and engineers in each industry is positively associated with the numbers of fast growing firms. This suggests technological innovation is an important determinant of entrepreneurial opportunity, and new firms represent an important way to commercialize new technologies. Yet Eckhardt and Shane do not fully address the endogeneity problem since the use of a lag structure is not sufficient to establish a clear causal link.

One of our central arguments is that the ST entrepreneurship is a potentially important knowledge spillover mechanisms leading to economic growth. Since knowledge is socially and institutionally dependent, economic growth is fueled by a process of technical, institutional and organizational changes that create and absorb new areas of profitable activities into the economic system (Antonelli, 1994; Metcalfe, 2003). Hence, spillover mechanisms such as ST entrepreneurship can have a differential impact on growth depending on prevailing industry contingencies. Following Nelson and Winter (1982) we base these contingencies on industries' *technological regimes* (Winter, 1984) and innovation intensity (Peneder, 2010). In our empirical test of these contingencies, we model these theoretical concepts as the *technology dependence* of industries (Rajan & Zingales, 2002)

Knowledge spillover theory and research in industry evolution suggest industries differ due to technological regimes and innovation intensity, and due to the degree of their dependence on the activities related to the commercial application of new technologies by entrepreneurs – the industry's technological regime (Audretsch & Acs, 1990). Industries with technology regimes characterized by high levels of innovation and entrepreneurship will be more dependent on such for growth (Nelson & Winter, 1982). Winter (1984, p.293) elucidates technological regimes as: “differences in a variety of related aspects, including such matters as the intrinsic ease or difficulty of imitation, the number of distinguishable knowledge-bases relevant to a productive routine, the degree to which successes in basic research translate easily into successes in applied research (and vice versa), the size of the resource commitment typical of a ‘project’ and so forth. To characterize the key features of a particular knowledge environment in these various respects is to define a ‘technological regime’.”

The essential thrust of our empirical tests is that industries differ in their innovative behavior and technological regimes, thereby offering surroundings that are more or less supportive to technology driven entrepreneurship. Hence, entrepreneurial firms will grow and profit differently due to structural differences in the importance of new technology for the industry’s evolution (Klepper, 1996). This is based on Winter’s (1984) notion of entrepreneurial and routinized regimes which encapsulates differences in how firms innovate and compete across industries. Technology regimes can be said to differ in terms of two major factors which potential entrepreneurs have to weigh before starting a new venture. The first is the opportunity cost of participating in the market. This will be the entrepreneur’s perception of price-cost margin, availability and appropriateness of novel ideas and future growth opportunities. The second factor is the cost of experimentation which is the compound of the cost of starting the firm and the potential cost of failure (both social and financial costs). In entrepreneurial regimes these costs are low, but tend to be high in routinized regimes. Related both to the concept of the technological regimes and Schumpeter’s perspectives on entrepreneurship and innovation is the industry’s creative vs. adaptive behavior. Creative or innovation intensive industries are more likely to rely on internal R&D, and to rapidly apply new technologies for commercial use. Adaptive industries are characterized by reactions to changes in exogenously given business conditions, imitation and technology adoption (Schultz, 1975) and alertness to price differentials caused by market frictions (Kirzner, 1979).

Summing up, our micro-meso model of endogenous growth contains the following properties. First, growth is an inherently endogenous process. If one seeks to model the effect of one theoretical variable for subsequent growth, the correlation between it and an unobservable theoretical construct must be purged by some exogenous proxy variable. Second, ST entrepreneurship is a link by which new sources of technological knowledge becomes exploited by new firms, facilitating economic growth. Third, the effect of ST entrepreneurship on growth is contingent on the technology dependence of an industry. These arguments lead to the following two hypotheses about industry-level and firm-level growth:

***Hypothesis 1*: The level of ST entrepreneurship will facilitate the growth of technology intensive industries when the technology dependence of these industries is controlled for.**

***Hypothesis* 2: New ST firms should perform significantly better than other new firms in technology intensive industries.**

Testing industry growth and ST entrepreneurship dependence

Our theoretical framework emphasizes the endogenous nature of growth, as well as the diversity of growth rates across industries (Metcalfe, 2003). This leads to some methodological challenges that must be addressed in order to test the causal hypothesis of ST entrepreneurship on growth. Recent research in economics investigates the endogenous nature of economic processes by relying on exogenous proxies that interact with the theoretical variables in question. We here draw upon the test developed in Rajan and Zingales' (1998) work on how financial developments affect economic growth. They investigated this by creating proxies based on the dependence of publicly traded US firms on external finance, using Compustat data to test if financial development has an effect on economic growth (using industry data from 41 countries for the period 1980-1990). Other recent papers have used similar methods to investigate financial conditions for firm growth (Beck et al., 2005) or the ways industries tend to co-agglomerate (Ellison, Glaeser & Kerr, 2010).

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We adapt the Rajan and Zingales' (1998) test to a single country, Sweden, for the period 1995 to 2002. Our hypothesis is that industries that are more dependent on ST entrepreneurship will have higher relative growth rates *if* new technological knowledge is important. If we can measure industry *i*'s dependence on ST entrepreneurship and Sweden's dependence on entrepreneurship while correcting for industry effects, we should find a positive coefficient of dependence and growth. Since knowledge spillover is an inherently endogenous process (Agarwal et al., 2007), we need to find a proxy that allows us to estimate industry technology dependence without relying on the industry's characteristics. The proxy variables used are explained in the method section entitled "Measures of new technology dependence". The independent variable is the number of ST startups in Sweden in year (j). Hence, the equation we test at the industry level is:

$$Growth_{ij}=Constant + \beta_1 industry\ dependence_{ij} + \beta_2 ST\ entrepreneurship_j + \beta_3 industry\ dependence_{ij} * ST\ entrepreneurship_j + \varepsilon_{ij}$$

Testing firm performance and ST entrepreneurship dependence

Industry growth can be decomposed into growth in number of firms, longevity and the growth of the average size of existing firms. In our second test, we investigate the latter, i.e., survival and growth of firms and especially new technology based firms relative to other firms. This is based on the reasoning that in order for people to continue to engage and persist in technology driven entrepreneurship, they need to believe the future payoffs of entrepreneurship are higher than the future payoffs of their current jobs. Also, current research indicates high growth entrepreneurship is of more economic value than any type of entrepreneurship (Henrekson & Johansson, 2010). Investigating the presence of high growth entrepreneurship at firm level should help us investigate (a) the mechanisms leading to economic growth and (b) the structural factors supporting these mechanisms.

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Our hypothesis is that technology intensive industries foster the survival and growth of firms started by ST entrepreneurs. Therefore, these firms should perform significantly better than entrepreneurial ventures created by people with other educational backgrounds. Data on all firms active in the technology intensive industries from 1995 to 2002 are used to predict survival and turnover growth for firm i in year j. Hence, the equation we test at firm level is:

$$Performance_{ij}=\alpha + \beta_1 industry\ dependence_{ij} + \beta_2 ST\ entrepreneurship_j + \beta_3 Other\ entrepreneurship_j + \beta_4 industry\ dependence_{ij}*ST\ entrepreneurship_j + \beta_5 industry\ dependence_{ij}*Other\ entrepreneurship_j\ \varepsilon_{ij}$$

METHOD

Data

Investigating how knowledge-intensive entrepreneurship affects economic growth necessitates longitudinal data on several levels of analysis, as well as a methodological framework allowing one to discern both the *differential demand* for knowledge-based new firms in industries and the *differential effect* such entrepreneurship might have on the growth of these industries. To fulfill these demands we draw upon a high-quality data set based on three matched longitudinal data sources on the entire Swedish labor market; these sources were gleaned from governmental registers and maintained for research purposes by Statistics Sweden (Folta et al., 2010). We combine these data with industry-level measures exogenous to the Swedish economy to purge our estimates from the demand for knowledge-based new firms.

The first data source is LOUISE, which has demographic information for all legal residents of Sweden over the age of 16, including type and level of education. The second source is RAMS, which tracks employment flows in the labor market based on an annual mandatory survey for all firms having at least one employee or earning a profit. The third source is SRU, which tracks financial information for each firm and is submitted annually to fiscal authorities. Our data set was originally commissioned for a broader project on entrepreneurship in high-technology sectors. Individuals were identified as working in these sectors if their employer was in an industry that met Eurostat and Organisation for Economic Co-operation and Development (OECD) classifications, which are based on the ratio of research and development expenditures to gross domestic product (Götzfried 2004). Sampling knowledge/R&D intensive industries is motivated by our theory which stresses the commercial use of new knowledge coming from R&D as a fundamental driver of economic growth (Lucas, 1988; Romer, 1990). We exclude the health care sector because of its large size, heavy regulation and domination of the public sector.

The data set has some notable virtues: First, it allows us to investigate a full population of firms based on high-quality, register data. This dramatically reduces problems related to inferences and problems of internal validity, since our estimates are not based on a mere sample of firms. Second, we only investigate the effect of technology driven entrepreneurship on the knowledge intensive industries. This provides a conservative test of our hypotheses inasmuch as we restrict possible variation in our variables. Third, we are able to link industry and firm level data; the data set allows us to investigate both aggregated and disaggregated effects as we are better able to separate the effects of industry on firms, and of firms on industry. Fourth, the data allow us to clearly separate genuinely new start-ups from other sorts of entrants, such as mergers and acquisitions, and those that move across industries.

Due to limitation in our industry-level outcome variables, the time period of investigation is limited to 1997-2002 for estimates of industry growth, and 1995-2002 for estimates of firm growth. We believe these time periods are sufficient for our investigation for two reasons. First, the latter time period allows us to include proxy variables collected during the early and mid 1990s in other nations, the difference in time and national origin making them exogenous to our industries of investigation. Second, by excluding the period

1990-1994, we exclude a unique period when the Swedish economy experienced its largest economic crisis since the 1930s, which would without doubt risk biasing our results.

Dependent variables

For our first test on industry growth, we look at growth in value added in the 1997-2002 period, and growth in turnover for 1995-2002 at the three digit level. This level is used in many similar analyses (Beck et al., 2009; Ellison et al., 2010; Hymer & Pashigian, 1962) and provides a sufficient number of observations on a cross-sectional basis. We cannot use a longer period of observation for value added because data are only available in previous years on a two digit (not three) level.

Industry growth in value added is measured as the difference between the production value and intermediate consumption of the industry, across two years. The advantage of this variable is its general acceptability as an indicator of economic growth. Value added includes expenditure on employment, depreciation on capital, and profits. Value added shows how much the industry has contributed to total national production - Gross Domestic Product (GDP) - or Gross Regional Product (GRP). Value added is not measured for the financial sector which represents a significant share of our population. We also test our model using turnover as a measure of industry growth. *Industry growth in turnover* is measured as the difference between the cumulated turnover of the industry across two years. We use 1995-2002 for industry turnover growth because we have data on turnover for all firms from 1995.

1995-2000 was a period of extraordinary growth in the economy overall, driven largely by information and communication technology (ICT) production value added (Edquist & Henrekson 2006). Investigating the effect of *entrepreneurship* on growth during the same period provides a conservative test of our model of knowledge spillovers at both industry and firm levels. The data set includes 372 industry-year observations for value added growth and

563 industry-year observations for turnover growth. Both variables are time variant and corrected for inflation.

For our second test of firm performance, we focus on turnover growth and survival for all *incorporated* firms in the knowledge intensive industries from 1995 to 2002, to restrict unobserved heterogeneity. Incorporated firms differ from other legal forms because of the larger initial investment (13,000 USD) for registration, and the requirement for external auditing, which means we have full balance sheet data for these firms. We draw on data from previous years to construct important controls such as firm age and previous growth, which minimizes problems of left censoring. The subpopulation includes 31,602 firms with 88,181 firm-year observations on which to estimate firm performance.

Firm survival. We measure firm survival as the number of years the firm is active: a firm needs to have at least one full-time employee to be considered active. We code a firm active as one and the year it exits as zero. The variable is time variant.

Firm growth in turnover. Following the work of Reichsten et al. (2009) , we measure firm growth in turnover, corrected for inflation, as the difference in log of turnover in year t compared to the log of turnover in year $t\text{-}1$, i.e. $log(FS_{ijt}) - log(FS_{ijt-1})$, where FS is firm size in terms of turnover and i is firm i in industry j. All independent and control variables are lagged one year to partially remedy for Granger causality.

Industry and firm level independent variables

Count of ST Startups. Following Rajan and Zingales (1998), we use the total number of firms created by one or several ST entrepreneurs in our population during year j, as the main indicator of the pool of technology entrepreneurship available to the Swedish economy. The variable is a count of hundreds of firms and is time variant. Depending on the year, firms created by ST entrepreneurs represent 8.6 to 12.3 percent of all new firms.

ST startup. This is a firm-level dummy variable measuring whether the firm was created by entrepreneurs with at least a 3 year or higher university degree in ST. The variable is time invariant. It is coded 1 if the new firm was created by one or several ST entrepreneurs and zero otherwise. It is time invariant.

Other startups. This is a firm-level dummy variable that is coded 1 if the firm was created by entrepreneurs without at least a 3 year or higher university degree in ST. This variable is time invariant.

Our two tests are based on these variables interacting with our proxies for technology dependence. In the second test, we hypothesize that ST startups should perform better than other startups.

Measures for industry technology dependence

As argued, the endogenous relationship between technology entrepreneurship and growth across industries as outlined in the theory necessitates we find relevant proxies to control for the technology dependence of each industry. Data on the actual importance of technology driven entrepreneurship are difficult to obtain, and most available data sets are not useful as they reflect the equilibrium between demand for entrepreneurship and its supply. In our case, this provides polluted information since we are very interested in the latter. While there is strong interest in how industry structure affects and is affected by entrepreneurship (Eckhardt and Shane 2010; Peneder 2008, 2010), few studies examine the *external* need of industries for entrepreneurship, either cross-sectionally or over time.

Following Rajan and Zingales' (1998) logic, we need to find some way to determine an industry's dependence on technology driven entrepreneurship, and to control for this to investigate *the causal effect* of ST entrepreneurship on growth. We use a set of proxies for

Swedish industry dependence on technology driven entrepreneurship.[1] The advantage of exogenous proxies is that they allow predictions about economic growth among industries. Therefore in the main we can correct for endogenous growth, the Achilles heel in many of the existing tests for entrepreneurship and economic growth. Using proxies instead of alternatives such as trying to find a suitable instrument, has the advantage of (i) overcoming reliance on weak instruments, and (ii) alleviating stubborn problems related to measuring the direct effects on industry growth rates using explanatory variables, often affected by multicollinearity and measurement error. Using interaction effects rather than direct effects to test for the endogenous human capital influences of industry growth rates reduces the number of variables needed, allowing a more precise measure of growth rates despite the limited degrees of freedom in a relatively short term within-country, across-industry study. To be sure, focused testing of the model only at the industry level may hide important insights about how the proposed theoretical mechanism works at a lower level of analysis. We recognized this and decided to conduct a second test of ST entrepreneurship and performance at the firm level.

To be a valid proxy for our theory, two assumptions are necessary. First, we assume that industries differ in their need for technology driven entrepreneurship. Schumpetarian research provides several theoretical arguments why some industries depend more on technology driven entrepreneurship than others (Schumpeter, 1942; Winter, 1984). If patenting, use of innovation generated within or outside the industry, size of typical resource commitment in a project, and how easily new knowledge translates into commercial success differ substantially between industries, then this is a valid assumption. Second, we assume that these technological differences are similar across countries. This means in effect that we can use an industry's dependence on technology driven entrepreneurship as identified in the

[1] A proxy is a variable that is highly correlated with the theoretical variable and can be considered indicative of the original, unavailable variable. Like controls, proxies are used to eliminate correlation between the error term and the variables of interest.

United States as a proxy for its dependence in another country, for example Sweden. This means we can use industry taxonomies of innovation behavior developed for other countries (Peneder, 2008; 2010) as a measure of its dependence in Sweden. While there are large country differences in relation to local conditions, here all that is necessary is that the following statement holds: If computer services are characterized by a high share of firms focusing on product innovations, and many firms perform higher intramural R&D than in the transportation sector in the Unites States, it will also function the same in Sweden.

US industry share of STLF. Our first proxy is based on US data on technological intensity, This variable measures an industry's share of employees with a university degree or similar in ST, relative to the total labor force in the US averaged over the years 1993 to 1996 at the three digit level. This measure is used in other research on entrepreneurship to control for industries' technology dependence (Eckhardt & Shane, 2010). The source is the National Bureau of Economic Research extracts of the Current Population Survey (see Eckhardt & Shane, 2010 for a detailed description). This variable is time invariant.

There are several advantages to this proxy. First, it can be argued the US labor market is among the most efficient (Beck et al., 2009). In a perfect market the supply of skilled labor is evenly matched to demand. The US market for technology skilled labor is among the most advanced in the world, and firms are less likely to have difficulty accessing skilled labor. This means the supply of labor is perfectly elastic at the proper income rates. Thus the share of STLF relative to the total labor force in the US represents a relative pure measure of industry demand for new technology. Second, in a state of ideal equilibrium, there obviously will be no need for technology entrepreneurship. Accordingly, much of the demand for entrepreneurship is likely to arise as a result of technological shocks (e.g. the increase in Internet technology), which increase the entrepreneurial opportunities beyond what industry can support (Shane, 2001). To the extent that Sweden and the US are somewhat similar; the need for new technology in the US represents a good proxy. Third, the measure is easily comparable to Swedish industry-level data.

We also choose to use other proxies since it can be argued labor market indicators are not sufficient measures of the need for technology entrepreneurship in an industry where much commercial application of new technologies resides not only in the people employed, but also in how the different industries are organized. The proxies we use are derived from cluster analyses on OECD data provided in Peneder (2008, 2010). These proxies provide three advantages. First, they are theoretically derived from research on industry evolution that is essential for our framework. Second, they provide a reduction of a large number of indicators of the demand for technology entrepreneurship. This reduces the need to throw additional variables into the model, making the estimations far more parsimonious than would be otherwise. Third, these proxies have been validated across several countries and thus afford the promise of providing high external validity. These analyses were developed to provide taxonomies to check differences among industries in terms of innovation intensity (Peneder, 2010), and technological regimes (Peneder, 2008).

Industry entrepreneurial or routinized regimes. This is a set of five dummy variables characterizing the differences among industries in terms of dominant mode of innovation and competition (Nelson & Winter, 1982). We use the empirical taxonomy relating to industry characteristics recently developed by Peneder (2008). This taxonomy is based on cluster analyses using OECD data for ten nations (not including Sweden) during the second half of the 1990s. Peneder's taxonomy includes five clusters that we use as five time invariant dummy variables based on the two digit industry level: (1) *Entrepreneurial industries with growing population*, (2) *Entrepreneurial industries with balanced population*, (3) *Other industries*, (4) *Routinized industries with balanced population* and (5) *Routinized industries with declining population*. The reference category is other industries.

Innovative intensity. Peneder (2010) developed an empirical classification using cluster analysis of these behavioral differences using Community Innovation Survey (CIS) data for 21 European countries (including Sweden) in 1998-2000. This provides very detailed data on innovation intensity. Peneder's analyses rendered a classification at the industry two digit level with five different rankings, ranging from one (low innovation intensity) to five (High innovation intensity). The specific industry characteristics of the different proxy measures and industry affiliations are presented in table 1. The variables are time invariant.

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Table 1 approximately here

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Industry and firm level control variables

Industry concentration. In line with most prior I/O economics studies, we measure industry concentration with the Herfindahl index, calculated as the sum of the squared share of turnover across the industry (Acar & Sankaran, 1999). This variable is higher the larger the average firm size in the industry. It is an approximation for the propensity of employees to work in larger establishments.

Minimum efficient scale or size (MES). MES is a standard concept in I/O. It is the smallest size or level of output enabling minimum long run average costs for a firm in a particular industry. At the industry level, MES is often associated with firm and industry growth. New firms need to enter to fill the gap between entry size and MES. MES is related to the competition intensity and market structure (Audretsch, 1995). We control for the industry MES of production by measuring the medium sized firms in the industry, based on employment statistics (Reichstein et al., 2009).

Market and industry instability. We control for industry instability using the Hymer and Pashigian approach, summing the absolute changes in market shares based on the three digit industry code. Industry instability is measured as changes in market share, and is related to concentration and crowding. The market shares of leading firms are more stable in highly concentrated industries, and industry growth has a significantly positive effect on the market (Kato & Honjo, 2006). The less concentrated the market, the easier it is for new firms to survive and grow based on their easier access to resources.

While the definition of the industry variables is the same in both tests, in the first test we calculate the variables on all firms independent of their legal form. In the second test, we calculate the variables only on incorporated firms.

Firm-level control variables

Proportion of ST employees. We control for the proportion of employees in the firm with at least a three year university degree in ST. It is likely firms started by entrepreneurs without such an educational background might compensate by hiring employees with the relevant knowledge.

Firm profits. Firm profit and growth are closely linked, and it has been suggested there is some type of causal relationship between them (Coad, 2007; Davidsson et al., 2009). Although profitable firms may not necessarily grow, and firms that show growth do not necessarily generate profits, firms able to generate profits demonstrate they possess sources of competitive advantages. Moreover, they can use their profits to invest in firm growth and avoid borrowing. This reduces the risks and costs associated with growth. For reasons of external validity, in these analyses we use the general profit measure - Returns on Assets (ROA).

Firm size. Firm turnover is used as an indicator of size. A large size is often associated with important advantages such as stronger market position, less competitive pressure and more resources (Barnett & McKendrick, 2004). Size also signals a successful firm, attracts higher quality personnel and is attractive in terms of strategic alliances. Size protects firms from the competition and the possession of slack resources means that the firm can weather periods of low turnover (George, 2005). This variable is adjusted for inflation.

Firm growth. To control for within-firm differences related to growth and to reduce the problems related to heteroscedasticity, we include a coefficient for past growth (Coad, 2007). This controls also for Gibrat's law of size-independence in growth rates. While some studies suggest Gibrat's law applies only to large firms, others indicate that growth diminishes with size (Dunne & Hughes, 1996). Also, previous growth (which is the outcome of performance in a previous time period) is a good proxy for unobserved factors that could affect firm growth (Wooldridge, 2002).

Firm age. The relationship between firm age and firm growth has been studied almost as frequently as the relationship between size and growth. Age is important because it may take several years for a new firm to establish structures and routines such as budget and control systems (Nelson and Winter, 1982).

Industry growth. Industry growth has been observed to have a positive effect on firm growth and survival (Audretsch, 1995). In growing markets, firms are not subject to such fierce competition, and have easier access to markets and more resources to exploit them. This variable corresponds to the dependent variable in our first test, with the difference that it includes only incorporated firms.

Correction for survival. We generate a variable (lambda) to control for survival bias in our firm growth models, using Lee's (1983) generalization of the Heckman selection model based on our survival analysis.

Finally, we control also for period and industry effects by including dummy variables for year and industry at the two digit level in our analyses. They are not included in the tables due to space limitations. The definition and specification of the variables are shown in table 2.

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Analytical strategy

To test our first hypothesis about industry growth, we use ordinary least square (OLS) regression on pooled yearly data. We adopt a hierarchical strategy starting with the main effects and adding the interaction effects. While the direct effects are interesting, our main interest is in the coefficient of the interaction effects. We want to check whether ST entrepreneurship has a positive effect on industry growth when interacting with our proxies for technology intensity. Because of the presence of outliers in our dependent variables, we use a Windsoring technique to truncate the extreme values to the minimum and maximum values at the 5th and 95th percentiles, respectively. As a robustness check, we also run the models on industry growth in terms of *employees*.

To test the second hypothesis on firm performance, we examine survival through a Cox regression and growth using OLS on pooled yearly data for all firms active in a specific year. We adopt the same hierarchical strategy as in test one, starting with the main effects and adding the separate interaction effects; the goal is to provide a stringent test of the same theoretical variables at both levels of analysis. We also examine whether the coefficients of new technology firms are significantly statistically different from the coefficients of other new firms, as to determine whether we are observing a real difference in performance.[2]

As a robustness checks, we first rerun the analyses exclusively with new firms, and next use employment rather than turnover growth as the dependent variable and then finally rerun the analysis of firm turnover growth using quantile regression (Mosteller & Tukey, 1977) inclusive of all firms. Quantile regressions are increasingly popular in sophisticated research on firm growth since distribution of growth rates are often fat-tailed, making OLS based analysis *prima facie* unsuitable (Coad, 2007). It is invaluable to bear in mind that most firms do not grow, or experience only marginal growth, in any given year. Based on our theoretical framework, it is likely that investigation of the determinants of growth for this category of firms would be of little interest. However, the fat-tailed nature of the growth rate distribution indicates a small share of firms do experience high-growth rates, and it is these firms that contribute disproportionately to the economy and industrial development.

RESULTS

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Table 3 approximately here

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Testing industry growth and technology entrepreneurship dependence

Table 3 presents the variables used to estimate the models related to our first test on technology entrepreneurship and industry growth. It is important to note the very low correlation between industry turnover growth and value added (r=.08). Data on value added,

[2] It should be noted that the coefficients observed are the coefficients for the whole investigated population. We use the convention of significance to give the reader a sense of the probability of the same result when testing a different population, or a sample from another country or time period.

industry turnover and employment are from Statistics Sweden (different databases). Our measures of turnover and employment were generated from our firm level data. The information on value added are aggregated industry data provided by Statistics Sweden. The counts of total startups and ST startups are highly correlated (r=.96), as is the correlation between industry turnover growth and employment growth (r=.85). One underlying assumption in this paper is that technology intensity is similar in the US and Sweden. An indicator of the relationship is the moderately high (r=.35) correlation between technology intensity across US industries and technology intensity across Swedish industries.

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Table 4 approximately here

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Table 4 presents the results of the regression models for industry growth. Models 1a to 6a show the results for growth in value added, while models 1b to 6b show the results for growth in turnover. For the proxy variables, we observe routinized industries with balanced populations have a positive effect on growth in value added. For industry turnover growth, we find entrepreneurial industries (both growing and balanced) have significant and positive effects. For both dependent variables, we find technology entrepreneurship has a negative direct effect. We find no effect of the interaction terms for value added. For industry growth in turnover, we find technology entrepreneurship has a positive and significant effect on industries with technological regimes defined as “entrepreneurial industries with growing populations” (β=.34; p<.05). This suggests ST entrepreneurship has a positive effect on economic growth in these industries.

As a first robustness check, we rerun our analysis using industry employment growth (results not displayed) as the dependent variable. The pattern is the same as for industry turnover growth, but more positive. We find a weak negative (but not statistically significant) direct effect. Once again, we find a positive effect of technology entrepreneurship on industry employment growth for “entrepreneurial industries with growing populations” (β=.22; $p<.01$). We also find a positive but weak effect of innovation intensity, with technology entrepreneurship firms becoming increasingly important for industry growth as the importance of innovation increases (β=.03; $p<.10$). As a second robustness check, we rerun our analyses, but instead using the ratio of technology start-ups to total start-ups to measure entrepreneurship. The results are the same, but the coefficients are substantially lower, suggesting technology entrepreneurship is probably relatively more important than entrepreneurship in general for industry growth.

In sum, we find only partial support for our hypothesis that industries more dependent on technology entrepreneurship will show relative higher growth rates if new technological knowledge is important. In the next section, we investigate whether the reason for this result may be that ST startups generally do not perform very well.

Testing firm performance and technology entrepreneurship dependence

Industry growth can be divided into the growth in the number of firms, longevity and growth in the average size of firms. In our second test, we investigate survival and turnover growth of ST firms relative to other firms. Our hypothesis is that technology intensive industries will foster survival and growth of these firms.

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Table 5 approximately here

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Table 5 presents the variables used in the firm level analyses. Some of the correlations are high. As expected, our variable for correction of survival bias, lambda, is strongly negatively correlated to firm size (r=-.54) and firm age (r=-.73). This indicates the importance of including a correction for survival when studying the evolution of young firms. This is confirmed by the high positive correlation between lambda and the dummy for “other startups” (r=.50). The variables “innovation intensity” and “entrepreneurial industries with growing populations” are highly correlated (r=-.82). This might cause problems of multicollinearity in our models and generate high standard errors in the coefficients. We reran the models excluding each of the two variables in turn: the results were substantially the same. Because both variables are theoretically relevant and we want the two tests to be coherent with each other, we decided to keep both of them in the models. Finally, the instability index and the Herfindahl concentration index are the industry variables most highly correlated with our proxies for technological intensity.

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Tables 6 & 7 approximately here

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Table 6 shows the results of OLS regressions on firm turnover growth, and table 7 shows the results of the Cox regression on firm survival. With the exception of the survival correction Lambda in table 6 that is based on the estimates of table 7, both tables include identical variables. The interaction effects between our proxy variables and the dummies for ST firms and other firms investigates whether new firms started by technology entrepreneurs show statistically significant higher performance than other startups. A positive coefficient in table 7 means higher probability of survival. In short, we find strong support for ST firms exhibiting higher survival, but no support for them exhibiting higher turnover growth.

We find that new firms started by ST entrepreneurs have significantly higher survival rates than other new firms with increasing innovation intensity (β=.17 and β=.-02 respectively; difference p<.001), and in routinized industries with balanced industries intensity (β= 1.32 and β=.07 respectively; difference p<.001). We also find support for our proposition that ST firms are likely to grow more in entrepreneurial industries with balanced populations, and in industries with a higher share of scientists and engineers; but ST firms are no different than other startups in this regard. However, we find that new firms started by ST entrepreneurs have a lower probability of survival in entrepreneurial industries with growing populations (β=--.35 and β=.10 respectively; difference p<.001).

For the control variables, we find as expected that higher firm profitability, age and size mean a higher probability of firm survival (Caves, 1998). We find no direct effects of our proxies, with the exception of the share of US employees in an industry. Interestingly, we find that the share of *employees* with a ST degree increases the probability of firm survival, indicating firms founded by non-ST entrepreneurs might acquire the relevant knowledge through recruitment. We also find that in industries that are highly concentrated (Herfindahl index) firms have a higher probability of survival. For firm growth, we find it is smaller firms with increasing profitability and age that are more likely to grow in terms of turnover. We find no effect of our survival correction lambda. We find also that the share of employees with a ST degree increases the probability of growth. Somewhat surprisingly, industry growth has a negative effect both on survival in (table 7) and on growth in (table 6).

When it comes to the difference between the two categories of startups (ST entrepreneurs and others) in firm growth, we observe small differences in both direct and interaction effects. Direct effects are predominantly positive and significant for new firms started by non-ST entrepreneurs. Interaction effects are mainly negative and individually not significant. Thus, we do not find evidence that ST startups should achieve more growth than other startups.

As a robustness test, we reran our models for survival and growth using only the subpopulation of new firms; the results were almost identical. For firm growth, we reran our analyses using firm employment as the dependent variable instead of turnover.[3] This provided an interesting picture of ST startups in technology intensive industries as generally not able to grow disproportionately over time. Other startups grow significantly more than ST startups in our model, with direct effects (β=.005 and β=-.002 respectively; difference $p<.05$). We find that ST startups grow significantly less in entrepreneurial regimes with growing populations and in routinized and balanced regimes, as well as in industries with a higher share of ST employees. As a third robustness check, we ran quantile regression without industry dummies. The results were unchanged until the 70th percentile, above which ST startups are significantly more likely to grow further. Because we cannot use the same control variables in these analyses as in our main models, we have chosen to be conservative in reporting these results. The quantile regression results do indicate the presence of high-potential entrepreneurship, but only in a small proportion of the population (Henrekson & Johansson, 2010).

In sum, we find mixed support for our second hypothesis that technology intensive industries will improve survival rates and foster rapidly growing entrepreneurial firms. We find that technology intensive firms are likely to survive better than similar nontechnology intensive firms, but are not able to grow more. Most of these firms remain small or grow only slowly, albeit with higher probabilities of survival.

[3] Results from all robustness tests available upon request.

DISCUSSION

In this paper, we examine the role of new knowledge for economic growth as proposed by endogenous growth theory. We argue ST entrepreneurship represents a potentially important force influencing economic growth by the mechanisms of knowledge spillover and the technology dependence of industries (Metcalfe, 2003). The theoretical framework outlined explains how economic growth is an evolutionary process contingent on the technology dependence of industries and diversity in growth rates among industries and over time. This framework allows us to develop two empirical tests that in part circumvent some of the endogeneity and causality problems evident in previous studies on entrepreneurship and economic growth.

Our paper tries to move the causality debate a step further by using proxies for our theoretical mechanisms. This allows us to examine whether technology driven entrepreneurship is likely to have a positive effect on growth, and if this effect can attributed to the contexts/factors shaping the evolution of these firms. The combined use of proxies and externally validated measures of technology intensity allows us to argue that the observed effects are not endogenous because our measures of technology intensity are generated outside the Swedish economy. This considerably narrows the range of competing explanations for our results.

In addition to these methodological contributions, the paper contributes theoretically to knowledge spillover theory, entrepreneurship research and research in industry evolution. We deal with knowledge spillover theory as a unique attempt to test the impact of one of the important mechanisms involved in converting new knowledge into commercial activities. Specifically, we argue first that ST entrepreneurship reflects the equilibrium between the demands for technology based entrepreneurship and its supply. Differently stated, it is both a cause and effect of economic growth. Further, we find differential impact of ST entrepreneurship based on the technology dependence of the industry. This vindicates the connection between the availability of new knowledge and the possibility for entrepreneurs to use such knowledge for commercial ends (Braunerhjelm et al., 2004). Our paper also contribute to entrepreneurship theory by providing a set of theoretical and methodological tools that allows research to start disentangling the nexus between entrepreneurship, economic development and industrial evolution (Acs, Desai & Hessels, 2008). We outline a theoretical framework linking micro to meso processes, where we propose and empirically scrutinize several distinct mechanisms linking technology driven entrepreneurship to growth. Our paper also contributes to an enhanced understanding how different levels of analysis affect each other, something frequently called for in the literature (Ireland, Reutzel & Webb, 2005). This is a very important observation, supportive of the notion that choice of industrial context is important for entrepreneurs and has strong effects on performance (Short et al., 2009).

Contributing to research in industry evolution, our paper provides a novel test of the theoretical contingencies of growth propagated by Nelson and Winter (1982). Our empirical findings provide a more contextualized view of the link between technology entrepreneurship and economic growth by showing that realized growth depends on technological regime of industries.

We have argued that the STLF, based on their education and privileged access to new technologies, would include individuals with a high probability of discovering and pursuing high-value opportunities. We find some support for the generality of this idea with technology intensive industries benefiting from the availability of ST entrepreneurship. However, our firm level results indicate that the reverse is not necessarily true. ST entrepreneurs seem to benefit only partially from the context provided by these industries. While they show higher rates of survival than other startups, they do not grow more. If the possibility to grow a new firm is an important incentive for entrepreneurs, this is a problematic conclusion. If ST entrepreneurs perceive (i) that they are not able to fully capture the commercial value of the new technologies they exploit, and/or (ii) that the cost of experimentation is too high (Nelson & Winter, 1982; Peneder, 2008), then over time the quality and quantity of their entrepreneurial activities will weaken, as will their contribution to economic growth. It can be discussed if the possibility to grow a new firm is a valid incentive indicator in the sectors studies. Other streams of literature argue with increasing uncertainty and technology dependence in an industry, firms need to become smaller to achieve flexible specialization to survive (Carlsson, 1992; Piore & Sable, 1984). If size is less interesting as a competitive advantage for technology intensive firms because it hinders on-going and rapid adaption to environmental changes, this would suggest that growth is a salient performance measure than survival on the firm level. If so, an interpretation is that ST entrepreneurs do perform better because they have a higher probability of survival and that growth is not a strategic goal for these new firms because it does not enhance the probability of survival.

However, previous empirical research on the Swedish economy indicates that there might be institutional reasons to why entrepreneurship as a mechanism for commercializing new knowledge at the firm level does not seem to be effective. Previous research has suggested three institutional factors that might also explain our results. A first possibility is the lack of an institutional environment supporting entrepreneurship such as high entry barriers, heavy administrative burden, or limited access to venture capital (Henrekson & Douhan, 2008). Yet, these factors should affect all types of firms uniformly, and we find this to not be the case since our analysis suggests different types of new firms perform differently across industries. Since access to venture capital and entry barriers tend to be industry specific, this can not be the only barrier limiting growth. A second possibility is that our findings might be related to negative selection into entrepreneurship. If we assume that the share of entrepreneurial individuals in the economy is relatively constant over time (Baumol, 1990), it is a possible that certain institutions will lead encourage them to work in incumbents firms rather than as independent entrepreneurs in new firms. In countries such as Sweden and Germany there is a well-known dominant tradition of large industrial companies producing most of the R&D and innovation (Granstrand & Alänge, 1995). It may be that the Swedish industrial structure is providing the STLF with large, international firms with a strong internal labor market and the possibility to engage in corporate entrepreneurship, the result being that only entrepreneurs with prior human capital not adapted to these firms will choose to create new firms. Although the Herfindahl index offers a rough proxy for the propensity of employees to work at large establishments in the industry, we do not directly control for the possibility of individual-level negative selection. It is possible that it has an effect on new firm evolution and merits further scrutiny. A third institutional factor may be that the industrial structures investigated to not facilitate new firm performance and growth. Our analysis does not show that industries normally characterized as entrepreneurial and growing or highly innovation intensive offer better growth opportunities. Rather, the results suggest there might be too little entrepreneurial activity in the economy for new knowledge to be transformed into new economic activity. Therefore, the industrial structure that we investigate appears to be imbalanced between knowledge *creation* and knowledge *exploitation* through entrepreneurial activity, the latter possibly being insufficient.

Conclusions and limitations

This study also comes with limitations, which also poses some important avenues for future research. First, the advantage of studying the micro foundations of endogenous growth in a small western economy is also a limitation: Our research design excluded variation in institutionally oriented boundary conditions, things such as are primarily found to reside in cross-national variation in institutions such as taxation rates, intellectual property protection, and freedom of doing business (Autio & Acs, 2010; Henrekson & Douhan, 2008). Second, our study relies on the industry as an indicator of this competitive space. Some research criticizes industry classifications as indicators of the competitive space that firms occupy (Aghion et al., 2005; Barnett & McKendrick, 2004). Methods based on network approaches to competitiveness might well generate different but equally informative results. Third, in order to reduce the various sources of unobserved heterogeneity, we purposively measured technology driven entrepreneurship in a limited set of industries, selectively using people with a ST education as a proxy for the availability of new and commercially valuable technology. Yet it is possible that many new innovations that are necessarily based on new knowledge are not based on knowledge from individuals with a background in ST. Many important new innovations are developments of new business models based on improved logistics or non-proprietary technologies that are then creatively combined with unique market knowledge. Hence, our proposed measure of technology driven entrepreneurship might well be too narrow. Third, our period of observation of eight years might be sufficiently long to capture and examine the major effects related to entry and survival, but too short to measure the effect of firm growth and its returns to economic growth. The emergence of firms that actually reshape an economy in the Schumpeterian sense is rare, and also takes time.

For public policy, our evidence supports Eliasson's (2000) suggestion that growth-oriented governments should be less concerned with the creation of new ST firms *per se*, and more concerned with commercial incentives to support the transformation of scientific knowledge into new business firms. If knowledge-based entrepreneurship constitutes an important vehicle for commercializing innovations, then a strong industry structure could enhance innovation and growth. However, we do not find this to be the case. According to a recent study based of GEM data (Acs et al., 2008), Sweden as a country is among the group of developed nations at an 'innovation driven stage' where entrepreneurship and, specifically technology driven entrepreneurship, is of increasing importance for economic development.

This would mean that if Sweden is to continue to grow there is an urgent need to examine the factors that need to be encouraged or changed to favor such development. Our results indicate that while there might be general problems that apply to the whole economy, it is vitally important to develop a more targeted policy favoring the establishment of growth-oriented entrepreneurship in industries of particular economic importance.

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TABLE 1: Description of proxy variables for industry technology dependence

<table>
<tr><th>Variable</th><th>Description</th><th>Examples of industries (ISIC two digit)</th></tr>
<tr><td>US Technology intensity</td><td>An industry's share of employees with a university degree or similar, in ST, relative to the total labor force in the US averaged over the years 1993 to 1996 at the three digit level of industry classification.</td><td>Not applicable</td></tr>
<tr><td>Entrepreneurial industries with growing population</td><td>Industries where firm turnover is high and the population rather mutable, implying that incumbent firms find it difficult to defend against entry by new ventures. The net entry of firms is growing and so is the net output. This allows for the maintenance high price-cost margins despite more firms and low productivity performance.</td><td>Post and telecommunications (64); Computers and related (72); Business services (74); Real estate (70-74)</td></tr>
<tr><td>Entrepreneurial industries with balanced population</td><td>The same as the above, but no growth in the population. Profits are above average despite low growth and productivity performance. Entry cost are likely to be low explaining a high level of entrepreneurial activity, but most new firms are small.</td><td>Business sector services (50-74); Other community social and personal services (90-93)</td></tr>
<tr><td>Routinized industries with balanced population</td><td>Routinized regimes are characterized by low rates of firm turnover, since high cost of experimentation confine the competitive threat of novel entrepreneurs and give a competitive edge to established business. There is no growth in the population. Profits are low, there is intense cost competition and limited scope for market expansion. Firm performance depends on technical efficiency of operations.</td><td>Pharmaceuticals (2423); Medical precision and optical instruments (33); Education (80)</td></tr>
<tr><td>Routinized industries with declining population</td><td>The same as the above but with a declining number of firms in the population. Profits are low and there is little demand growth but enduring productivity growth.</td><td>Other transport equipment (35); Financial intermediate excluding pension and insurance (65)</td></tr>
<tr><td>Other industries</td><td>Industries not positioned around the two clustering dimensions of opportunity incentives and cost of experimentation.</td><td>Chemicals (24); Machinery and equipment (29); Transport and storage (60-63); Financial services (67);R&D (73); Health and social work (85)</td></tr>
<tr><td colspan="2">High Innovation intensity industries (5): Sectors are characterized by a high share of creative firms focused on product innovation and many firms performing high intramural R&D. Typically, the appropriability regime depends on the use of patents and knowledge is highly cumulative.</td><td>Computer and related activities (72); Research and development (73); Machinery and equipment (29);</td></tr>
<tr><td colspan="2">Intermediate to high innovation intensity industries (4): This group is comprised of sectors with an intermediate share of creative firms mostly involved in process innovations, and many firms are performing R&D albeit expenditures are than 5% of turnover. Cumulativeness of knowledge is high or intermediate and firms frequently use patents for appropriation.</td><td>Post and telecommunications (64); Chemical and chemical product (24)</td></tr>
<tr><td colspan="2">Intermediate innovation intensity industries (3): This group is the most heterogeneous =, but all sectors share a large number of firms pursuing opportunities through the acquisition of external innovations. Accordingly, appropriability measures are relative weak, with some importance ascribed to strategic means.</td><td>Business sector services (74); Financial intermediates (65-67)</td></tr>
<tr><td colspan="2">Intermediate to low innovation intensity industries (2): The main characteristics of this group is the high share of firms with adaptive behavior, pursuing opportunities through the adaptation of new technology. Accordingly, the prevalent mode of innovation is the acquisition of new technology. For most firms the appropriability conditions are weak and the cumulativeness of knowledge low.</td><td>Air transportation (62); Electricity and gas (40-41); Insurance or pension funding (66)</td></tr>
<tr><td colspan="2">Low innovation intensity industries (1): A homogenous class defined by firms pursuing opportunities not based on new technologies. Innovation is not pursued and there is no cumulativeness of knowledge</td><td>Whole sale trade (50-52)</td></tr>
</table>

Note. Complete description of industries are found in Peneder (2008) and (2010)

TABLE 2: Definition of variables

Variable Description		***Calculation***
Dependent variable:		
Value added	Value added per industry and year., i.e. the difference between the production value and the intermediate consumption of the specific industry.	*Provided by Statistics Sweden*
Firm sales growth	Firm sales growth (FS) Year j– Year j-1	*(log(FSij) − log(FSij−1))*
Independent variable		
Count ST startups	Total number of firms created by ST entrepreneurs (Count ST startups) in Sweden in a given year j	$\sum$*Firm Ent* ST_j
ST Entrepreneurial firm	A firm in year j and industry i started by at least on person with a three university degree or higher in	*Dummy variable new firm with at least one person with ST degree in year of establishment*
Other entrepreneurial firm	A firm in year j and industry i started by with no one with a three university degree or higher in	*Dummy variable new firm with at no person with ST degree in year of establishment*
Firm level variables:		
Proportion ST employees	Proportion of employees (Empl. ST) with a 3 year or higher university degree in science and technology in firm i in year j	*Emp ST ij/Emp total ij*
Firm profits	Logarithm of RoA in Year j for Firm i	*(log (ROAij)*
Lambda	Selection correction for survival using Lee's (1983) generalization of the Heckman selection model	*See table 4 model 1a for specification*
Firm size	Logarithm of firm size i in terms of Year j-1 sales in thousands of Swedish Crowns corrected for inflation	*(log(FSij))*
Firm age	Logarithm of firm age	*(log(Year j – establishment year)*
Firm sales growth previous year	Firm sales growth (FS) Year j-1– Year j-2 corrected for inflation	*(log(FSij-1) − log(FSij−2))*
Proxy variables for new technology dependence		
US industry share of STLF	Proportion of employees (Emp ST) with a 3 year or higher university degree in science and technology in industry i in year j in the US	*Emp ST ij/Emp total ij*
Industry routinized or entrepreneurial regime	The technological regime that dominates in the industry	*Adapted from Peneder (2008)*
Innovation cumulativeness	The level of innovation cumulativeness in an industry. An industry is highly cumulative if internal sources are more important than external sources	*Adapted from Peneder (2010) only available on two digit level*
Industry level variables		
Industry concentration	Herfindahl concentration index, calculated by the sum of the squared share of sales across the industry.	$\left(\sum_{i=1}^{n} \left[FS\frac{ij}{\sum_{i=1}^{n} FSij}\right]^{2}\right)$
Industry instability	Sum of absolute changes in market shares by three digit industry codes (Hymer & Pashigian, 1962).	$\sum_{\downarrow}(i=1)^{\uparrow}n \,\lvert(FSijt/\sum_{\downarrow}(i=1)^{\uparrow}n \;[\![F$
Industry minimum efficient scale (MES)	Industry minimum efficient scale of production measured by medium sized firms in the industry, based on employment statistics.	*Mean(Indsit)*
Industry growth	Growth of the industry measured by the differences in the logarithmic industry sales (IndS) for year j-1 to j, using a three digit industry level of aggregation.	*(log(IndSij) − log(IndSij−1))*

	Table 3: Variable means and correlation for industry growth															
	Variable	Mean	Sd	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Value added growth	.034	.523														
2	Turnover growth	.924	4.454	.076													
3	Employee growth	.123	2.174	.048	.853												
4	Count Startups	147.790	8.35.4	-.079	-.010	-.032											
5	Count ST Startups	15.819	2.246	-.066	.002	-.019	.961										
6	Entr. ind. with growing pop.	.215	.411	.069	.108	.146	.005	.004									
7	Entr. ind. with balanced pop.	.134	.342	.034	-.047	-.006	.004	.003	-.206								
8	Rout. ind. with balanced pop.	.175	.380	.045	.022	.040	.005	.004	-.241	-.181							
9	Rout. ind. with declining pop.	.056	.231	.032	-.064	-.097	.007	.000	-.128	-.096	-.113						
10	Innovation intensity	3.325	1.869	-.141	-.084	.002	.004	.006	.154	-.470	-.042	.088					
11	US industry share of STLF	.031	.059	-.021	-.087	-.049	-.001	.003	-.040	-.108	.023	.235	.231				
12	Industry concentration	.284	.268	.010	-.021	-.100	-.031	-.026	-.139	-.075	-.076	.182	.085	.004			
13	Industry instability	-.054	.420	.011	.051	-.005	-.003	-.009	-.148	.055	.028	.069	.059	-.051	.350		
14	Industry MES	1.305	1.247	-.048	-.088	-.071	.018	.029	-.294	-.180	.186	.173	.193	.031	.266	.167	

N=372

Table 4: Regression results predicting the effect of ST entrepreneurship on industry growth

	DV: Value added growth						DV: Turnover growth					
Variables	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a	Model 6a	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b	Model 6b
Count ST startups	-0.011*	-0.011*	-0.010+	-0.011*	-0.011*	-0.011*	-1.823***	-1.890***	-1.831***	-1.801***	-1.825***	-1.823***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.073)	(0.078)	(0.076)	(0.077)	(0.075)	(0.073)
Entrepreneurial industries with	0.003	0.000	0.003	0.003	0.003	0.003	2.247+	2.255+	2.249+	2.251+	2.248+	2.247+
	(0.070)	(0.073)	(0.070)	(0.070)	(0.070)	(0.070)	(1.345)	(1.339)	(1.345)	(1.344)	(1.345)	(1.345)
Entrepreneurial industries with	-0.015	-0.015	0.000	-0.015	-0.015	-0.015	7.194*	7.213*	7.192*	7.240*	7.203*	7.192*
	(0.074)	(0.074)	(0.077)	(0.074)	(0.074)	(0.074)	(3.341)	(3.325)	(3.340)	(3.339)	(3.342)	(3.341)
Routinised industries with bala	0.155	0.155+	0.155+	0.157	0.155+	0.156+	0.935	0.939	0.938	0.933	0.937	0.937
	(0.094)	(0.094)	(0.094)	(0.096)	(0.094)	(0.094)	(1.816)	(1.807)	(1.815)	(1.815)	(1.816)	(1.816)
Routinised industries with decli	0.043	0.043	0.043	0.043	0.041	0.000	0.184	0.158	0.183	0.186	0.187	0.185
	(0.056)	(0.056)	(0.056)	(0.056)	(0.066)	(0.000)	(2.274)	(2.263)	(2.274)	(2.273)	(2.274)	(2.274)
Innovation type	-0.011	-0.006	-0.006	-0.006	-0.006	-0.006	-0.396	-0.389	-0.395	-0.399	-0.397	-0.396
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.480)	(0.477)	(0.480)	(0.479)	(0.480)	(0.480)
US Tech. Int.	-0.109	-0.109	-0.109	-0.109	-0.109	0.075	-4.832	-4.761	-4.828	-4.788	-4.833	-4.659
	(0.205)	(0.206)	(0.205)	(0.206)	(0.206)	(1.147)	(3.946)	(3.927)	(3.945)	(3.944)	(3.946)	(14.216)
The Herfindahl concentration inde	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004	0.035	-0.067	0.036	0.046	0.051	0.041
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.958)	(0.953)	(0.956)	(0.956)	(0.959)	(0.956)
The instability index	0.023	0.024	0.024	0.024	0.024	0.024	0.453	0.540	0.460	0.448	0.448	0.453
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.557)	(0.555)	(0.557)	(0.556)	(0.558)	(0.557)
Industry minimum efficient scale	-0.007	-0.008	-0.008	-0.008	-0.008	-0.008	-0.195	-0.181	-0.196	-0.184	-0.195	-0.196
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.207)	(0.205)	(0.206)	(0.207)	(0.207)	(0.206)
ST firms X innov. Intensity	0.002						0.003					
	(0.002)						(0.031)					
ST firms X ent. Ind. growing		0.002						0.341*				
		(0.010)						(0.142)				
ST firms X ent. ind. balanced			-0.009						0.061			
			(0.013)						(0.165)			
ST firms X rout. Ind. balanced				-0.001						-0.133		
				(0.011)						(0.155)		
ST firms X rout. Ind. declining					0.001						0.027	
					(0.019)						(0.210)	
ST firms X US Tech. Int.						-0.012						-0.012
						(0.071)						(0.974)
Constant	0.298*	0.285*	0.261+	0.277*	0.280*	0.273*	38.984***	39.919***	39.099***	38.666***	39.009***	38.978***
	(0.134)	(0.138)	(0.136)	(0.137)	(0.134)	(0.138)	(2.313)	(2.334)	(2.333)	(2.341)	(2.321)	(2.351)
Observations	372	372	372	372	372	372	563	563	563	563	563	563
R-squared	0.149	0.146	0.147	0.146	0.146	0.146	0.675	0.678	0.675	0.675	0.675	0.675
	Standard errors in parentheses					*** p<0.001, ** p<0.01, * p<0.05, + p<0.10						

	Table 5 Means and correlation for firm growth									
	Variable	**Mean**	**Sd**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Firm growth turnover	.970	.178	1.000						
2	ST startup	.028	.164	-.003	1.000					
3	Other startup	.146	.353	.004	-.070	1.000				
4	Percent ST emp.	.001	.003	.007	.375	-.143	1.000			
5	Firm profits	.005	.001	.010	.030	.048	.017	1.000		
6	Firm size	14.216	1.516	-.034	-.013	-.113	.015	-.019	1.000	
7	Firm age	.019	.005	.016	-.226	-.532	-.030	-.074	.107	1.000
8	Firm growth	.001	.000	-.010	.003	.001	-.005	.006	.074	-.034
9	Lambda	.886	.565	.002	.117	.505	-.014	-.217	-.549	-.725
10	Ent. Ind. with growing pop.	.880	.325	.017	-.002	.072	.011	.071	-.269	-.068
11	Ent. Ind. with balanced pop.	.013	.112	-.010	-.015	-.024	-.016	-.016	.088	.021
12	Rout. Ind. with balanced pop.	.042	.202	-.011	-.013	-.052	-.036	-.046	.087	.066
13	Rout. Ind. with declining pop.	.004	.063	-.001	-.010	-.007	-.016	-.022	.090	.007
14	Innovation intensity	3.197	.635	-.016	.010	-.060	-.002	-.060	.241	.059
15	US industry share of STLF	.105	.126	.012	.046	-.059	.217	-.013	.039	.049
16	Industry concentration	.000	.000	-.018	-.022	-.050	-.054	-.056	.229	.014
17	The instability ind.	-.002	.002	-.012	.008	-.125	.105	-.039	.102	-.036
18	Industry MES	.003	.098	.000	-.001	-.004	-.002	-.006	.036	-.003
19	Ind. Growth	.000	.001	-.022	-.013	-.027	-.009	-.027	.134	-.036

	Table 5 Means and correlation for firm growth (continued)											
	Variable	8	9	10	11	12	13	14	15	16	17	18	19
8	Previous growth	1.000											
9	Lambda	.030	1.000										
10	Ent. Ind. With growing pop.	-.026	.281	1.000									
11	Ent. Ind. with balanced pop.	.008	-.034	-.308	1.000								
12	Rout. Ind. with balanced pop.	.010	-.141	-.570	-.024	1.000							
13	Rout. Ind. with declining pop.	.013	-.057	-.172	-.007	-.013	1.000						
14	Innovation type	.025	-.280	-.819	.192	.542	.079	1.000					
15	US ind. share of STLF	-.011	-.240	.083	.000	-.018	.026	-.045	1.000				
16	Ind. Concentration	.026	-.135	-.653	.221	.304	.305	.401	-.240	1.000			
17	Industry instability	-.039	-.204	-.272	.096	.145	.053	.223	.516	.162	1.000		
18	Industry MES	.001	-.018	-.018	.002	.002	.030	.021	-.002	.087	.011	1.000	
19	Ind. Growth	.272	.086	-.036	-.001	.035	.020	.052	-.012	.079	-.056	.000	1.000

Table 6: Regression results for the effect of ST entrepreneurship on firm turnover growth 1995-2002							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ST startup (dummy)	0.003	0.031*	-0.006	0.003	0.002	0.003	0.004
	(0.004)	(0.013)	(0.008)	(0.004)	(0.004)	(0.004)	(0.005)
Other Startup (Dummy)	0.006*	0.023*	0.000	0.006*	0.006*	0.006*	0.007*
	(0.003)	(0.010)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Proportion ST employees	0.415	0.395	0.401	0.413	0.425	0.417	0.389
	(0.263)	(0.263)	(0.264)	(0.263)	(0.263)	(0.263)	(0.264)
Firm profits (log)	3.278*	2.857*	3.038*	3.273*	3.351*	3.307*	3.178*
	(1.333)	(1.345)	(1.345)	(1.333)	(1.335)	(1.333)	(1.335)
Firm size (log)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm age (log)	1.189**	1.032*	1.102**	1.188**	1.217**	1.201**	1.156**
	(0.412)	(0.417)	(0.417)	(0.412)	(0.413)	(0.412)	(0.413)
Firm growth	-1.578	-1.492	-1.531	-1.575	-1.597	-1.583	-1.558
	(2.528)	(2.528)	(2.529)	(2.528)	(2.528)	(2.528)	(2.528)
Lambda	0.004	0.003	0.004	0.004	0.005	0.005	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Entr. ind. with growing pop.	0.001	0.002	-0.000	0.001	0.001	0.001	0.001
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Entr. ind. with balanced pop.	-0.034	-0.036	-0.035	-0.033	-0.034	-0.033	-0.034
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Rout. ind. with bal. pop.	0.014	0.015	0.015	0.015	0.011	0.015	0.014
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Rout. ind. with decl. pop.	0.027	0.026	0.027	0.027	0.027	0.024	0.027
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)
Innovation intensity	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
US ind. share of STLF	0.018*	0.016*	0.017*	0.018*	0.018*	0.018*	0.021*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Industry concentration	23.423	21.563	22.973	23.634	23.231	23.664	23.678
	(16.146)	(16.160)	(16.153)	(16.159)	(16.146)	(16.168)	(16.148)
Industry instability	0.609	0.645	0.631	0.610	0.594	0.611	0.697
	(0.527)	(0.527)	(0.528)	(0.527)	(0.527)	(0.527)	(0.532)
Industry MES	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Industry growth	-3.729***	-3.628**	-3.692***	-3.742***	-3.743***	-3.741***	-3.725***
	(1.115)	(1.116)	(1.115)	(1.115)	(1.115)	(1.115)	(1.115)
ST startup X inno. int.		-0.009*					
		(0.004)					
Oth. startup X inno. int.		-0.006+					
		(0.003)					
ST startup X ent. ind. grow.			0.010				
			(0.008)				
Oth. startup X ent. ind. grow.			0.006				
			(0.006)				
ST startup X ent. ind. bal.				-0.015			
				(0.033)			
Oth. startup X ent. ind. bal.				-0.003			
				(0.017)			
ST startup X rout. ind. bal.					0.027+		
					(0.014)		
Oth. startup X rout. ind. bal.					0.004		
					(0.010)		
ST startup X rout. ind. dec.						0.057	
						(0.057)	
Oth. startup X rout. ind. dec.						0.008	
						(0.027)	
ST startup X ind. share STLF							-0.010
							(0.020)
Oth. startup X ind. share STLF							-0.016
							(0.013)
Constant	0.951***	0.960***	0.961***	0.952***	0.950***	0.950***	0.954***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
R-squared	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Observations	88181	R-squared	0.005	*** p<0.001, ** p<0.01, * p<0.05, + p<0.10			

Table 7: Results for Cox hazard rate model ST entrepreneurship predicting survival							
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ST startup (dummy)	0.152**	0.378*	0.458***	0.144*	0.127*	0.155**	0.055
	(0.056)	(0.177)	(0.134)	(0.056)	(0.056)	(0.056)	(0.065)
Other Startup (Dummy)	0.141***	0.209	0.047	0.139**	0.141***	0.141***	0.102*
	(0.042)	(0.133)	(0.088)	(0.043)	(0.042)	(0.042)	(0.045)
Proportion ST employees	-2.641	-2.708	-1.689	-2.455	-2.260	-2.687	-1.983
	(4.484)	(4.478)	(4.500)	(4.490)	(4.489)	(4.483)	(4.493)
Firm profits (log)	195.781***	195.920***	196.312***	196.015***	196.226***	195.680***	195.204***
	(18.216)	(18.218)	(18.219)	(18.217)	(18.219)	(18.216)	(18.209)
Firm size (log)	0.126***	0.127***	0.126***	0.126***	0.127***	0.126***	0.127***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm age (log)	54.908***	55.191***	54.938***	54.870***	55.115***	54.878***	55.079***
	(3.304)	(3.305)	(3.304)	(3.304)	(3.305)	(3.304)	(3.304)
Firm growth	-0.096***	-0.096***	-0.095***	-0.096***	-0.096***	-0.097***	-0.099***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Entr. ind. with growing pop.	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entr. ind. with balanced pop.	-0.240	-0.222	-0.250	-0.274	-0.236	-0.240	-0.230
	(0.227)	(0.227)	(0.227)	(0.229)	(0.227)	(0.227)	(0.227)
Rout. ind. with balanced pop.	0.193	0.175	0.154	0.193	0.054	0.193	0.191
	(0.380)	(0.380)	(0.380)	(0.380)	(0.381)	(0.380)	(0.380)
Rout. ind. with declining pop.	-1.702	-1.696	-1.639	-1.708	-1.683	-1.568	-1.669
	(1.055)	(1.055)	(1.055)	(1.055)	(1.055)	(1.134)	(1.054)
Innovation intensity	-0.142	-0.161	-0.137	-0.141	-0.122	-0.143	-0.138
	(0.355)	(0.355)	(0.355)	(0.355)	(0.355)	(0.355)	(0.355)
US ind. share of STLF	0.626***	0.633***	0.630***	0.626***	0.630***	0.627***	0.465***
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.130)
Industry concentration	715.327**	740.501**	706.101**	704.035**	695.503**	714.828**	701.870**
	(269.316)	(269.246)	(269.730)	(269.583)	(269.257)	(269.662)	(268.773)
Industry instability	4.766	4.506	4.825	4.686	4.194	4.771	0.599
	(9.072)	(9.070)	(9.081)	(9.073)	(9.073)	(9.073)	(9.143)
Industry MES	2.293	2.280	2.230	2.295	2.231	2.216	2.305
	(1.709)	(1.704)	(1.688)	(1.709)	(1.685)	(1.702)	(1.719)
Industry growth	-43.334**	-43.081**	-43.450**	-43.072**	-43.051**	-43.341**	-42.780**
	(14.086)	(14.083)	(14.073)	(14.103)	(14.090)	(14.089)	(14.076)
ST startup X inno. int.		0.174**					
		(0.056)					
Oth. startup X inno. int.		-0.021					
		(0.042)					
ST startup X ent. ind. grow.			-0.351*				
			(0.137)				
Oth. startup X ent. ind. grow.			0.103				
			(0.084)				
ST startup X ent. ind. bal.				0.341			
				(0.314)			
Oth. startup X ent. ind. bal.				0.033			
				(0.168)			
ST startup X rout. ind. bal.					1.320**		
					(0.417)		
Oth. startup X rout. ind. bal.					0.066		
					(0.169)		
ST startup X rout. ind. dec.						-0.794	
						(0.638)	
Oth. startup X rout. ind. dec.						-0.149	
						(0.470)	
ST startup X ind. share STLF							0.889**
							(0.328)
Oth. startup X ind. share STLF							0.512*
							(0.206)
-Loglikelihood	90632.719	90627.483	90627.887	90632.066	90624.989	90632.06	90626.821

Note: N=120,705, No of subjects= 31,602; No. of failures = 9,435; *** p<0.001, ** p<0.01, * p<0.05, + p<0.10 ; Standard errors in parentheses