Journal of Business Venturing 26 (2011) 412–430

Contents lists available at ScienceDirect

Journal of Business Venturing

Industry changes in technology and complementary assets and the creation of high-growth firms

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ARTICLE INFO

Article history:
Received 6 March 2009
Received in revised form 27 January 2010
Accepted 28 January 2010
Available online 19 March 2010

Keywords:
Entrepreneurship
Industry evolution
Technological innovation
Commercialization of science
Human capital

ABSTRACT

This study uses employment data to examine why some industries host more new high-growth firms than others. Using a unique data base of 201 industries over a 15-year period, we find that increases in the proportion of employment of scientists and engineers in industries are positively associated with counts of fast-growing new firms; however, we do not detect a relationship between fluctuations in the proportion of employment in sales and production occupations and counts of fast-growing new firms. The findings suggest that technological innovation is an important determinant of entrepreneurial opportunity. Further, they suggest that private new firms are an important means of organizing commercial innovation and that new firms may be less constrained by complementary assets than has been previously understood.

1. Executive summary

If entrepreneurship involves the study of the discovery and exploitation of entrepreneurial opportunities, an important question in the field is the investigation of conditions that foster favorable conditions for the formation and growth of new firms (Venkataraman, 1997). In this paper, in the first economy-wide study to examine this question, we examine whether changes in the utilization of technology and complementary assets within industries influence the distribution of new high-growth firms. In regards to technology, this study indicates that changes in the application of technology within industries over time–as measured as the employment of scientists and engineers–are positively associated with counts of new high-growth firms. Further, these findings are robust to the exclusion of the influence of computing, an important source of technological change over the past 20 years. This suggests that a fundamental relationship exists between technological innovation and the prevalence of opportunities to form high-growth firms.

Despite research that appears to indicate that entrepreneurs often form firms based on factors that are not correlated with success (Shane, 2008), we find that industry conditions associated with the prevalence of high-growth start-ups appear to be the same as those associated with firm formation rates. This result suggests that entrepreneurs may form firms with the knowledge of factors that are associated with growth. Further, we failed to find support for a relationship between the industry utilization of complementary assets and industry counts of high-growth firms. It is important to note that our inability to detect a relationship between complementary assets and counts of high-growth new firms may be due to measurement error. However, this study suggests that this issue warrants additional investigation, as our failure to detect a relationship may be an indication that new firms may be less constrained by complementary assets than has been previously understood.

An important feature of this study is the utilization of employment data to track innovation instead of Research and Development (R&D) expenditures or the industry utilization of patents (Merrill and McGeary, 2002). The use of R&D and patent-

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0883-9026/$ – see front matter
doi:10.1016/j.jbusvent.2010.01.003

based measures of innovation in academic research has clearly yielded important insights. However, these measures are not well suited for examining the relationship between innovation and the growth rates of new firms, as reliable data on R&D expenditures are not widely available for small firms and patent-based measures fail to capture innovations that are not patented (Levin et al., 1987; Klevorick et al., 1995). In contrast, employment-based measures track changes in technological innovation throughout the economy by measuring changes in the industry utilization of individuals who are involved in the systematic application of advanced scientific and mathematical knowledge to commercial problems in industry (Merrill and McGeary, 2002). This approach, combined with fixed effects regressions, facilitates the isolation of the relationship between technological innovation and the distribution of new high-growth firms.

This study also has implications for practicing entrepreneurs and policy makers. For entrepreneurs, the findings from this study can facilitate opportunity assessment, by linking performance to specific identifiable attributes of particular contexts. For policy makers interested in encouraging the formation of high-growth firms, this study suggests that a fundamental relationship exists between the technological innovation of industries and growth. In addition, this study supports the notion that new firms play an important role in bringing scientific innovation into the economy.

2. Introduction

Approximately 600,000 new employer firms are formed in the United States each year. Most live a Hobbesian life—nasty, brutish, and short. The majority of new firms are out of business within five years and less than 3% become gazelles, growing at 20% per year for four or more years. A few are very successful, however, and experience dramatic sales growth. Why some new firms grow and most do not is a question of central importance to the field of entrepreneurship (Bhide, 2000; Delmar et al., 2003; Davidsson et al., 2006).

Despite the perceived importance of this question (Fesser and Willard, 1990; Barron et al., 1994; Aldrich, 1999) and the significant personal and financial costs often incurred by those involved in the formation of new businesses, surprisingly little research has examined the contingencies that enhance the success of new commercial organizations (Shane, 2003). We argue that a central contingency that makes some firms more likely to grow rapidly are changes that occur through time within industries in innovation and complementary assets. Since Schumpeter (1934), researchers have argued that identifying new products, new markets, new raw materials, new ways of organizing, and new production processes in response to technological change are key factors that benefit a small number of entrepreneurs who create new high-growth companies (Acs and Audretsch, 1990; Audretsch, 1995). This critical response to technological change is affected by the allocation of talent across different activities. For example, innovation is often believed to foster conditions that facilitate entrepreneurship. Likewise, the development of new knowledge, as well as the transfer of innovative knowledge from academics to industry, is generally conducted by individuals with expertise in specific domains (Rosenberg, 1974; Bercovitz and Feldmann, 2006).

In this study we use a unique economy-wide data set covering 201 three-digit industries across 15 years to examine whether changes in the utilization of human capital are associated with the growth prospects of new firms. Specifically, we examine if increases in technological employment and decreases in sales and production employment are associated with increases in industry counts of the number of fastest growing new firms in the United States. Our examination focuses on these three specific occupation groups, as prior single industry studies suggest that changes in technological intensity, as well as fluctuations in the importance of complementary assets in sales and distribution, may influence the growth rates of new firms (Tushman and Anderson, 1986; Tripsas, 1997, 2000).[1]

Systematically studying the relationship between industry conditions and the existence of new high-growth firms has important implications for scholarly work in entrepreneurship and organization theory. First, scholars have long argued that new firms are an important means of bringing innovation to market (Schumpeter, 1934; Sarasvathy, 1997; Venkataraman, 1997; Fontes, 2005), and that industries differ in their relationship between innovation and commercial outcomes (Bania et al., 1993; Klevorick et al., 1995; Bhide, 2000; Bercovitz and Feldman, 2007). Hence, industry conditions are likely to be a major factor that influences the distribution and characteristics of entrepreneurial opportunities (Eckhardt and Shane, 2003). However, as we outline in more detail below, in contrast to the literature that has examined conditions when established firms succeed or fail (Tripsas, 1997, 2000; King and Tucci, 2002), we know very little about the relationship between technical change and the prospects of new firms outside of single industry or single sector studies. Hence, this research has the potential to advance our understanding of the appropriate mode of organization in specific settings.

Second, scholars who study industry evolution have postulated that industry conditions influence the prospects of new firms (Winter, 1984). However, data constraints have limited researchers to the investigation of the effects of changes in industry attributes on firm entry, rather than on firm performance (Dean et al., 1998). Because entrepreneurs may establish new firms disproportionately in industries that are easy to enter, even if new firms tend to perform rather poorly on average in those industries (Busenitz and Barney, 1997; Caves, 1998; Shane and Venkataraman, 2003), an accurate understanding of the effect of industry context on the growth of new firms is necessary to assess which specific aspects of industries are favorable and unfavorable to new firms.

[1] In this study, we define technology as a specific means that can be used to accomplish a specific end (Simon, 1973). We define technological change or innovation as a new means, a new end, or the application of a means known in one domain to another. This is similar to Rosenberg and Nelson's (1994) conceptualization of the activities undertaken by scientists in industry. We follow Teece (1986) and define complementary assets as the infrastructure or capabilities of firms that are needed to support the successful commercialization and marketing of products and innovations.

Third, our methodology allows us to examine technology in a wide range of industries. Commonly used measures of innovation, such as research and development intensity, typically undercount innovation that occurs in new firms as well as in certain sectors of the economy, resulting in biased estimates of the effects of innovative activity (Merrill and McGeary, 2002). By using employment data drawn from a nationwide household survey to examine our hypotheses, we can measure key constructs over time and across a wide range of industries, and thus more accurately estimate the relationship between technological intensity and the performance of new firms. This is important, as innovation can occur in any sector of the economy, not merely in industries classified in the Standard Industrial Classification (SIC) system as high technology (Mowery, 1999; Rothaermel et al., 2007). In our study we use employment data to track innovation occurring within all sectors of the economy.

Despite the importance of understanding attributes of situations in which new firms grow rapidly (Dean et al., 1998; Katila and Shane, 2005), a significant gap exists between theoretical arguments and rigorous empirical findings (Aldrich, 1999). For example, prior studies that have examined the effect of changes in the deployment of technology on the prospects of new firms have tended to undertake in-depth analyses of one or a few industries, such as automobile manufacturing, computer hardware, or photographic imaging (Utterback and Abernathy, 1975; Anderson and Tushman, 1990; Christensen and Bower, 1996; Tripsas, 1997; Carroll and Hannan, 2000), or to examine a cross-section of manufacturing industries (Acs and Audretsch, 1988). While these are important studies, the prior approaches do not control for unique unobserved characteristics of the industries or sectors that are likely to be correlated with important aspects of industry evolution (Malerba and Orsenigo, 1996), and have overlooked the service sector, a potentially important area of the economy for new high-growth firms. In addition, by studying industry contexts where specific industry characteristics are occurring–such as changes in technology–many of these studies fail to analyze industries or sectors in which technology is *not* changing. By taking that approach, it is impossible to assess whether a general relationship exists between technological change and the growth prospects of new firms.

3. Theory and hypotheses

3.1. Technological intensity

Research indicates that industries differ in the amount and characteristics of their technological opportunity, where technological opportunity is defined as the set of commercially applicable possibilities for technological advance (Klevorick et al., 1995). For example, survey evidence illustrates that biotechnology and semiconductor industries directly benefit from advances in basic scientific understanding, while in the case of other industries, such as restaurants, the relationship is much weaker (Klevorick et al., 1995). Using different approaches, both Dosi (1984) and Schmookler (1966) also report that differences exist between industries in innovative activity. Importantly, Narin et al. (1997) provide evidence that the relationship between scientific advance and technological opportunities changes over time. Hence, technological opportunities are driven by the production and stock of knowledge relevant to commercial enterprise in given industries (Malerba and Orsenigo, 1997) and opportunities for firms and entrepreneurs to build businesses around novel technologies is likely to differ across industries and time.

Advances in scientific understanding and technological innovation are crafted into commercial outputs through the direct actions of individuals with the specific knowledge that enables them to understand the innovation, as well as knowledge of the industry context (Rosenberg and Nelson, 1994). As Klevorick et al. (1995, 189) and colleagues explain, “scientists and engineers engaged in industrial R&D employ science as a set of tools and stock of knowledge to be tapped in problem-solving.” As a result, fluctuations in the industry employment of research scientists are a good indication of changes in the technological opportunity of industries through time.

Scientists and engineers may work for established organizations or for nascent organizations, and they may use their skills to create or improve existing processes, or create new products. However, prior research provides several explanations for why industries that are undergoing technological change foster conditions that benefits new firms (Pennings, 1980; Tripsas, 1997; Nerkar and Shane, 2003). First, technological innovation may undermine the existing advantages of incumbent firms, thereby fostering opportunities for new firms. Hence, industries that are undergoing technological change place several unique stresses on incumbent organizations. Incumbent organizations make decisions and control their organization routinely, even subconsciously, thereby freeing up managerial resources (Nelson and Winter, 1982). While routines can increase efficiency when an alignment exists between the routine and a specific technological environment, changes in technology can undermine the usefulness of specific routines, thereby decreasing their value. In addition, the subconscious nature of routines renders them difficult for managers to explicitly identify and modify (Nelson and Winter, 1982; Henderson and Clark, 1990).

Second, technological change can alter the market segments, a situation that advantages new firms, which do not yet have a customer base, at the expense of existing firms who have customers that they need to satisfy (Christensen and Bower, 1996). While a stable customer base can enhance performance by providing a reliable source of revenue, this stability decreases the pressures on established organizations to adapt to changing conditions. Existing customers reward established firms that can reliably provide specific products and services with known attributes (Hannan and Freeman, 1984). Reliability reduces adaptability, however, because it is achieved by reducing variation in the organization's activities that otherwise would have provided opportunities to innovate (Miner, 1994). Further, while existing customers can provide important information regarding ways to improve specific technologies (von Hippel, 1986), this emphasis on meeting the needs of existing customers biases the direction of the innovative efforts of established firms towards fulfilling the technological needs that existing customers can anticipate (Christensen and Bower, 1996). Research indicates that this bias can lead established firms to fail to capitalize on potentially profitable technologies, even in cases where the established firm pioneered the technology (Christensen, 1997).

In contrast, new firms generally lack a portfolio of established routines, as well as a large established customer base. Hence, they can consciously design routines to more fully utilize novel technologies, as well as avoid the biases that arise out of serving an existing customer base. Further, new firms lack formal, functional information-processing structures (Blau and Scott, 1962; Thompson, 1967; Arrow, 1974; Cardinal et al., 2004). The absence of such structures facilitates their ability to apply new technologies to drive firm growth. The open and informal decision-making structure in new firms, combined with fewer decision makers and employees, enables these firms to process decisions quickly (Teece, 1996). The lack of an existing structure enables managers to tailor information-processing activities to a given application of a technology and its related products (Hannan and Freeman, 1984; Carroll and Hannan, 2000; Sine et al., 2006). In contrast, large established organizations rely on formal hierarchies, functional specialization, and established information-processing systems. This can leave them large firms poorly suited to the management of technology, and hinder their ability to apply new technology to drive firm growth.

Lastly, technological changes, such as shifts in product architecture, can demand changes in the structure of organizations serving an industry, benefiting new firms with new structures at the expense of existing firms whose structures are difficult to change (Henderson and Clark, 1990). Established firms often have monitoring mechanisms that are designed to harvest profits from routine activities based on existing technologies but they can detract from technological innovation that may enhance growth. For example, to manage employees, large established organizations create monitoring systems that compare employee performance to specific goals (Holmstrom, 1989). While well suited to encourage routine activity in stable environments, such monitoring systems discourage the creative activity necessary to exploit new technologies, because the application of technical knowledge to commercial applications is fraught with errors, blind alleys, failed experimentation, and surprise successes (Simon, 1955; Teece, 1996; Zenger, 1994). In contrast, new firms tend to use high-powered incentives, such as stock ownership, that directly tie the compensation of employees to their performance and encourage the creative activity necessary to apply technology to drive firm growth (Holmstrom, 1989; Zenger, 1994; Audretsch, 1997; Elfenbein et al., 2008). Hence, industries that are undergoing technological change are likely to foster challenges for incumbents, as well as encourage opportunities for new high-growth firms.

Innovation in industry is necessarily directed, modified, and carried out by individuals whose specialized skills will result in the application of novel technologies to commercial contexts. To create and integrate existing technological innovations into products and processes, incumbent firms and start-ups utilize scientists and engineers who have the requisite skills to apply novel technologies to the commercial context (Rosenberg and Nelson, 1994). These individuals may either be used to create new products, or improve existing products. Therefore, the rate of technological innovation in an industry is influenced by the number of scientists and engineers working in that industry.

Hypothesis 1. Increases in the proportion of industry employment in science and engineering occupations will be positively associated with the number of high-growth new firms in the industry.

3.2. Production, sales, and distribution intensity

We expect the number of rapidly growing new firms to decrease as employment in production, sales, and distribution increases within the industry. Although sales, distribution, and production assets are generally necessary for most firms to sell products and services to customers (Mitchell, 1989; Teece, 1992; Tripsas, 1997), scholars have argued that, for several reasons, large established firms are relatively better suited than new firms to succeed in industries where these assets are becoming relatively more important. First, industries that have a large proportion of their employment in sales and production shield established firms from competition from new entrants because production facilities, sales networks, and distribution systems increase the minimum efficient scale and required capital investment for new entrants (Audretsch, 1991; Siegfried and Evans, 1994). Further, these activities become a resource of established firms that newer firms find difficult to duplicate since they often develop through interaction with interrelated business functions as firms grow over time (Teece, 1986, 1992; Teece, 1998). As a result, their use is most effective in established firms where experienced-based learning has co-evolved with the development of integrated business units.

Second, the prevalence of sales and production activities often shifts the focus of competition away from technological superiority to other factors, such as production and distribution, at which large established firms tend to be more efficient (Teece, 1986; Holmstrom, 1989). In an extensive study of the competitive effects of complementary assets in the typesetter industry, Tripsas (1997) found evidence indicating that these activities buffered incumbents from competition by new entrants—even in cases when the technological performance of the incumbents was inferior to that of the new entrants. Thus, in industries where employment in production, distribution, and sales occupations is more prevalent, the basis of competition shifts toward large established firms, facilitating their growth.

Third, even in industries in which patents are effective at deterring imitation, scholars have argued that patents often do not necessarily enable small firms to profit from their intellectual property (Teece, 1986). In particular, contracting for production, distribution, and sales activities can be difficult (Arrow, 1971; Teece, 1980, 1998), hindering the ability for new firms to access needed production, sales, and distribution activities to profit from innovation. Even when these activities can successfully be obtained through contracting, the arms–length relationship between contracted activities and activities conducted directly by the firm impairs the transfer of crucial tacit knowledge that is important for serving customers. Thus, the performance of firms that must rely on arms–length relationships for their production, distribution, and sales activities suffers (Chandler, 1977; Mitchell, 1989). As a result, the proportion of employment in production, sales, and distribution occupations within an industry increases, and new firms become less likely to grow rapidly. These arguments lead to the following hypotheses.

Hypothesis 2. Increases in the proportion of industry employment devoted to production will be negatively associated with the number of new high-growth firms in the industry.

Hypothesis 3. Increases in the proportion of industry employment devoted to sales and distribution will be negatively associated with the number of new high-growth firms in the industry.

4. Research design

To examine the relationship between changes in industry characteristics and changes in the number of new high-growth firms, data must (1) be available for a wide range of industries and industry sectors; (2) be measured the same way across all industries; (3) be comparable across years; and (4) be available at a level of industry detail adequate to measure the variables accurately. These data requirements are stringent. For example, most detailed federal data is collected by programs that target specific sectors of the economy–such as the census of manufacturers–which makes this data not comparable across industry sectors. Hence, to meet these stringent data requirements we collected data from a variety of federal and private sources including *Inc Magazine*, the Current Population Survey, the National Bureau of Economic Research's (NBER) patent file, County Business Patterns from the U. S. Department of the Census, and SDC Platinum's VentureXpert database. As we describe in more detail below, these databases were combined into a multi-year panel based on a single industry classification system. To our knowledge, this is the first study that has conducted this cross-economy analysis.

The period of time covered in our analysis, 1983–1997, was determined by data availability. The Inc. 500 list was first published in 1982. We start our analysis in 1983, and end in 1997, due to major changes in the industry classification systems that occurred outside this window. The CPS industry system used in the CPS underwent a major revision in 1983, and the North American Industrial Classification System replaced the Standard Industrial Classification system in several of our databases following the end of our panel. Applying a concordance across the entire period that would incorporate these different classification systems would result in a loss of precision in the early period of our analysis where important trends occurred.

4.1. Industries

We define industries using the three-digit industry classification (SIC) scheme produced by the U.S. government. As our study spans several SIC systems, we developed a consistent panel of data comparable across all years in this study by following the classification procedure developed by Autor et al. (1998). Data pertaining to industries that are consistent across all years in the study were left unchanged. Data for distinct 1977 industries that were combined with other industries in the 1977 or 1987 revisions were aggregated in the 1977 SIC system to match the later revisions. Similarly, industry data that were disaggregated in later years were aggregated to match the 1977 SIC classification system.

The official 1977 and 1987 three-digit SIC systems contained, respectively, 423 and 416 distinct three-digit industries. Recombination reduced the number of industries to 353. With this procedure, the smaller number of industries does not represent dropped industries or firms, as industries are combined through aggregation. Because we focused on commercial firms, we dropped the 22 public sector industries, leaving 331 distinct industries available for analysis. Missing data reduced to 283 the number of industries available for analysis. Of the 283 industries, 201 hosted at least one high-growth start-up in our panel.

4.2. Dependent variable

Inc. 500 Counts: We measure the number of new high-growth firms in each industry year, by summing the total number of *Inc. 500* firms located in each industry for each year. The *Inc. 500* is a list of the 500 fastest growing firms in the United States, as published annually since 1982 by *Inc. Magazine* (Boston, MA). To be listed, firms must have been in business for five years–which is consistent with age cutoffs typically used in the literature to identify new firms (Zahra, 1996; Bantel, 1998)–and have achieved at least $100,000 but no more than $25 million in sales in the first year. Firms are ranked in the *Inc. 500* list according to their five-year growth rates.

Our choice of using industry counts of *Inc. 500* firms to measure the distribution of high-growth start-ups across industries in the U. S. economy is due to the limitations of other measures. For example, financial data is not widely available on private companies, and hence we are unable to directly compute the growth rates of small businesses (Kirchhoff, 1994; Aldrich, 1999). Similarly, existing government and commercial databases–including Dunn and Bradstreet data (Kalleberg et al., 1990)–are inaccurate at measuring the growth rate of new firms across a wide range of industries, because of an emphasis on collecting information on establishments, rather than firms (Aldrich, 1999).

Each firm in the *Inc. 500* list was assigned a primary SIC code, using the following procedure. First, published three-digit SIC codes were located for most of the firms through a search of several databases using Lexis Nexus. For the 3500 firm-years that could not be assigned to an industry using these databases, three-digit SIC codes were assigned by selecting the code assigned to another *Inc.* firm with the most similar business description. Lastly, if a code could not be assigned using the methods above, a three-digit SIC code was assigned by matching the business description provided by *Inc. Magazine* to descriptions of industry sectors as listed in the 1987 SIC Manual (OMB, 1987). We did not find any *Inc. 500* firms in our sample whose activities spanned more than a single three digit industry.

4.3. Hypothesized covariates

We use employment-based measures to assess the influence of technological intensity, sales intensity, and production intensity on the industry distribution of high-growth start-ups. We chose employment-based measures for three reasons. First, this approach permits us to develop consistent measures spanning multiple years and a wide range of industries. In addition, by using employment-based measures, we are able to disentangle R&D activities from marketing and materials expenses across all industries in our study—a problem that, as scholars have noted, has limited the ability to examine technological intensity outside of certain industry sectors (Mowery, 1999).

Second, these employment-based measures compare favorably to other approaches used to measure these constructs. For example, in the case of technological intensity, R&D expenditures are not widely available for small firms, National Science Foundation (NSF) data on research expenditures does not span the entire economy and under-samples small firms,[2] and patent-based measures of innovation fail to capture innovations that are not patented (Levin et al., 1987; Klevorick et al., 1995). In contrast, employment-based measures track changes in technological innovation throughout the economy by measuring changes in the industry utilization of individuals who are involved in the systematic application of advanced scientific and mathematical knowledge to commercial problems in industry (OMB, 1987; Merrill and McGeary, 2002). While use of this measure as an indicator of technological intensity is relatively rare in the empirical literature, some studies have validated its use. Allen (1996) reports that the correlation for 1989 between the Current Population Survey (CPS) ratio of scientific and engineering employment share and the NSF employment share data for manufacturing industries is 0.96, while the correlation between the same statistic and a company's own R&D funds as a percentage of sales reported by NSF for selected manufacturing industries is 0.86. Similarly, by using employment-based measures of the use of complementary assets, we are able to construct a measure that spans all industries in the economy.

Third, as the CPS is a household survey, it does not suffer from the systematic under-sampling of small firms, which is common with other employee and establishment based surveys conducted by the government (BLS, 1997; Stephan, 2002). Hence, the CPS is well suited to measuring the actual utilization of employment across all firms in the industries in our sample.

To compute the employment-based measures, counts of the industry employment for each variable were drawn from the NBER extracts of the merged outgoing rotation groups (MORG) of the CPS administrated by the Bureau of Labor Statistics (BLS).[3] The NBER extracts contain employment and occupation information on approximately 360,000 individuals each year (Feenberg and Roth, 2001). For each month, each record in the file contains detailed labor market information on a single individual, including occupation, employment classification, and industry of employment.

The procedure used to extract occupation data from the annual CPS files is as follows. First, individual employment records were extracted and weighted annually for the month of March for each year from 1983 through 1997 for individuals in occupation codes that were representative of four broad occupations of technological employment.[4] Employment across all technological occupation categories, including self-employment, was summed to create a single measure of technological occupation employment.

Second, two adjustments were necessary to generate industry occupation employment counts from the annual Current Population Surveys. Autor et al.'s (1998) CPS industry classification system was used to correct changes made to the CPS industry coding system that rendered the data incomparable across years (Autor et al., 1998).[5] Similar to the procedure utilized to combine the 1972, 1977, and 1987 OMB SIC systems, Autor's procedure aggregates industries that were disaggregated in later years, and aggregated industries in earlier years that were aggregated by the BLS in later years. For a more detailed description of this procedure, see Autor et al. (1998).

Once the data were transformed into a consistent panel across the 1983 through 1997 period, an additional step was necessary before the data could be utilized. The BLS uses the Census Industry Classification (CIC) system in the current population survey, instead of the OMB SIC systems on which this study is based. We developed a concordance between the CIC industry system and the OMB SIC system, based on the concordance included in the documentation provided by BLS between the CIC system and the 1987 OMB SIC system. In cases when more than one CIC industry corresponded to more than one panel industry in the BLS concordance, counts of technology employees were allocated to industries using weights based on relative total industry employment for each industry across each category (Autor et al., 1998).

[2] The National Science Foundation publishes detailed statistics on the research and development activities of industries as well as the employment shares of research scientists. However, several limitations preclude the use of the NSF data in this study. First, the NSF data are available for only 25 2-to-3 digit SIC codes (Klenow, 1996). Second, the data are biased towards industries known for having high R&D outlays, thereby limiting the ability of the data to capture fundamental changes in R&D activities.

[3] Information on the NBER MORG CDs can be found at the NBER's Internet web site (www.nber.org). Information on the history and current implementation of the survey can be found at the BLS Internet web site (www.bls.gov).

[4] The weights used in this study to compute our measures of industry employment are the same weights used to compute the official U. S. Government labor force statistics released each month (Feenberg and Roth, 2001). The weights are used to yield annual employment counts from the March MORG.

[5] The authors thank David Autor for providing assistance in utilizing the CPS for this research.

Like the SIC system, the occupation classification system utilized in the Current Population Survey are divided up into broad categories, such as Sales Occupations and Precision Production Occupations, with more fine-grained classifications with broad categories. We utilized the broad categories that are part of the CPS to identify occupations that fit our constructs. For example, the CPS identifies all occupation codes between 243 and 283 as Sales Occupations. This range includes occupations such as sales representatives, sales workers, and individuals involved in the supervision of sales activities. Our measures are based on broad categories within the survey that matched our constructs. We also compared occupation descriptions as published in the *Standard Occupational Classification Manual* (OMB, 1980) to confirm consistency with our constructs. We describe each conceptual grouping below, and the specific occupations that comprise each grouping are identified in Table A1.

4.3.1. Technology intensity

We measure technological intensity as the annual percentage of total employment in the industry (including self-employment) of scientists, engineers, mathematicians, and natural scientists as reported in the NBER MORG extracts of the BLS Current Population Survey.

4.3.2. Sales and distribution intensity

We measure sales and distribution intensity as the annual percentage of total employment in the industry that occurs in sales and sales management occupations as reported in the NBER MORG extracts of the BLS Current Population Survey.

4.3.3. Production intensity

We measure production intensity as the annual percentage of total employment in the industry that occurs in production and related occupations, as reported in the NBER MORG extracts of the BLS Current Population Survey.

4.4. Control variables

4.4.1. Percentage of large establishments

Because we examine the relationship between specific hypotheses and the prevalence of small new *high-growth* firms and large established firms, we control for the percentage of establishments with more than 500 employees to capture changes over time in the size of the typical establishment in the industry. This variable is calculated from data provided by County Business Patterns.

4.4.2. Applied Tech Intensity

Life-cycle theorists argue that once the commercial application of a technology solidifies, that established organizations can be quite effective and utilizing and profiting from the technology (Utterback and Abernathy, 1975; Utterback and Suarez, 1993; Klepper, 1997). For example, before computers were created, the occupations “computer operator” and “computer programmer” didn't exist in any industry. By 1983, the use of computers was widespread across most industries in the economy, and employees were found working in the previously mentioned computing occupations. This line of argumentation suggests that an increasing emphasis on the value of those who apply existing technologies in standard ways, as opposed to scientists and engineers, may influence the performance of new firms in an industry. Hence, we include as a covariate in our analysis the measure of applied technology intensity, to capture changes in the type of technology utilized in industries. The specific occupations that comprise this measure are shown in Table A4.

4.4.3. Patent counts

Research indicates that patents provide holders with protections that enable them to obtain complementary assets through contracting (Levin et al., 1987; Klevorick et al., 1995), and one source of patented technologies for start-ups are patents held by non-commercial entities such as universities. Hence, we include as a covariate the total number of patents awarded to government and non-profit institutions by industry by year. We assign patents to industries using Silverman's (1996) two-step concordance between the international patent classification system and the Canadian Standard Industrial Classification system (CSIC), and between the CSIC and the U.S. SIC system. See Silverman (1996, 1999) and McGahan and Silverman (2001) for more information on the industry-patent classification system used in this study.

4.4.4. Total establishments

Because the likelihood that an industry will foster high-growth firms may be correlated with the number of firms in an industry, we control for the total number of establishments by industry, by year. We draw the counts of total establishments from the County Business Patterns database produced by the U.S. Department of the Census.

4.4.5. Industry IPOs

To control for changes in investment patterns across industries and time which might stimulate the growth of new firms, we include as a covariate the count of the number of Initial Public Offerings per industry year, as reported in SDC Platinum's VentureXpert database.

4.4.6. Industry sales growth

As industry counts of *Inc. 500* firms may be influenced by the overall growth in sales of the industry, in selected models we include as a covariate, *Industry Sales Growth*, which is calculated as the one year percentage change in industry sales as provided by COMPUSTAT.

4.4.7. Time period effects

To control for changes in industry counts of high-growth new firms that may be driven by temporal factors, we include annual dummy variables in our analysis, with 1997 as the omitted case (Certo and Semadeni, 2006). Table 1 summarizes the variables used in the analysis.

4.5. Statistical analysis

We analyze our hypotheses with fixed effects regressions, in which the unit of analysis is the industry year, and all independent variables are lagged three years, which seems reasonable given prior research. For example, Schoonhoven et al. (1990) report that the mean time from firm formation to product launch is 21.07 months in the semiconductor industry. The use of fixed effects regression on our panel data allows us to control for unobservable characteristics of industries that may confound our results, such as differences in the utilization of skilled labor in innovation between the software and automotive manufacturing industries (NSF, 2002), while permitting us to examine how industry changes in technology intensity, production intensity, and sales and distribution intensity, are associated with industry changes in the count of high-growth firms.

Because our dependent variables measure industry counts of high-growth firms by year, a Poisson distribution is generally appropriate. However, the variance of the dependent variable is not equal to the mean of the dependent variable–a characteristic of the data known as overdispersion–making the Poisson model inappropriate and leading us to use a negative-binomial fixed effects model (Haveman, 1995; Greene, 2000). We use a conditional rather than the more commonly used unconditional fixed effects model to avoid the incidental parameters problem as described by Cameron and Trivedi (1998). Further, because a requirement of the negative-binomial fixed effects model is that each industry experience an event–in our case, host at least one high-growth *Inc. 500* firm–our analysis is based on those 201 industries that hosted at least one *Inc. 500* firm over the length of the study (Hausman et al., 1984; Greene, 2000; Sorenson and Stuart, 2001).

As the number of high-growth firms published by *Inc. Magazine* is limited to 500 firms each year, a potential concern is whether this procedure will result in a lack of independence between observations. We address this concern by selecting a growth rate of 1000% over a five-year period for a firm to be classified as high growth, instead of using a cap of 500 firms per year established by *Inc. Magazine* (Frees, 2004). This growth rate is close to the lowest growth rate required to be included in the *Inc. 500* list for most years. The use of this growth cap limits the number of observations in the data to fewer than the 500 firms per year on the *Inc. 500* list.

5. Results

Table 2 reports the number of new high-growth firms by industry for the ten industries that contained the greatest number of high-growth firms (by category) across the entire panel. Table 2 indicates that new high-growth firms do not appear to be

Table 1
Description of variables.

Variable	Description
Inc. 500	Industry counts of Inc. 500 firms as provided by Inc. Magazine.
Firm births	Industry counts of new firms with one or more employees where a firm is defined as the aggregation of all establishments owned by a parent company. This data is available for only 9 years. (Source: Small Business Administration under contract from the U. S. Census Bureau).
Tech. Intensity	Industry employment of individuals employed or self employed in occupations concerned with the application of scientific and mathematical knowledge to the conduct of research and development and related activities in industry divided by total industry employment (Source: Current Population Survey).
Sales and rel. intensity	Sales employment. Industry employment of individuals employed or self employed in occupations concerned with selling goods and services, divided by total industry employment (Source: Current Population Survey).
Production and operators intensity	Individuals working in production occupations (employed and self employed) divided by total industry employment (Source: Current Population Survey).
Applied Tech. Intensity	Applied technological employment. Industry employment (self and employed) of individuals operating and programming technical equipment, testing, and related activities, including technical assistance in provision of health care, divided by total industry employment (Source: Current Population Survey).
Total establishments	Total establishments by industry year (Source: County Business Patterns).
Patent counts (public)	Patents granted to government and public entities (Source: NBER).
Percent large establishments	Count of establishments by industry year employing greater than 500 employees divided by total industry establishments. Measure of tendency of typical production function in industry to favor large establishments (Source: County Business Patterns).
Industry IPOs	Count of Initial Public Offerings by Industry, as compiled from SDC Platinum's VentureXpert database.
Year: 19XX	Year dummy variables, set to 1 for the corresponding year, and 0 otherwise
Industry sales growth	One year percentage change in industry sales. (Source: Compustat)

Table 2
Industry rankings (1983–1997).

Top 10 industries in terms of number of fast-growing new private firms with sales less than or equal to $25 million dollars a year in base year		
N	SIC	Label
1159	737	Computer programming, data processing, and computer services (Computer services)
525	873	Research, development, and testing services (R&D and testing)
482	573	Radio, television, consumer electronics, and music stores
350	357	Computer and office equipment
295	506	Electrical goods
269	871	Engineering, architectural and surveying
222	736	Personnel supply
215	152	General contractors—residential buildings
186	738	Miscellaneous business services
163	356	General industrial machinery

Note: Abbreviated industry labels used in Fig. 2 due to space constraints are shown in parentheses.

distributed uniformly across all industries in the economy. Over half (52%) of the new high-growth firms are located in just ten industries. Hence, it appears that industry-specific conditions are likely to be important in understanding the counts of high-growth start-ups. This observation reinforces the value in conducting fixed effects regression to control for unobserved characteristics of industries to examine our hypotheses.

Fig. 1 indicates the importance of examining multiple industry sectors over an extended period to test our hypotheses. Fig. 1 indicates that, over the 1983–1997 period, there was a notable increase in services as compared to manufacturing in counts of high-growth new firms. Hence, a study that examined only the manufacturing sector would likely overlook important causal determinants of the industry distribution of new high-growth firms. Fig. 2 provides additional detail for the service sector for those industries that hosted at least one *Inc. 500* firm in 1983 or 1997. Fig. 2 shows a dramatic increase in the number of *Inc. 500* firms in the computer services SIC code from 1983 to 1997, as well as an increase in the number of employment agencies (personnel supply) over the same period.

Table 3 shows descriptive statistics and the pooled correlation matrix. The highest correlation among independent variables is 0.56. The Technology Intensity covariate (Tech Int.) is positively correlated with the dependent variable, while the correlation between the other two hypothesized covariates and the dependent variable is low. Table 4 reports the results for the negative-binomial fixed effects regressions to predict the variation in the rates of creation of new high-growth firms. Overall, all models are significant (Chi-square of 59.57 for model 1, 60.60 for model 2, 34.44 for model 3, 31.78 for model 4, 27.28 for model 5 and 26.34

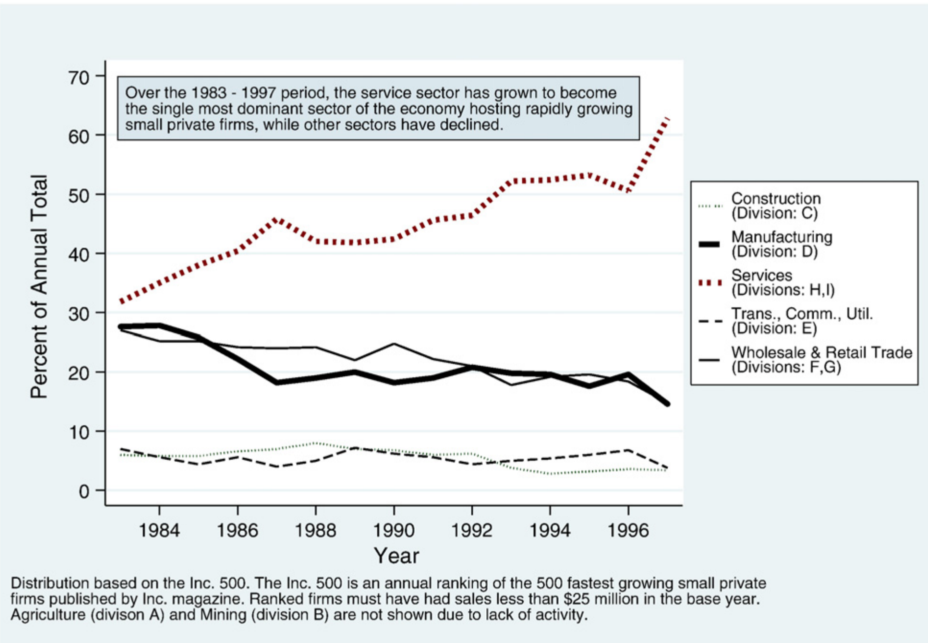

Fig. 1. Distribution of the 500 fastest growing small private firms by industry.

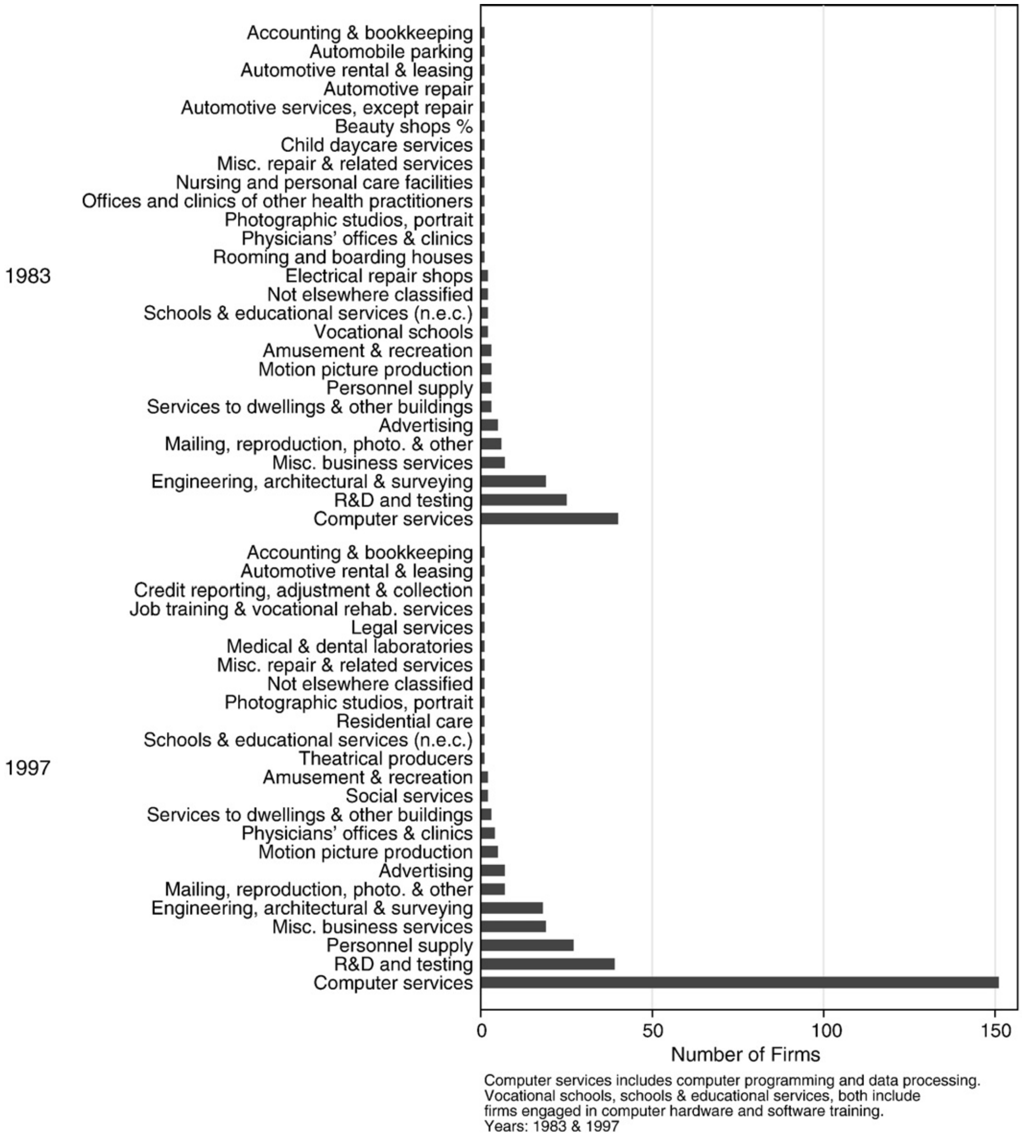

Fig. 2. Inc. 500 firms in the service industries.

for model 6, where $p<0.01$ for all models). Column 1 includes all industries in the analysis, and Column 2 includes controls for industry sales and advertising intensity, for those industries for which these data were available. We use columns 1 and 2 of Table 4 to examine the primary hypotheses. As the data includes lagged covariates, the analysis in Table 4 is based on twelve years of data and eleven year dummies are reported in the table.

Overall, in our analysis we find strong support for Hypothesis 1, and we fail to find support for Hypotheses 2 and 3. For Hypothesis 1, we find that changes in the technical intensity of an industry are positively associated ($\beta=3.81$, $p<0.01$) with changes in the number of new high-growth firms. Specifically, the estimates in column 1 of Table 4 indicate that a 1% increase in the employment of scientists and engineers of an industry is associated with an increase of over 3.80, or more than twice the mean of the dependent variable of new high-growth firms. For Hypotheses 2 and 3, we fail to find a statistically significant relationship between changes in the level of production and sales employment and the count of new firms in the industry. Therefore, after including a wide range of industries in our sample and using this information to control for static differences across all industries, we fail to find support for a general relationship between the importance of complementary assets of an industry and the success of new firms.

In column 2 of Table 4, we add the log of industry sales as an additional covariate to test the alternative explanation that changes in the distribution of high-growth firms are driven by changes in the level of sales in the industry (McDougall et al., 1994).

Table 3
Summary statistics and correlation matrix.

	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Inc. 500	2.31	7.22	1.00										
(2) Tech Int.	0.00	0.03	0.63	1.00									
(3) Sales and Rel Int.	0.14	0.19	0.00	−0.08	1.00								
(4) Production and Oprs. Int.	0.19	0.19	−0.13	−0.07	−0.31	1.00							
(5) Applied Tech Intensity	0.00	0.02	0.52	0.48	−0.10	−0.13	1.00						
(6) Industry Patents	9.33	43.8	0.21	0.29	−0.12	0.09	0.19	1.00					
(7) Total establishments	3.35	6.47	0.27	0.08	0.08	−0.23	0.10	0.01	1.00				
(8) % Large establishments	0.03	0.06	−0.05	0.00	−0.26	0.29	0.23	0.19	−0.19	1.00			
(9) Industry IPOs	1.68	5.11	0.54	0.43	−0.03	−0.06	0.43	0.56	0.23	0.07	1.00		
(10) Industry sales growth	0.08	0.17	0.14	0.05	0.03	−0.05	0.06	0.04	0.09	−0.04	0.11	1.00	
(11) Adv. Intensity (L3)	0.03	0.07	0.00	−0.03	0.11	−0.12	0.01	−0.01	0.02	−0.05	0.04	0.04	1.00
(12) Firm births [a]	2843	5578	0.32	0.12	0.02	−0.27	0.15	−0.04	0.90	−0.20	0.24	0.14	0.04

[a] Firm births correlations shown are the dependent variables for Table 5, and is calculated for 1989–1997 only due to data availability.

The results are robust to the inclusion of this additional covariate. In addition, in unreported regressions we find that our core results are robust with respect to variation in the lag period of the independent variables, ranging from 1 through 5 years. It is important to recognize that increasing the lag period decreases the number of years in the analysis.

Computing is a significant technological innovation that was being integrated into commercial activities during our period of study (Autor et al., 1998; Fairlie, 2006). To examine whether our results are being driven specifically by computing instead of by innovation in general, in columns 3 and 4 of Table 4 we repeat our analysis, where employment in computing occupations (computer systems analysts and scientists) is dropped from our analysis. Although the magnitude of the coefficient declines to 3.007 from 3.81, we still find support for Hypothesis 1 after dropping computing occupations. Hence, our findings suggest that industry changes in technological innovation in general, and not computing per se, are associated with the prevalence of high-growth firms. To further examine the effect of computing, in columns 5 and 6 of Table 4 we repeat our analysis where we omit SIC 737 (Computer Services). This exercise indicates that our support for Hypothesis 1 remains, while we continue to fail to find support for Hypotheses 2 and 3. In addition, the applied technology intensity covariate is no longer significant, which may be driven in part by the inclusion of computer operators and programmers in the applied technology occupation measure.

The analysis reported in Table 4 also indicates that the relationship between technology and the prevalence of new high-growth firms is not universal. Specifically, we find that while the employment of scientists and engineers is positively associated with counts of new high-growth firms, nevertheless, growing employment in applied technology occupations is negatively associated with counts of new high-growth firms. This finding is consistent with the industry life-cycle literature that argues that the regimes that favor new firms are more likely to be driven by the application of new knowledge than the application of known knowledge and technologies (Utterback and Abernathy, 1975; Winter, 1984).

In unreported regressions we also examined several interactions to explore if technology intensity, applied technology intensity, and industry patents may work in concert with other key covariates in our analysis. For example, a negative sign on the interaction between technical intensity and sales employment may indicate that the formation of high-growth new firms is less likely to occur in industries that are experiencing increases in technology intensity and increases in sales employment.[6] This might suggest that complementary assets in sales employment may hinder the ability for new start-ups to capitalize on changes in the application of technology in industries. Specifically, we interacted our measures of Tech Int., Applied Tech. Intensity, and Industry Patents with the first 5 variables listed in Table 4. In all but one case, we failed to reject the null hypothesis of no relationship between the interaction term, and industry counts of high-growth start-ups. We did find a marginally significant negative relationship between the interaction of Applied Tech Intensity and Sales Employment in one model, but further analysis indicated that this relationship was not robust.

Scholars have noted that entrepreneurs often are observed forming companies at odds with factors that predict success. For example, the correlation between the industry failure rate and the rate at which new businesses are founded in an industry is 0.77 (Shane, 2008). In Table 5, we use data on firm births provided by the Small Business Administration to examine whether industry conditions associated with the prevalence of high-growth start-ups are associated with the formation rates of new firms. This variable is described in Table 1, and is available for only 12 of the 15 years in our study. Due to the three-year lag, only 9 years are included in our analysis. The results shown in Table 4 indicate that the industry conditions associated with a prevalence of high-growth start-ups are the same as those associated with firm formation rates.

[6] We thank an anonymous referee and the associate editor for encouraging us to conduct this analysis.

Table 4
Negative-binomial fixed effects regressions of industry counts of high-growth start-ups.

Variables	Base		No computing occupations		Drop SIC 737	
	Primary	Sales	Primary	Sales	Primary	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Tech Int.	3.811***	3.772***	3.007*	2.929*	3.195*	3.303*
	(0.770)	(0.754)	(1.755)	(1.760)	(1.748)	(1.739)
Sales and Rel Int.	0.192	−0.199	0.277	−0.079	0.341	−0.02
	(0.368)	(0.409)	(0.364)	(0.402)	(0.367)	(0.407)
Production and Oprs. Int.	0.415	0.311	0.413	0.312	0.472	0.374
	(0.359)	(0.366)	(0.360)	(0.368)	(0.359)	(0.365)
Applied Tech Intensity	−2.100**	−2.039**	−3.610***	−3.521***	1.952	4.195
	(0.902)	(0.872)	(1.185)	(1.158)	(3.506)	(3.762)
Industry Patents	0.001*	0.001*	0.001**	0.001**	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total establishments	0.013**	0.010*	0.013**	0.011*	0.009	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
% Large establishments	−0.363	−0.509	−0.677	−0.78	−0.975	−1.293
	(2.739)	(2.773)	(2.657)	(2.690)	(2.766)	(2.816)
Industry IPOs	0.001	0.002	0.001	0.001	0	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
1986	0.178**	0.164*	0.190**	0.181*	0.217**	0.218**
	(0.084)	(0.089)	(0.087)	(0.093)	(0.086)	(0.091)
1987	0.252***	0.240***	0.254***	0.240***	0.292***	0.285***
	(0.081)	(0.084)	(0.085)	(0.089)	(0.084)	(0.087)
1988	0.299***	0.285***	0.279***	0.264***	0.304***	0.289***
	(0.082)	(0.084)	(0.085)	(0.087)	(0.084)	(0.086)
1989	0.225***	0.206**	0.231***	0.216**	0.264***	0.244***
	(0.082)	(0.084)	(0.086)	(0.088)	(0.085)	(0.087)
1990	0.231***	0.213**	0.246***	0.235***	0.269***	0.255***
	(0.081)	(0.083)	(0.084)	(0.086)	(0.084)	(0.086)
1991	0.208***	0.206**	0.198**	0.199**	0.219***	0.221***
	(0.079)	(0.081)	(0.083)	(0.085)	(0.083)	(0.084)
1992	0.187**	0.182**	0.202**	0.201**	0.237***	0.239***
	(0.080)	(0.081)	(0.083)	(0.085)	(0.083)	(0.084)
1993	0.169**	0.169**	0.180**	0.182**	0.190**	0.192**
	(0.079)	(0.081)	(0.083)	(0.086)	(0.083)	(0.086)
1994	0.174**	0.162**	0.156*	0.142*	0.185**	0.175**
	(0.078)	(0.080)	(0.082)	(0.085)	(0.082)	(0.085)
1995	0.09	0.091	0.103	0.104	0.122	0.125
	(0.076)	(0.077)	(0.082)	(0.084)	(0.082)	(0.083)
1996	0.136*	0.128*	0.112	0.101	0.128	0.121
	(0.077)	(0.077)	(0.082)	(0.083)	(0.082)	(0.083)
Industry sales growth		−0.039		−0.023		−0.057
		(0.105)		(0.109)		(0.109)
Adv. Intensity		−0.501		−0.52		−0.443
		(0.374)		(0.381)		(0.374)
Constant	3.628***	3.895***	3.402***	3.551***	3.822***	4.171***
	(0.485)	(0.559)	(0.362)	(0.378)	(0.640)	(0.797)
Observations	2364	2025	2364	2025	2352	2013
Number of industries	201	184	201	184	200	183
Years	12	12	12	12	12	12
Industries	201	184	201	184	200	183
Chi-square	59.566	60.602	34.436	31.78	27.278	26.339

Standard errors in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

6. Discussion and conclusions

Using a unique data set comprised of 201 industries over 15 years, we examined whether changes in technology, as well as complementary assets, influence the distribution of new high-growth firms. We find that growth in the employment of scientists and engineers is positively associated with counts of new high-growth firms. Further, these findings are robust to the exclusion of the influence of computing, an important source of technological change over the past 20 years. We fail to find support, however, for a relationship between growth in complementary assets and industry counts of high-growth firms.

Table 5
Fixed effects regressions of industry counts of new firms.

Variables	Primary	Sales
	(1)	(2)
Tech Int.	3.026 [a]	3.009 [a]
	(0.469)	(0.493)
Sales & Rel Int.	−0.041	−0.06
	(0.036)	(0.045)
Production & Oprs. Int.	−0.004	−0.007
	(0.030)	(0.033)
Applied Tech Intensity	−2.625 [a]	−2.638 [a]
	(0.446)	(0.469)
Industry Patents	0.000	0.000
	(0.000)	(0.000)
Total establishments	0.007 [a]	0.007 [a]
	(0.001)	(0.002)
% Large establishments	0.216	0.257
	(0.319)	(0.337)
Industry IPOs	0.001	0.001
	(0.001)	(0.001)
1990	0.009	0.01
	(0.009)	(0.010)
1991	0.055 [a]	0.060 [a]
	(0.009)	(0.010)
1992	0.019 [b]	0.018 [c]
	(0.009)	(0.011)
1993	0.024 [a]	0.023 [b]
	(0.009)	(0.011)
1994	0.024 [a]	0.024 [b]
	(0.009)	(0.011)
1995	0.041 [a]	0.043 [a]
	(0.009)	(0.011)
1996	0.101 [a]	0.108 [a]
	(0.009)	(0.010)
1997	0.049 [a]	0.053 [a]
	(0.009)	(0.011)
Industry sales growth		0.025
		(0.016)
Adv. Intensity		−0.029
		(0.045)
Constant	0.222 [a]	0.233 [a]
	(0.015)	(0.018)
Number of industries	201	191
R-squared	0.171	0.182
*R*2-within	0.171	0.182
Industries	201	191
Years	9	9

Standard errors in parentheses.
[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

6.1. Limitations

This study is not without limitations. First, our focus on examining our hypotheses across a wide variety of industry sectors comes at the cost of a reduction of detail. As a result, we are unable to examine fine-grained hypotheses, such as those that relate to specific attributes of organizations or characteristics of technologies. However, our approach allows us to avoid sampling biases that might otherwise distort our findings. In particular, this study overcomes a major limitation of previous studies that have examined the relationship between innovation and organizational performance in industries where technological innovation tends to occur with regularity. The sampling procedure used in those studies precludes the ability to examine the overall relationship between technological innovation and organization performance because they fail to include information on industries where little to no technological innovation is occurring. Notably, by examining industries over time, we are able to control for the effects of unobserved characteristics of industries. This is an important consideration because, as Fig. 1 indicates, a focus on specific industry sectors masks important shifts across industry sectors that influence the likelihood that particular industries will foster the formation of high-growth firms.

A second limitation that comes from examining our hypotheses across a wide variety of industry sectors is that we are unable to examine how our hypotheses relate to strategic groups within industries. Our theory is about how specific aspects of the commercial context influence the creation of high-growth firms, and in our study the competitive context is bounded by the industry. However, our study suggests that the prevalence of high-growth new firms within a specific strategic group is also likely to be influenced by changes through time in technological opportunities within the strategic group, and that this is a potential area for additional research.

A third limitation is that our results may not generalize outside the specific period of study. We measured industries between 1983 and 1997. This period coincided with major innovations in the application of knowledge from specific scientific fields to the commercial economy. Concern about this limitation may be mitigated by our occupation-based measures of technology intensity. Our count is based on the number of individuals involved in the application of scientific concepts to industry broadly, instead of counting specific occupations or technologies, such as biotechnology or computers. However, our categorization may be less likely to have the same relationship between the formation and growth rates of new firms, as does the application of scientific knowledge in general.

6.2. Implications

This study has several important implications for research in entrepreneurship. First, the findings indicate that the performance of new firms is affected by the characteristics of the industries in which they are founded. In particular, our research supports the argument that changes in the use of technology as industries evolve over time are likely to foster opportunities for entrepreneurs to launch successful new firms. From a theoretical perspective this finding is important because scholarly work has postulated that technological change opens up opportunities for entrepreneurs to create new high-growth companies, ushering in creative destruction that challenges existing large established firms (Schumpeter, 1934; Winter, 1984). Our study is consistent with this theoretical perspective, providing a rare empirical test, across several years and a diverse set of industries, of the proposition that increases in the technological intensity of industries are associated with increases in opportunities for entrepreneurs to launch highly successful firms. Virtually no prior empirical tests have examined whether technological change enhances the growth of new firms over long periods, spanning a diverse set of industries.

In addition, by using employment-based measures, we provide a way to measure industry characteristics that compares favorably to measures that are currently predominant in the literature. For example, commonly used measures of technological intensity, such as research and development intensity, often overlook activities undertaken by individuals and new firms, while patent intensity tends to capture only those technologies that can be codified (Levin et al., 1987). As a result, those measures tend to under-represent the activities of new firms in comparison to the employment-based measure used in this study (Merrill and McGeary, 2002).

This study provides a breadth of analysis that enables the application of fixed effects regression to control for unobserved characteristics of industries. With this methodology, we failed to detect a generic relationship between the importance of complementary assets in an industry and decreases in the counts of new high-growth firms. One interpretation is that even in industries marked by deeper sales and production capabilities, high-growth entrepreneurial opportunities may exist for new firms. This is surprising, as theory and research in specific contexts have led researchers to extrapolate that a generic negative relationship is likely to exist between the existence of complementary assets and the success of new firms (Teece, 1996; Tripsas, 1997, 2000). One interpretation of this aspect of our study is that idiosyncratic characteristics of the contexts examined in single industry studies may confound the ability for researchers to isolate the relationship between complementary assets and the prospects of new firms. Alternatively, perhaps in some contexts the complementary assets of incumbent firms impede the growth of new firms. Additional research is necessary to understand under what conditions this relationship exists and how these assets should be identified. For example, prior research suggests that specific characteristics of technologies and how technologies may integrate with other complementary technologies and industry processes may be important issues to examine (Tushman and Anderson, 1986; Anderson and Tushman, 1990). Another issue to consider is that new firms may be able to contract with established firms to access complementary assets in many industry contexts. Hence, exploring when and under what conditions young firms can contract for complementary assets may be a fruitful area for additional research. For example, perhaps competitive industries provide new firms with a variety of feasible parties to contract with to gain access to complementary assets, while in less competitive industries or industries where idiosyncratic capabilities of incumbents are durable; contracting may not be feasible on favorable terms for new firms. Lastly, it is important to acknowledge that additional research may indicate that these economy-wide measures of complementary assets may fail to fully measure industry-specific linkages between key activities that may impede the growth of new firms. This study suggests that additional single- and multi-industry studies are necessary to more completely understand the relationship between complementary assets and the prospects of new and established firms.

It is also important to acknowledge that in this study we do not examine the relationship between innovations in complementary assets and the prevalence of new high-growth firms. However, as postulated by Drucker (1985) and others (Eckhardt and Shane, 2003), technological disruptions that fundamentally alter key processes in industry value chains such as production or distribution may very well foster conditions that facilitate the growth of newly started firms. While we were unable to examine this hypothesis in our study, this is an important hypothesis that warrants additional research.

6.3. Conclusion

Using a unique data set of the U.S. economy spanning 14 years, we examine how changes in the distribution of human capital across occupations are associated with industry counts of rapidly growing new organizations. We find that growth in the employment of scientists and engineers is positively associated with increases in the counts of new high-growth companies. Our findings provide empirical support for theoretical arguments that industry environments are likely to be important determinants of the suitability of new firms as an appropriate method of exploiting opportunities (Winter, 1984). This suggests important implications for research, as well as practice, in the management of technological innovation.

Acknowledgments

The authors wish to thank the publishers of *Inc. Magazine*, the National Bureau of Economic Research, the Bureau of Labor Statistics, and the U. S. Census Department for providing data; and David Autor and Brian Silverman for advice on research design. Further, we thank Brent Goldfarb, Gerry George, Phil Kim, Wes Sine, S. Venkataraman, and seminar participants at Imperial College and the University of Wisconsin for providing valuable comments. Further, anonymous reviewers and associate editor Phil Phan provided helpful suggestions that improved this work. We gratefully acknowledge financial support from the U. S. Small Business Administration. The first author greatly appreciates the financial support that has been provided by the Kauffman Faculty Fellowship Program.

Appendix A

Table A1
Technology occupations.

Code	Description
44	Aerospace engineers
45	Metallurgical and materials engineers
46	Mining engineers
47	Petroleum engineers
48	Chemical engineers
49	Nuclear engineers
53	Civil engineers
54	Agricultural engineers
55	Electrical and electronic engineers
56	Industrial engineers
57	Mechanical engineers
58	Marine and naval architects
59	Engineers, n.e.c.
66	Actuaries
67	Statisticians
68	Mathematical scientists, n.e.c.
64	Computer systems analysts and scientists
65	Operations and systems researchers and analysts
69	Physicists and astronomers
73	Chemists
74	Atmospheric and space scientists
75	Geologists and geodesists
76	Physical scientists, n.e.c.
77	Agricultural and food scientists
78	Biological and life scientists
79	Forestry and conservation scientists
83	Medical scientists

Table A2
Sales occupations.

Code	Description
243	Supervisors and proprietors, sales occupations
253	Insurance sales occupations
254	Real estate sales occupations
255	Securities and financial services sales occupations
256	Advertising and related sales occupations
257	Sales occupations, other business services
258	Sales engineers
259	Sales representatives, mining, manufacturing, and wholesale
263	Sales workers, motor vehicles and boats
264	Sales workers, apparel
265	Sales workers, shoes
266	Sales workers, furniture and home furnishings
267	Sales workers; radio, TV, hi-fi, and appliances
268	Sales workers, hardware and building supplies
269	Sales workers, parts
274	Sales workers, other commodities

Table A2 (*continued*)

Code	Description
275	Sales counter clerks
276	Cashiers
277	Street and door-to-door sales workers
278	News vendors
283	Demonstrators, promoters and models, sales
284	Auctioneers
285	Sales support occupations, n.e.c.

Table A3
Production and operator occupations.

Code	Description
634	Tool and die makers
635	Tool and die maker apprentices
636	Precision assemblers, metal
637	Machinists
639	Machinist apprentices
643	Boilermakers
644	Precision grinders, filers, and tool sharpeners
645	Patternmakers and model makers, metal
646	Lay-out workers
647	Precious stones and metals workers jewelers
649	Engravers, metal
653	Sheet metal workers
654	Sheet metal worker apprentices
655	Miscellaneous precision metal workers
703	Lathe and turning machine set-up operators
704	Lathe and turning machine operators
705	Milling and planing machine operators
706	Punching and stamping press machine operators
707	Rolling machine operators
708	Drilling and boring machine operators
709	Grinding, abrading, buffing, and polishing machine operators
713	Forging machine operators
714	Numerical control machine operators
715	Miscellaneous metal, plastic, stone, and glass working machine operators
717	Fabricating machine operators, n.e.c.
719	Molding and casting machine operators
723	Metal plating machine operators
724	Heat treating equipment operators
725	Miscellaneous metal and plastic processing machine operators
726	Wood lathe, routing, and planing machine operators
727	Sawing machine operators
728	Shaping and joining machine operators
729	Nail and tacking machine operators
733	Miscellaneous woodworking machine operators
734	Printing press operators
735	Photoengravers and lithographers
736	Typesetters and compositors
737	Miscellaneous printing machine operators
738	Winding and twisting machine operators
739	Knitting, looping, taping, and weaving machine operators
743	Textile cutting machine operators
744	Textile sewing machine operators
745	Shoe machine operators
747	Pressing machine operators
748	Laundering and dry cleaning machine operators
749	Miscellaneous textile machine operators
753	Cementing and gluing machine operators
754	Packaging and filling operators
755	Extruding and forming machine operators
756	Mixing and blending machine operators
757	Separating, filtering, and clarifying machine operators
758	Compressing and compacting machine operators
759	Painting and paint spraying machine operators
763	Supervisors, handlers, equipment cleaners, and laborers, n.e.c.
764	Washing, cleaning, and pickling machine operators
765	Folding machine operators
766	Furnace, kiln, and oven operators, exc. food
768	Crushing and grinding machine operators

(continued on next page)

Table A3 (*continued*)

Code	Description
769	Slicing and cutting machine operators
773	Motion picture projectionists
774	Photographic process machine operators
777	Miscellaneous machine operators, n.e.c.
779	Machine operators, not specified
783	Welders and cutters
784	Solderers and brazers
785	Assemblers
786	Hand cutting and trimming occupations
787	Hand molding, casting, and forming occupations
789	Hand painters, coating, and decorating occupations
793	Hand engraving and printing occupations
794	Hand engraving and polishing occupations
795	Miscellaneous hand working occupations
796	Production inspectors, checkers, and examiners
797	Production testers
798	Production samplers and weighers
799	Graders, and sorters, exc. agricultural
803	Supervisors, motor vehicle operators
804	Truck drivers, heavy
805	Truck drivers, light
806	Driver-sales workers
808	Bus drivers
809	Taxi cab drivers and chauffeurs
813	Parking lot attendants
814	Motor transportation occupations, n.e.c.
823	Railroad conductors and yardmasters
824	Locomotive operating occupations
825	Railroad brake, signal, and switch operators
826	Rail vehicle operators, n.e.c.
828	Ship captains and mates, except fishing boats
829	Sailors and deckhands
833	Marine engineers
834	Bridge, lock, and lighthouse tenders
843	Supervisors, material moving equipment operators
844	Operating engineers
845	Longshore equipment operators
848	Hoist and winch operators
849	Crane and tower operators
853	Excavating and loading machine operators
855	Grader, dozer, and scraper operators
856	Industrial truck and tractor equipment operators
859	Miscellaneous material moving equipment operators
864	Helpers, mechanics and repairers
865	Helpers, construction trades
866	Helpers, surveyor
867	Helpers, surveyor
868	Helpers, extractive occupations
869	Construction laborers
873	Production helpers
874	Production helpers
875	Garbage collectors
876	Stevedores
877	Stock handlers and baggers
878	Machine feeders and offbearers
883	Freight, stocks, and material handlers, n.e.c.
885	Garage and service station related occupation
887	Vehicle washers and equipment cleaners.
888	Hand packers and packagers
889	Laborers, except construction

Table A4
Applied technology occupations.

Code	Occupation
203	Clinical laboratory technologists and technicians
204	Dental hygienists
205	Health record technologists and technicians
206	Radiology technicians

Table A4 (*continued*)

Code	Occupation
207	Licensed practical nurses
213	Electrical and electronic technicians
214	Industrial engineering technicians
215	Mechanical engineering technicians
216	Engineering technicians, n.e.c.
224	Chemical technicians
229	Computer programmers
233	Tool programmers, numerical control
228	Broadcast equipment operators
235	Technicians, n.e.c.
308	Computer operators
309	Peripheral equipment operators

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