Innovation and Small Business Performance:

Examining the Relationship Between Technological Innovation and the Within Industry Distributions of Fast Growth Firms

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Purpose

Theory holds that industry conditions favorable to the performance of small private firms are fundamentally different from industry conditions favorable to the performance of large, established firms. However, research into this question has been hindered by data limitations. This report seeks to determine empirically, via examination of a unique data-set, how changes in conditions of some industries, e.g., technological intensity and production and sales intensity, impact the performance of small fast growing small firms and fast growing large public firms in those industries.

Overall Findings

Industries that are more technically oriented (as evidenced by increased employment of scientists and engineers) are more accommodating to small fast growing private firms. As industries become more production oriented, they become more accommodating to large fast growing public firms.

Highlights

• Distribution of large high growth established firms and small high growth private firms is not even across industries. Forty percent of the large firms are concentrated in ten industries; 54 percent of the small firms are also found in just ten industries.

• Small and large high growth firms were concentrated in differing industries. Of the top ten small and large high growth industries, only computer programming and data processing, as well as computer and office equipment were on both lists.

• Of the 283 industries studied, 192 had at least one private high growth firm and 154 had at least one public high growth firm.

• By major industry, about 60 percent of high growth small private firms were in services versus about 28 percent for large public firms. Manufacturing had the highest number of large public high growth companies. From 1984 to 1997, the share of high growth small private firms in services surged, while the percent of high growth large public firms in the services sector declined.

• The econometric models found that changes in the technical intensity of an industry are positively linked to the number of high growth small private firms, and change in production intensity is negatively linked. The results were reversed for high growth large public firms.

• A relationship between an industry's mix of sales and distribution employees and the number of high growth private firms was not found.

• The results of the paper support the notion that as an industry evolves over time, opportunities for new entrepreneurs will change based on how the industry evolves. They also support the notion that small private and large public firms perform different roles in different industries, and in the economy as a whole.

Scope and Methodology

Following the number of high growth companies by industry from 1984 to 1997, regression models for small private and large public firms were created. The lagged percentage of technical, sales and distribution, and production workers in an industry were independent variables. Model controls included patent counts, establishment counts, and large establishment counts to account for variations among the industries (as a further check, an industry's total sales were also included).

Data from various sources were used. *Inc.* magazine's "*Inc*. 500" were used as a data set for high growth small private firms. The Inc. 500 is a group of high sales growth firms at least 5 years old with sales between $100,000 and $25 million. (Because of the limited availability of information on private firms, industry counts were used in the models.) Using Standard and Poor's COMPUSTAT database and the Inc. 500 methodology for picking high growth companies, the 500 high growth public firms were selected and judged to be large firms. Employment levels were created from occupation data in the U.S. Census Bureau's Current Population Survey. Industries were coded using the U.S. government's three-digit Standard Industrial Classification (SIC) system.

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ABSTRACT

Researchers have argued that the relative importance of different parts of the value chain influences the relative growth of new and established firms. However, to date, we have no empirical evidence on this question. This study examines the effects of industry-level changes in the relative importance of parts of the value chain over time on changes in the industry distribution of high growth new private and established public companies. Using a unique database of 192 industries over a 14 year period, we find that industries that are becoming increasingly more technical, as represented by an increase in the employment counts of scientists and engineers, are associated with increasing counts of fast growing new private firms, and negatively associated with counts of fast growing established public companies. Further, we find that an increase in the emphasis on production within industries is negatively associated with counts of fast growing new private companies and positively associated with counts of fast growing established public companies. Lastly, we find a rather dramatic shift in the allocation of high growth new private firms from the manufacturing sector to the service sector between 1984 and 1997.

Keywords: Entrepreneurship; Industry Evolution; Technological Innovation

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INTRODUCTION

Scholars have theorized that industry conditions that are favorable to the performance of new private firms are likely to be fundamentally different than industry conditions that are favorable to the performance of large, established producers (Schumpeter, 1934; Winter, 1984; Audretsch, 1997; Malerba & Orsenigo, 1997; Aldrich, 1999; Gans & Stern, 2003). Drawing on arguments made in the innovation management literature (Schumpeter, 1934; Teece, 1986; Tushman & Anderson, 1986; Klepper & Grady, 1990; Utterback, 1994; Tripsas, 1997), we argue that the relative importance of different parts of the value chain is the key factor affecting the relative favorability of industry conditions to new private and established public firms because industry value chains represent the way firms typically organize inputs to generate profits (Porter, 1980; Utterback & Suarez, 1993).

In this study we use a unique employment based dataset covering 192 industries across 14 years to examine whether changes that occur in industry value chains over time are differentially associated with the growth prospects of new private firms and large established public firms. We examine whether increases in technological intensity will be positively associated with increases in the industry counts of the number of fastest growing small new private firms in the United States and negatively associated with increases in the industry counts of the number of rapidly growing large established public companies in the United States. We also examine whether increases in production and sales and distribution intensity will be positively associated with increases in the industry counts of the number of rapidly growing large established public companies and negatively associated with increases in industry counts of the number of small new private firms.

Systematically studying how the evolution of the industry value chain affects the growth of small new firms and large established firms has important theoretical implications for scholarly work in entrepreneurship, strategic management and organization theory for several reasons. First, scholars have long argued that small new firms are an important mechanism through which innovation and change are incorporated into the economic system (Schumpeter, 1934; Sarasvathy, 1997; Venkataraman, 1997). Further, theory suggests that changes in industries over time are likely to influence the effectiveness of new small firms as a mechanism to exploit business opportunities (Lawrence & Lorsch, 1967; Winter, 1984; Scott, 1992; Malerba & Orsenigo, 1997).

Empirical evidence addressing this question is scarce because data constraints generally have limited researchers to the investigation of the effects of changes in industry attributes on entry, rather than on firm performance (Dean *et al.*, 1998). However, 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 & Barney, 1997; Caves, 1998; Shane & Venkataraman, 2003). Therefore, an accurate understanding of the effect of industry changes on the growth of new small firms is necessary to assess which specific aspects of industry are favorable and unfavorable to new small firms.

Moreover, while the determinants of firm performance of large public firms – such as those monitored by Standard & Poor's COMPUSTAT database – have been well studied, the determinants of firm performance of small private firms has not been well investigated (Aldrich, 1999). By simultaneously examining whether large established firms are more (or less) likely to grow rapidly in environments that are found to support many high growth new small firms, we can examine whether these different types of organizations are advantaged by different changes in the composition of the industry value chain. This is important, as the fit between organization design and environmental conditions is central to strategic management and organization theory (Chandler, 1962; Scott, 1992).

Despite the importance of this question to understanding the appropriate mode of organizing in specific settings, (Dean et al., 1998; Katila & Shane, 2005), a significant gap exists between theoretical arguments and rigorous empirical findings (Aldrich, 1999), Prior studies on this topic have tended to undertake in depth analysis of one or a few industries, such as automobile manufacturing, computer hardware or photographic imaging (Utterback & Abernathy, 1975; Anderson & Tushman, 1990; Christensen & Bower, 1996; Tripsas, 1997; Carroll & Hannan, 2000), or examine a cross section of manufacturing industries (Acs & Audretsch, 1988). These prior approaches are unable to control for unique unobserved characteristics of the industries studied that are likely to be correlated with the value chain composition, (Malerba & Orsenigo, 1996), and have overlooked the service sector, a potentially important area of the economy for high growth new private firms.

Moreover, commonly used measures of innovation, such as research and development intensity, typically overlooks innovation that occurs in small firms as well as in certain sectors of the economy, resulting in biased estimates of the effects of innovative activity (Merrill & McGeary, 2002). We utilize employment data drawn from a nationwide survey to examine our hypotheses, which permits us to measure key constructs over time, in the same manner, across a wide range of industries, and allows us to estimate accurately the relationship between technological intensity and the performance of new firms.

The results of this study are useful to practitioners. We identify changes in industry conditions that are favorable to the growth of new small and large established firms. While a significant body of research identifies the industry characteristics associated with new company formation (Geroski, 1991; Geroski, 1995; Dean et al., 1998), such research is not of much use to practitioners seeking to build high growth companies because the factors associated with entry of new firms may not be associated with post entry performance. Our examination of the changes in the value chain associated with the counts of high growth companies helps to provide practitioners with information to identify value chain configurations that are favorable to the growth of small new and large established firms.

Lastly, from a public policy perspective, the identification of industry attributes that are associated with increases in the industry count of high growth firms is valuable. Significant public resources are allocated to support the creation of new firms, but this allocation occurs largely in the absence of information about which factors lead to the creation of high growth new firms. By contributing to our understanding of the relationship between changes in industry attributes and changes in the industry count of high growth new firms, our results will help policy makers to better target initiatives to increase the number of these entities.

THEORY AND HYPOTHESES

We argue that changes over time within industries in specific aspects of the value chain composition will be differentially associated with changes in the number of high growth new and high growth established firms. In particular, we expect that increases in the industry allocation of resources to the creation of new products and processes through investment in technology will be positively associated with increases in the number of high growth small new private firms and negatively associated with the number of high growth large established public firms, whereas increases in the industry allocation of resources to production, marketing, and distribution will be negatively associated with the number of high growth small new private firms and positively associated with the number of high growth large established public firms.

Technology Intensity

We expect that the number of rapidly growing large established organizations in an industry will decline as the relative importance of the application of technology to the industry value chain increases, while we expect the opposite relationship to hold for the number of rapidly growing small new organizations. Although technological innovation provides opportunities for all economic actors to recombine resources in ways that allow for firm growth (Schumpeter, 1934), new small firms are relatively better suited to do this than are large established firms, because of their customer relationships, routines, structures, and incentive systems.

First, customers reward established firms that can reliably provide products and services with known attributes (Hannan & Freeman, 1984). However, reliability reduces adaptability, because it is achieved by reducing variation in the organization's activities that otherwise would have provided opportunities to innovate, in order to satisfy expectations of existing customers (Miner, 1994). In contrast, new small firms lack a large established customer base, and hence are more able to make the trade-off of adaptability for reliability that is necessary to achieve growth through the application of technology.

Second, large established firms often have routines that are difficult to modify, which hinders their ability to use technology to drive firm growth. An important benefit of routines is to guide organization actions and decision making subconsciously (Nelson & Winter, 1982). However, the subconscious nature of routines renders them difficult to explicitly identify and modify (Nelson & Winter, 1982). As a result, the use of technology to drive firm growth is often incompatible with the portfolio of difficult-to-change routines of existing organizations (Arrow, 1974; Hannan & Freeman, 1984; Henderson & Clark, 1990). Because new small firms do not have long-standing routines that are difficult to modify, they are able to explicitly design routines to meet the demands of novel technologies (Teece, 1996), thereby enhancing firm growth.

Third, new small firms lack formal, functional specialization and information processing structures (Blau & Scott, 1962; Thompson, 1967; Arrow, 1974; Cardinal et al., 2004). The absence of such structures facilitates their ability to apply new technology to drive firm growth. The open and informal decision making structure in new small firms, combined with fewer decision makers and employees, enables these firms to process decisions quickly (Teece, 1996). Further, 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 & Freeman, 1984; Carroll & Hannan, 2000; Sine et al., forthcoming). In contrast, the formal hierarchies, functional specialization, and established information processing systems of large established organizations are poorly suited to the management of technology, and hinder the ability to apply new technology to drive firm growth.

Fourth, large established firms often have monitoring mechanisms, which are designed to harvest profits from routine activities based on existing technologies, but hinder their ability to harness technological innovation to drive firm growth. To manage employees, large established organizations create monitoring mechanisms that compare employee performance to specific goals (Holmstrom, 1989). While well suited to encourage routine activity in stable environments, these monitoring mechanisms discourage the creative activity necessary to exploit technology, because the application of technical knowledge to commercial applications is fraught with errors, blind alleys, failed experimentation, and surprise successes (Simon, 1955; Zenger, 1994; Teece, 1996). In contrast, new small firms tend to use high powered incentives, such as stock ownership, that 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). These arguments lead to the first set of hypotheses:

Hypothesis 1a: Increases in the proportion of the industry value chain devoted to the application of technical knowledge will be positively associated with the number of high growth small new private firms in the industry, ceteris paribus.

Hypothesis 1b: Increases in the proportion of the industry value chain devoted to the application of technical knowledge will be negatively associated with the number of high growth large established public firms in the industry, ceteris paribus.

Production, Sales, and Distribution Intensity

We expect the number of rapidly growing large established organizations in an industry to increase as the relative importance of production, sales, and distribution to the value chain increases, while we expect the opposite relationship to hold for the number of rapidly growing small new organizations. Although sales, distribution, and production assets are generally necessary for all firms to sell products and services to customers (Mitchell, 1989; Teece, 1992; Tripsas, 1997), large established firms are relatively better suited than small new firms to industries where these assets are becoming relatively more important for several reasons. First, these assets 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 & Evans, 1994). Further, these assets are a resource of established firms that new small firms find difficult to duplicate because 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, these assets shift 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 that indicated that these assets 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, as production, distribution, and sales assets become more important to an industry, the basis of competition shifts toward large, established firms, facilitating their relative growth.

Third, with the exception of the small number of industries in which patents are effective at deterring imitation, contracting for complementary assets is difficult (Arrow, 1971; Teece, 1980, 1998), hindering efforts by small new firms to quickly access needed production, sales, and distribution assets (Teece, 1986). Moreover, even when these assets can be obtained through contracting, the arms-length relationship between them and other aspects of the value chain hinders the transfer of crucial tacit knowledge that is important for serving customers; thus the performance of firms that have to rely on arms-length relationships to obtain these assets suffers (Chandler, 1977; Mitchell, 1989). In particular, large established firms tend to have better ties between different parts of their value chain than new small firms that use contracting to access those aspects of the value chain. As a result, as the importance of production, sales, and distribution assets within an industry increases, large established firms become more likely to grow rapidly and small new firms become less likely to grow rapidly. These arguments lead to the next set of hypotheses.

Hypothesis 2a: Increases in the proportion of the industry value chain devoted to production will be negatively associated with the number of high growth small new private firms in the industry, ceteris paribus.

Hypothesis 2b: Increases in the proportion of the industry value chain devoted to production will be positively associated with the number of high growth large established public firms in the industry, ceteris paribus.

Hypothesis 3a: Increases in the proportion of the industry value chain devoted to sales and distribution will be negatively associated with the number of high growth small new private firms in the industry, ceteris paribus.

Hypothesis 3b: Increases in the proportion of the industry value chain devoted to sales and distribution will be positively associated with the number of high growth large established public firms in the industry, ceteris paribus.

RESEARCH DESIGN

To examine the relationship between changes in industry characteristics and changes in the number of high growth new private and established public firms, data must (1) be available for a wide range of industries; (2) be measured the same way across all industries; (3) be comparable across years; (4) be available at a level of industry detail adequate to measure the variables accurately; and (5) be available over enough years to capture changes in the variables. These data requirements are stringent. As a result, to our knowledge this is the first study that has conducted this analysis.

Industries

We define industries using the three-digit standard industry classification (SIC) scheme produced by the U.S. Government.[1] To examine data over time using the standard industry classification scheme, we need to accommodate the modifications of the 1972 SIC system that occurred in 1977 and 1987. To develop a consistent panel of data comparable across all years in this study, we followed the industry classification procedure developed by (Autor et al., 1998), where data pertaining to industries that are consistent across all years in the study were left unchanged. Data for distinct 1972 industries that were combined with other industries in the 1977 or 1987 revisions were aggregated in the 1972 SIC system to match the later revisions. Similarly, industry data that were disaggregated in later years were aggregated to match the 1972 SIC classification system.

The official 1972 and 1987 three-digit SIC systems contained respectively 423 and 416 distinct three-digit industries. Recombination reduced the number of industries to 353. (Note that with this procedure, the smaller number of industries does not represent dropped industries or firms, as industries are combined through aggregation, not by a censoring procedure.) Because we focused on private sector industries, we dropped the twenty-two 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 192 hosted at least one high growth startup, and 154 hosted at least one high growth public firm over the period of study.

Dependent Variables

<u>Inc. 500 Counts</u>: We measure the number of high growth small new private firms in each industry year, by summing the total number of Inc. 500 firms located in each industry for each

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[1] Although we would be able to define industries more precisely if we examined them at the 4-digit SIC code level, this increased precision would be offset by the decreased precision of measuring the independent variables at the 4-digit SIC code level, because 4-digit data on key independent variables is unavailable across all sectors of the economy. Because the data at the 3-digit SIC codes are an average of the 4-digit SIC codes that compose the 3-digit codes, our test is conservative. The averaging effect of measurement at the 3-digit level will decrease parameter estimates and increase standard errors, resulting in an understatement of results (Allison, 2002).

year. The Inc. 500 is a list of the 500 fastest growing private 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 based on five-year growth rates.

We use industry counts of Inc. 500 firms to measure the distribution of high growth startups across industries in the U. S. economy, 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 are notoriously inaccurate at measuring the growth rate of small firms across a wide range of industries, because of an emphasis on collecting information on establishments, rather than firms (Aldrich, 1999). Hence, we utilize the Inc. 500 list as our measure of high growth new private firms by industry.

Each firm in the Inc. 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 LexisNexus™. For the 3,500 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 Standard Industrial Classification Manual (OMB, 1987).

<u>Public 500</u>. Annual industry counts of the number of the fastest growing large, public established firms were computed using a method that was designed to mimic the method used by *Inc. Magazine* for the computation of the Inc. 500 rankings. We ranked, by their five-year growth rates, all firms in Standard & Poor's COMPUSTAT database that met a sales cutoff of at least $500 million in the base year of the growth rate computation.[2] We then took annual counts of the number of firms in each 3-digit SIC code.

[2] Our findings are robust compared to alternative specifications of the $500 million sales cut-off.

Covariates

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. Panel A of Table 1 provides a list of technical occupations that were used to compute this measure. Counts of industry employment of scientific fields were drawn from the National Bureau of Economic Research's (NBER) extracts of the merged outgoing rotation groups (MORG) of the current population survey administrated by the Bureau of Labor Statistics. We transform the BLS industry occupation data into a longitudinal panel based on the standard SIC codes, using the procedure developed by Autor et al. (1998). This procedure is described in the data appendix.

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, using data from the NBER MORG extracts of the BLS Current Population Survey. Panel B of Table 1 provides a list of sales and sales management occupations.

Production Intensity. We measure production intensity as the annual percentage of total employment in the industry that occurs in production and related occupations, using data from the NBER MORG extracts of the BLS Current Population Survey. Panel C of Table 1 provides a list of sales and sales management occupations.

Use of Employment-Based Measures. We use employment-based measures of our key predictor variables because alternative approaches have significant disadvantages. Among alternative technology variables, R&D intensity systematically under represents the research and development activities of small firms, startups, and independent inventors, because government surveys of industry-level R&D expenditures, such as those conducted by the National Science Foundation—do not attempt to measure R&D expenditures in small firms (BLS, 1997, 2002). Further, patents under report the application of technology, because many uses of technology are not or cannot be patented (Levin *et al.*, 1987). In contrast, the employment based measured used in this study do not suffer from these limitations, in part as the measures are based on a household survey, instead of a survey of existing firms (Merrill & McGeary, 2002). Among alternative production variables, employment measures are used instead of asset measures, because employment data is available for a wider range of industries, and differences exist across industries in the reporting of physical assets .

Prior work has used similar employment based measures. For example, Sine et al. (2003) used total employment in high technology industries as an indication of the technological intensity of specific regions, while Hecker (1999) used technology occupation data to classify industries as high technology or low technology.

Control Variables

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). Hence, we include as a covariate the total number of patents awarded to non-government institutions by industry by year. We assign patents to industries utilizing 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 & Silverman (2001) for more information on the industry-patent classification system used in this study.

Total establishments. Because the propensity with which an industry will contain high growth firms is likely to 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 Department of the Census.

Percent of Large Establishments. Because we examine the relationship between specific hypotheses and the prevalence of *high growth* small new and large established firms, we control for the percent 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.

Time Period Effects. To control for period effects, we include two dummy variables, one set to one for the period 1983-1987, and another set to one for the period 1988- 1992, with 1993-1997 being omitted as the base case. Table 2 summarizes the variables used in the analysis.

Statistical Analysis

We analyze our hypotheses by utilizing fixed effects regression, in which all independent variables are lagged one year. Fixed effects models estimate the relationship between deviations from the industry mean value of each covariate and deviations in the mean count of the dependent variable over the length of the panel. The use of fixed effects regression allows us to control for unobservable differences across 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 changes in technology intensity, production intensity, and sales and distribution intensity, within industries over time, are associated with within industry changes in the count of high growth firms.

Because our dependent variables measure industry counts of high 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 fixed effects negative-binomial model (Haveman, 1995; Greene, 2000). 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 or Public 500 firm – our analysis is based on those 192 industries for the Inc. 500 regressions, and 154 industries for the Public 500 regressions, that hosted at least one Inc. 500 or Public 500 over the length of the study (Hausman et al., 1984; Greene, 2000; Sorenson & Stuart, 2001).

RESULTS

Table 3 reports the counts of the number of high growth established and small new firms by industry for the ten industries that contained the greatest number of high growth firms (by category) across the entire panel. Inspection of Table 3 provides two important pieces of information. First, high growth large established and small new firms do not appear to be distributed uniformly across all industries in the economy. Just over 40% of the high growth large established firms are located in just ten industries, while over half (54%) of the high growth small new firms are again located in just ten industries. Hence, it appears that industry-specific conditions are likely to be important in understanding the counts of high growth firms. This observation reinforces the value in conducting fixed effects regression to examine our hypotheses.

Second, only two industries are ranked on both lists: Computer programming and processing, and computer office equipment. Thus, Table 2 suggests that changes in technology intensity, production intensity, and sales and distribution intensity are unlikely to have the same effects on the number of high growth small new and large established firms (McDougall *et al.*, 1994).

Figures 1 and 2 indicate the importance of examining multiple industry sectors over an extended period to test our hypotheses. Figure 1 indicates that, over the 1984 through 1997 period, rapidly growing small new firms became much more common in services than in manufacturing. Hence, a study that examined only the manufacturing sector would likely overlook important causal determinants of the industry distribution of high growth small new firms.

Figures 3 and 4 illustrate the arguments behind our hypotheses. Figure 3 shows the relationship between the annual count of Inc. 500 firms in the computer industry and the annual level of technology intensity, while Figure 4 shows the relationship between the annual count of Public 500 firms in the automotive industry and the annual level of production intensity. The count of Inc. 500 companies in an industry increases with the technology intensity of the industry, while the count of Public 500 companies in an industry increases with the production intensity of the industry.

Table 4 shows descriptive statistics and the pooled correlation matrix. The highest correlation among independent variables is 0.55.

Table 5 reports the results for the negative binomial fixed effects regressions to predict the variation in the rates of creation of high growth private new firms (model 1) and the variation in the counts of high growth established public companies (model 2). Overall, both models are significant (Chi-square of 107.78 and 49.56, $p < 0.00001$, respectively).

In Table 5, hypotheses 1a and 1b are strongly supported. We find that changes in the technical intensity of an industry are positively associated ($\beta = 3.80$, $p < .0001$) with changes in the number of high growth small new private firms (Hypothesis 1a), and that changes in the technical intensity of an industry are negatively associated ($\beta = -3.98$, $p < .0001$) with changes in the number of high growth large established public firms. Specifically, the estimates in Column 1 of Table 5 indicate that a one percent increase in technological intensity of an industry is associated with an increase of over 3.80 (141% from the mean of the dependent variable) high growth small new private firms and a decrease in almost 4 (165% from the mean of the dependent variable) of high growth large established public firms.

In support of hypothesis 2a, we find a statistically significant and economically substantive negative relationship between changes in the level of production intensity and the count of small new private firms in the industry ($\beta = -.656$, $p < .05$). A one percent increase in production intensity is associated with a decrease of 24% in the industry-count of high growth small new private firms. Further, we also find support for hypothesis 2b. Changes in the level of production intensity are positively associated with changes in counts of high growth large established public firms in the industry ($\beta =.835$, $p < .002$). A one percent increase in the production intensity of an industry is associated with an increase of almost one (35%) high growth large established public firm within an industry. However, we do not find support for hypotheses 3a and 3b, as we fail to reject the null hypothesis of no relationship between changes in sales and distribution intensity and within industry changes in counts of Inc. 500 firms ($\beta = -0.222$, $p > 0.43$) and Public 500 firms ($\beta = -0.227$, $p > .54$).

We provide several robustness checks of our results. In Columns 3 and 4 of Table 5, 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). Our results are robust to the inclusion of this additional covariate, ruling out this alternative explanation.

We also include as an additional covariate a measure of applied technology intensity, to capture changes in the type of technology utilized in industries. Lifecycle theorists argue that innovation shifts to process improvements once a dominant design emerges in an industry (Utterback & Abernathy, 1975; Utterback & Suarez, 1993; Klepper, 1997). This line of argumentation suggests that an increasing emphasis on the utilization of applied technologists who utilize existing technologies in standard ways (as opposed to basic scientists) is likely to be negatively associated with the count of small new private firms in an industry. However, the overall technical employment measure should remain positively associated with the count of small new private firms in an industry.

In Columns 1 and 2 of Table 6, we show that changes in the applied technology intensity of an industry are negatively associated with changes in the count of high growth small new private firms ($\beta = -2.17$, $p < .01$), but that the inclusion of the applied technology covariate leaves evidence in support of our primary hypothesis intact. However, we fail to reject the null hypothesis of no relationship between changes in the applied technology intensity of an industry and changes in the count of high growth large established public companies ($\beta = -0.578$, $p > .70$).

In Columns 3 and 4 of Table 6, we examine whether our results are being driven by a single technology, computing, which was an important technological innovation over the period of study (Autor *et al.*, 1998). In Columns 3 and 4, we omit from our analysis industries where computing is the primary product or service, such as SIC 357, Computer and Office Equipment. Overall, our findings are robust to this analysis, although we observe a decrease in the significance of some key variables.

Lastly, in Columns 5 and 6, we omit from our analysis the commercial banking industry, in order to examine the sensitivity of our results to omitting the most important industry that hosts the fastest growing large established public firms. Our results are robust to this analysis.

DISCUSSION

Using a unique dataset that tracked 192 industries over 14 years, we find that changes in the value chain favorable to the formation of high growth new private companies are different from changes in the value chain favorable to high growth established public firms. Specifically, we find that growth in the technical intensity of the value chain is positively associated with within industry changes in the distribution of high growth small new private firms, while growth in the production intensity of the value chain is negatively associated with within industry changes in the distribution of high growth small new private firms. In contrast, we find that growth in the technical intensity of the value chain is negatively associated with the distribution of high growth large established public firms, while growth in the production intensity of the value chain is positively associated with the within industry distribution of high growth large established public firms.

Further, the multi-sector sample utilized in this study enabled us to detect a shift in the distribution of high growth new firms across the economy. Specifically, as shown in Figure 1, over the 1984 through 1997 period, rapidly growing small new firms became much more common in services than in manufacturing. Further, we also find that over this period (see

Figure 2), that the fastest growing large public firms become much less common in services than in other sectors. These shifts are important, as it is an indication that these different types of firms are likely to perform fundamentally different roles in the economy.

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 the specific characteristics of organizations or technologies. However, our approach also allows us to avoid sampling biases that might otherwise distort findings on this topic. In particular, this study overcomes a major limitation of studies that have examined the relationship between technological 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 those studies fail to include information on industries where little to no investment in technology is being made.

Second, our results may not generalize outside the specific period of study. We measured industries between 1984 and 1997. This period coincided with major innovations in the application of knowledge from specific scientific fields to the commercial economy. However, we mitigate this limitation by examining the sensitivity of our findings to computing, an innovation of particular importance over the period of study.

Implications

This study has several important implications for research in strategy and entrepreneurship. First, our findings indicate that environmental conditions are likely to influence the performance of new private firms. In particular, our research supports the argument that changes in the utilization 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 (Schumpeter, 1912; Tripsas, 1997; Shane, 2004) 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. Our study is consistent with this theoretical perspective, providing a rare empirical test of the proposition that increases in the technological intensity of industry value chains are associated with increases in opportunities for entrepreneurs to launch highly successful firms across a long time period and a diverse set of industries. Virtually no prior empirical tests have examined whether technological change enhances the growth of new firms over long periods, spanning such a diverse set of industries. Existing work has focused on the initial creation of firms, short periods, or narrow sets of industries. Because newly created firms may not necessarily be successful, the examination of the effect of technological change on the success of new firms is an important contribution.

Second, we find that changes in the industry value chains that are conducive to the rapid growth of new private firms are different from changes in industry value chains that are favorable to the growth of large established public companies. This finding is important, because it suggests that new small private firms and established large public firms are likely to perform different economic roles in the innovation system of modern economies (Lawrence & Lorsch, 1967; Winter, 1984; Scott, 1992). Unfortunately, prior historical empirical examination of this hypothesis has been limited due to an emphasis on examining the determinants of new firm entry or formation, instead of growth.

Third, we find that industry counts of the highest performing large established companies are negatively associated with technological intensity. While research on technology strategy has tended to examine ways that incumbents manage technological innovation (Tripsas, 1997; Ahuja & Lampert, 2001; King & Tucci, 2002), or specific industry conditions that are likely to provide incumbents with an advantage, our results support the general hypothesis that technological innovation is problematic for established firms (Utterback, 1994). However, our findings do not examine whether, or under what conditions, established producers are able to adapt to technological innovation.

Fourth, we show support for Teece's (1998) argument that the growth of established firms can arise from their control over complementary assets. Specifically, we found a positive relationship between growth in the production intensity of the industry value chain and the prevalence of high growth established large public firms, while we found the inverse relationship for high growth new small private companies. This finding suggests that established firms may be able to achieve growth by investing in complementary assets. Our failure to find support for the effect of sales and distribution intensity may be an indication that small new private firms may be more able to contract for some types of complementary assets than others.

Lastly, we make an important methodological contribution. By using employment-based measures, we provide a way to measure industry characteristics in studies of new and small firms 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 small firms (because of the government's sampling procedures and disclosure regulations), 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 and small firms in comparison to the employment based measure used in this study (Merrill & McGeary, 2002).

CONCLUSION

Using a unique dataset of the U.S. economy spanning 14 years, we examine how changes in the technology, production, and sales and distribution intensities of the value chain are associated with industry counts of rapidly growing small new and large established organizations. We found that changes in the value chain associated with increases in the number of high growth small new private companies appear to be different from those that are associated with increases in the number of high growth large established public firms. Specifically, we found that growth in technical intensity is positively associated, and production intensity is negatively associated, with increases in the counts of high growth new small private companies. We found the reverse relationships when predicting counts of high growth large established public firms. Our findings provide empirical support for theoretical arguments that new organizations and established organizations are likely to perform different economic roles in the innovation system of modern economies, with important implications for research as well as practice of the management of technological innovation.

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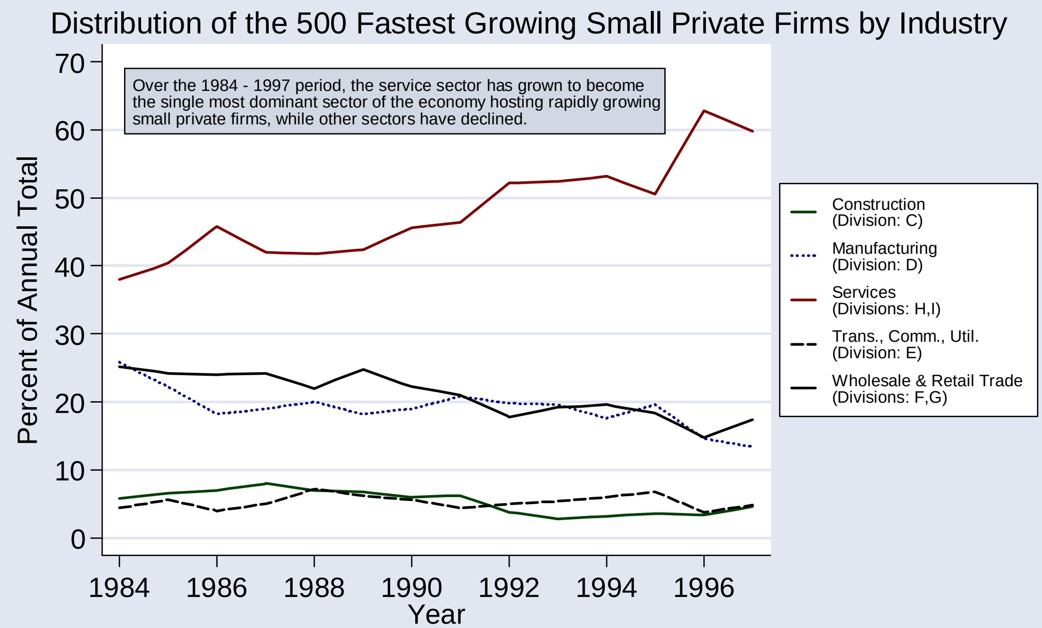
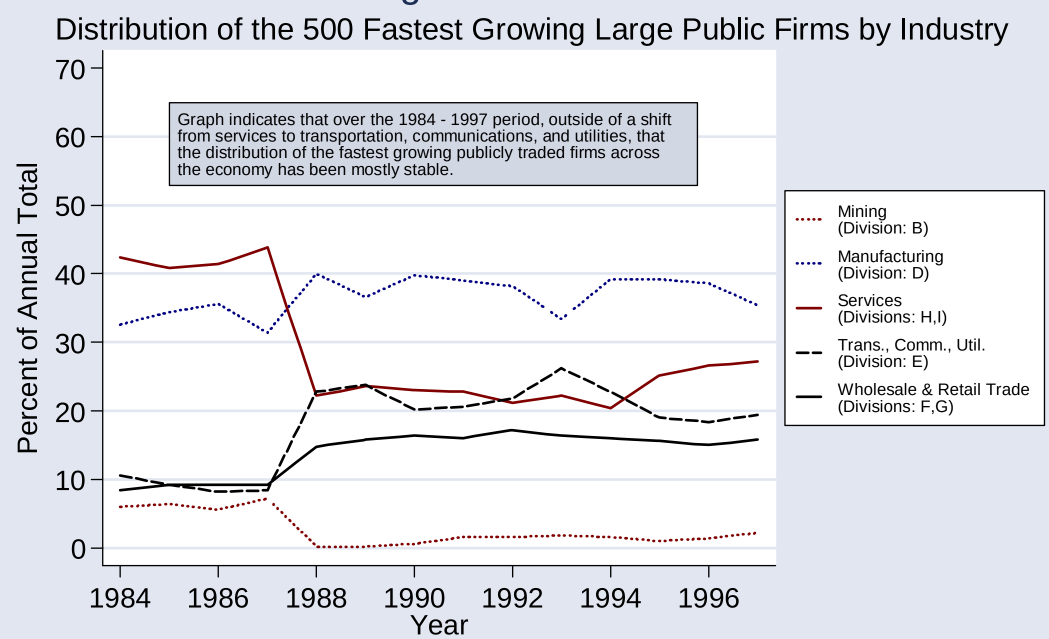
Figure 1



Distribution based on the Inc. 500. The Inc. 500 is an annual ranking of the 500 fastest growing small private firms published by Inc. magazine. Ranked firms must have had sales less than $25 million in the base year. Agriculture (divison A) and Mining (division B) are not shown due to lack of activity.

Figure 2



The 500 fastest growing large public firms by industry are computed by ranking, based on 5 year growth rates in sales, the 500 fastest growing publicly traded firms based on data provided by COMPUSTAT (see text). Agriculture (division A), and Construction (division C) are omitted due to lack of activity.

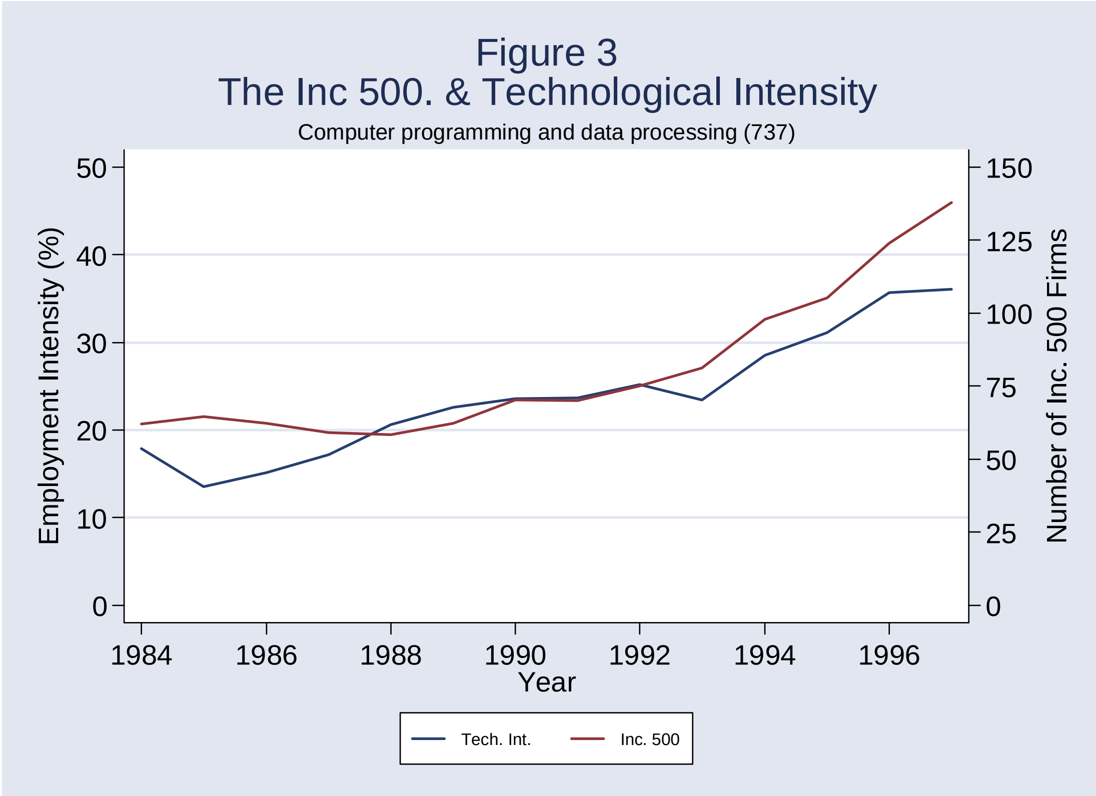


Figure 3
The Inc 500. & Technological Intensity
Computer programming and data processing (737)
Employment Intensity (%)
Number of Inc. 500 Firms
0
10
20
30
40
50
0
25
50
75
100
125
150
1984
1986
1988
1990
1992
1994
1996
Year
Tech. Int.
Inc. 500

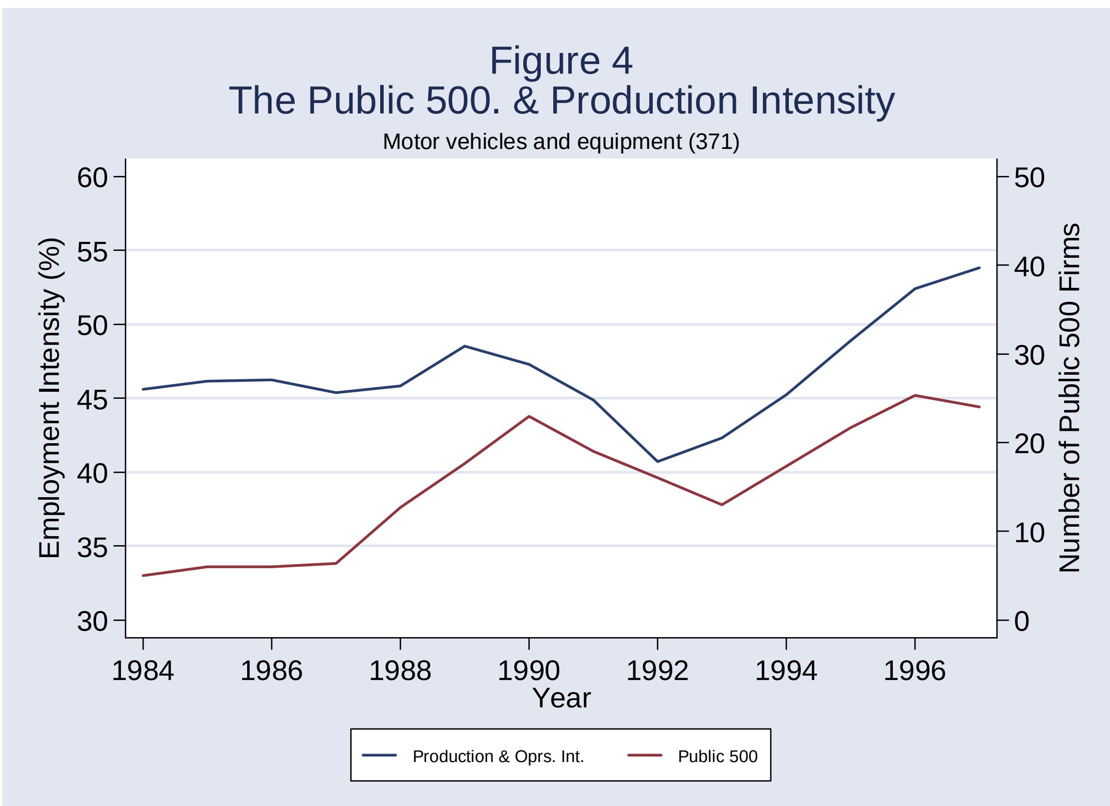


Figure 4
The Public 500. & Production Intensity
Motor vehicles and equipment (371)
Employment Intensity (%)
Number of Public 500 Firms
30
35
40
45
50
55
60
0
10
20
30
40
50
1984
1986
1988
1990
1992
1994
1996
Year
Production & Oprs. Int.
Public 500

Table 1: Occupations

Panel A: Technology Occupations
Actuaries
Aerospace engineers
Agriculturial engineers
Atmospheric and space scientists
Chemical engineers
Chemists, except biochemists
Civil engineers
Computer systems analysts and scientists
Electrical and electronic engineers
Engineers, n.e.c.
Geologists and geodesists
Industrial engineers
Marine and naval architects
Mathematical scientists, n.e.c.
Mechanical engineers
Metallurgical and materials engineers
Mining engineers
Nuclear engineers
Operations and systems researchers and analysts
Petroleum engineers
Physical scientists, n.e.c.
Physicists and astronomers
Statisticians

Panel B: Sales & Distribution Occupations
Advertising and related sales occupations
Auctioneers
Cashiers
Demonstrators, promoters and models, sales
Insurance sales occupations
News vendors
Real estate sales occupations
Sales counter clerks
Sales engineers
Sales occupations, other business services
Sales representatives, mining, manufacturing & wholesale
Sales support occupations, n.e.c.
Sales workers, apparel
Sales workers, furniture and home furnishings
Sales workers, hardware and building supplies
Sales workers, motor vehicles and boats
Sales workers, other commodities
Sales workers, parts
Sales workers, shoes
Sales workers; radio, TV hi-fi & appliances
Securities & financial services sales occupations
Street and door-to-door sales workers
Supervisors and proprietors, sales occupations

Panel C: Production & Production Operators
Assemblers
Boilermakers
Bridge, lock, and lighthouse tenders
Bus drivers
Cementing and gluing machine operators
Compressing and compacting machine operators
Construction laborers
Crane and tower operators
Crushing and grinding machine operators
Drilling and boring machine operators
Driver-sales workers
Engravers, metal
Excavating and loading machine operators
Extruding and forming machine operators
Fabricating machine operators, n.e.c.
Folding machine operators
Forging machine operators
Freight, stocks, and material handlers, n.e.c.
Furnace, kiln, and oven operators, exc. food
Garage and service station related occupation
Garbage collectors
Grader, dozer, and scraper operators
Graders, and sorters, exc. agricultural
Grinding, abrading, buffing, & polishing machine operators
Hand cutting and trimming occupations
Hand engraving and polishing occupations
Hand engraving and printing occupations
Hand molding, casting, and forming occupations
Hand packers and packagers
Hand painters, coating, and decorating occupations
Heat treating equipment operators
Helpers, construction trades
Helpers, extractive occupations
Helpers, mechanics and repairers
Helpers, surveyor
Hoist and winch operators
Industrial truck and tractor equipment operators
Knitting, looping, taping & weaving machine operators
Laborers, except construction
Lathe and turning machine operators
Lathe and turning machine set-up operators
Laundering and dry cleaning machine operators
Lay-out workers
Locomotive operating occupations
Longshore equipment operators
Machine feeders and offbearers
Machine operators, not specified

Panel C (continued): Production & Production Operators
Machinist apprentices
Machinists
Marine engineers
Metal plating machine operators
Milling and planing machine operators
Miscellaneous hand working occupations
Miscellaneous machine operators, n.e.c.
Miscellaneous material moving equipment operators
Miscellaneous metal & plastic processing machine operators
Miscellaneous metal, plastic, stone & glass working machine operators
Miscellaneous precision metal workers
Miscellaneous printing machine operators
Miscellaneous textile machine operators
Miscellaneous woodworking machine operators
Mixing and blending machine operators
Molding and casting machine operators
Motion picture projectionists
Motor transportation occupations, n.e.c.
Nail and tacking machine operators
Numerical control machine operators
Operating engineers
Packaging and filling operators
Painting and paint spraying machine operators
Parking lot attendants
Patternmakers and model makers, metal
Photoengravers and lithographers
Photographic process machine operators
Precious stones and metals workers, jewelers
Precision assemblers, metal
Precision grinders, filers, and tool sharpeners
Pressing machine operators
Printing press operators
Production helpers
Production inspectors, checkers and examiners
Production samplers and weighers
Production testers
Punching and stamping press machine operators
Rail vehicle operators, n.e.c.
Railroad brake, signal, and switch operators
Railroad conductors and yardmasters
Rolling machine operators
Sailors and deckhands
Sawing machine operators
Separating, filtering, and clarifying machine operators
Shaping and joining machine operators
Sheet metal worker apprentices
Sheet metal workers

Panel C (continued): Production & Production Operators
Ship captains & mates, except fishing boats
Shoe machine operators
Slicing and cutting machine operators
Solderers and brazers
Stevedores
Stock handlers and baggers
Supervisors, handlers, equipment cleaners, and laborers
Supervisors, material moving equipment operators
Supervisors, motor vehicle operators
Taxi cab drivers and chauffeurs
Textile cutting machine operators
Textile sewing machine operators
Tool and die maker apprentices
Tool and die makers
Truck drivers, heavy
Truck drivers, light
Typesetters and compositors
Vehicle washers and equipment cleaners
Washing, cleaning, and pickling machine operators
Welders and cutters
Winding and twisting machine operators
Wood lathe, routing & planing machine operators

Table 2: Description of Variables

Variable	Description
Inc. 500	Industry counts of Inc. 500 firms as provided by *Inc.* Magazine.
Public 500	Industry counts of Public 500 firms, computed as the 500 fastest growing firms in sales over 5 a year period per year with at least 500 million dollars in sales in base year.
Tech. Intensity	Technological employment (scientists, engineers, etc). Industry employment of individuals employed or self employed in occupations concerned with the application of scientific and mathematical knowledge to the conduct or research and development and related activities in industry divided by total industry employment (see data appendix).
Sales & 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 (see data appendix).
Production & Operators Intensity	Individuals working in production occupations (employed and self employed) divided by total industry employment (see data appendix).
Total Establishments	Total establishments by industry-year.
Patent Intensity	Patents granted to non-government entities (commercial firms and individuals) divided by total industry employment.
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.
Year 1983 - 1987	Year dummy variable, set to 1 for year 1983 - 1987, 1993 - 1997 omitted case.
Year 1988 - 1992	Year dummy variable, set to 1 for year 1988 - 1992, 1993 - 1997 omitted case.
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.
Log Industry Sales	Log of the total sales in the industry by year.

Table 3: Industry Rankings
(1984- 1997)

Panel A: Top 10 Industries in Terms of Number of Fast Growing Publicly Traded Firms with Sales of at Least 500 Million Dollars a Year in Base Year

N	SIC	Label
577	602	Commercial banks
366	491	Power Generation, Transmission, or Distribution
343	737	Computer programming, data processing, and other computer related services
303	481	Telephone
281	283	Drugs
231	371	Motor vehicles and equipment
211	357	Computer and office equipment
183	493	Combination utility services
183	541	Grocery stores
144	451	Scheduled air transportation and air courier services

Panel B: 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
1,222	737	Computer programming, data processing, and other computer related services
504	873	Research, development, and testing services (except noncommercial research organizations)
467	573	Radio, television, consumer electronics, and music stores
309	357	Computer and office equipment
264	506	Electrical goods
247	871	Engineering, architectural, and surveying services
235	736	Personnel supply services
203	152	General contractors--residential buildings
194	738	Miscellaneous business services
146	356	General industrial machinery

Table 4: Correlation Table

		Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Inc. 500	2.69	8.68	1										
(2)	Public 500	2.41	5.29	0.27	1									
(3)	Tech. Int.	0.01	0.04	0.47	0.34	1								
(4)	Sales & Rel Int.	0.13	0.18	0.00	-0.05	-0.17	1							
(5)	Production & Oprs. Int.	0.20	0.18	-0.16	-0.08	-0.10	-0.36	1						
(6)	Total Establishments	3.63	6.96	0.28	0.04	0.02	0.12	-0.25	1					
(7)	Patent Int.	16.62	65.63	-0.04	0.02	0.29	-0.15	0.12	-0.10	1				
(8)	Percent Large Establishments	0.03	0.06	-0.07	0.12	0.04	-0.29	0.27	-0.22	0.10	1			
(9)	Years 1983 - 1987	0.27	0.44	0.00	0.02	-0.06	-0.10	-0.13	-0.02	-0.05	0.03	1		
(10)	Years 1988 - 1992	0.63	0.48	0.00	0.01	-0.03	-0.08	-0.07	-0.03	-0.04	0.03	0.47	1	
(11)	Applied Tech. Intensity	0.01	0.03	0.51	0.29	0.55	-0.15	-0.21	0.09	0.18	0.18	-0.02	0.00	1
(12)	Log Industry Sales	10.60	3.60	0.23	0.46	0.34	-0.08	0.04	0.12	0.09	0.22	-0.07	-0.09	0.26

Table 5: Negative Binomial Fixed Effects Regressions

	Inc 500	Public 500	Inc 500	Public 500
	(1)	(2)	(3)	(4)
Tech. Int.	3.80***	-3.98***	3.89***	-3.75***
	(.533)	(.833)	(.534)	(.849)
Sales & Rel Int.	-0.222	-0.227	-0.407	-0.172
	(.284)	(.37)	(.294)	(.372)
Production & Oprs. Int.	-.656**	.835***	-.746**	.843***
	(.319)	(.273)	(.323)	(.274)
Total Establishments	.0167***	.0148**	.0131**	.0162**
	(.00525)	(.00697)	(.00573)	(.00693)
Patent Int.	-0.00173	0.000414	-0.00173	0.000436
	(.00106)	(.000278)	(.00106)	(.000278)
Percent Large Establishments	3.87	1.56	3.58	1.80*
	(2.39)	(.989)	(2.42)	(1.01)
Years 1983 - 1987	0.0593	-0.0643	.0687*	-0.0785
	(.04)	(.0529)	(.0414)	(.0534)
Years 1988 - 1992	.0805**	-.0693*	.0719**	-.0938**
	(.0356)	(.0418)	(.0366)	(.0436)
Log Industry Sales			0.00846	-.0378**
			(.0118)	(.0182)
Constant	3.98***	1.59***	3.98***	2.11***
	(.494)	(.142)	(.524)	(.287)
Observations	2608	2110	2317	2110
Number of Industries	192	154	180	154
Years	14	14	14	14
Chi-Square	107.78	51.01	112.16	54.66

Standard errors in parentheses. * significant at 10%; ** significant at 5%;
*** significant at 1%. All independent variables are lagged one period.

Table 6: Negative Binomial Fixed Effects Regressions

	Inc 500	Public 500	Inc 500 (Drop Computing SICs)	Public 500 (Drop Computing SICs)	Inc 500 (Drop Commercial Banking SIC)	Public 500 (Drop Commercial Banking SIC)
	(1)	(2)	(3)	(4)	(5)	(6)
Tech. Int.	3.75***	-3.76***	3.48***	-2.44**	3.80***	-3.63***
	(.501)	(1)	(1.09)	(1.13)	(.533)	(.833)
Sales & Rel Int.	-0.215	-0.226	-0.178	-0.393	-0.222	-0.185
	(.277)	(.37)	(.328)	(.375)	(.284)	(.365)
Production & Oprs. Int.	-.645**	.823***	-.554*	.752***	-.656**	.934***
	(.316)	(.274)	(.334)	(.277)	(.319)	(.273)
Total Establishments	.0139***	.0149**	.0128**	.0142**	.0167***	0.0105
	(.00527)	(.00697)	(.00547)	(.00692)	(.00525)	(.00725)
Patent Int.	-0.00157	0.000412	-0.00168	0.000345	-0.00173	0.000396
	(.00106)	(.000278)	(.00116)	(.000284)	(.00106)	(.000278)
Percent Large Establishments	3.91	1.58	6.19**	1.19	3.87	1.6
	(2.37)	(.99)	(2.93)	(.976)	(2.39)	(.988)
Years 1983 - 1987	0.0318	-0.0655	0.0229	-0.0754	0.0593	-0.0355
	(.0402)	(.0529)	(.0461)	(.0541)	(.04)	(.0533)
Years 1988 - 1992	.0989***	-0.0677	.137***	-0.0586	.0805**	-.082*
	(.0352)	(.042)	(.0399)	(.0432)	(.0356)	(.0426)
Applied Tech. Intensity	-2.17***	-0.578				
	(.678)	(1.49)				
Constant	4.59***	1.59***	3.86***	1.56***	3.98***	1.52***
	(.758)	(.143)	(.616)	(.144)	(.494)	(.143)
Observations	2608	2110	2552	2063	2608	2105
Number of Industries	192	154	188	150	192	153
Years	14	14	14	14	14	14
Chi-Square	134.08	50.93	41.16	29.87	107.78	49.02

Standard errors in brackets. * Significant at 10%; ** significant at 5%; *** significant at 1%. All independent variables are lagged one period.

DATA APPENDIX

The data for the occupation employment measures of technological employment, sales employment, and production employment, were drawn from the current population survey and allocated to three digit 1987 SIC codes using the procedure describe in this appendix.

We utilize employment based measures of technological intensity, sales intensity, and production intensity for two reasons. First, this approach permits us to develop consistent measures spanning multiple years thereby allowing us to utilize fixed effects models that enable us to control for unobserved heterogeneity between industries that could potentially confound our findings (Greene, 2000). Second, these measures compare favorably to other approaches used to measure these constructs. For example, in the case of technological intensity, research and development expenditures are not widely available for small firms, National Science Foundation data on research expenditures does not span the entire economy and under-samples small firms,[3] 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 involved in the systematic application of advanced scientific and mathematical knowledge to commercial problems in industry (OMB, 1987; Merrill & 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 correlations for 1989 between the CPS ratio of scientific and engineering employment share and the NSF employment share data for manufacturing industries is .96, while the correlation between the same statistic and a company's own R&D funds as a percent of sales reported by NSF for selected manufacturing industries is .86.

Source

Counts of industry employment of scientific fields were drawn from the National Bureau of Economic Research's (NBER) extracts of the merged outgoing rotation groups (MORG) of the current population survey administrated by the Bureau of Labor Statistics.[4] The NBER extracts contain employment and occupation information on approximately 360,000 individuals each year (Feenberg & Roth, 2001). For each month, each record in the file contains detailed

[3] 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, data coverage is biased towards industries traditionally known for extensive R&D expenditures, thereby limiting the ability of the data to truly capture fundamental changes in R&D activities.

[4] Information on the NBER MORG CDs can be found out the National Bureau of Economic Research's Internet web site at www.nber.org. The specific url at the time of writing is: www.nber.org//data/morg.html. Detailed information on the history and current implementation of the survey can be found at Bureau of Labor Statistics' Internet web site: www.bls.gov.

labor market information on a single individual, including occupation, employment classification, and industry of employment. Like individuals and weights are estimated and assigned by the BLS so estimates of actual counts of individuals can be computed directly from the raw survey (BLS, 2002). The weights used in this study to compute estimates of total technological industry employment are the same weights used to compute the official U. S. Government labor force statistics released each month (Feenberg & Roth, 2001). As the CPS is a household survey, it does not suffer from systematic under-sampling of small firms, which is common with other employee and establishment based surveys conducted by the government (BLS, 1997). Hence, the CPS is well suited to measuring the actual utilization of employment across all firms in the industries in our sample.

Procedure

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 1984 through 1997 for individuals in occupation codes that were representative of four broad occupations of technological employment. Employment across all technological occupation categories, including self-employed, 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'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 the procedure utilized, see Autor et al. (1998, 1207).

Once the data was transformed into a consistent panel across the 1984 through 1997 period, an additional step was necessary before the data could be utilized. The Bureau of Labor Statistics uses the Census Industry Classification (CIC) system in the current population survey, instead of the OMB SIC systems on which this study is based. A concordance between the CIC industry system and the OMB SIC system was developed that is based on the concordance included in the documentation provided by BLS between the CIC system and the OMB 1987 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).

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