# Where Do New Firms Come From?

## Science and Innovation Precursors of de Novo Population Emergence in Nanotechnology 1970-2004 *

Claudia Bird Schoonhoven[a] and Sang-Joon Kim[b]
[a]Paul Merage School of Business
University of California, Irvine
Irvine, CA 92617
kschoonh@uci.edu
[b]Paul Merage School of Business
University of California, Irvine
Irvine, CA 92617
sangjok@uci.edu

**Abstract**

Where do new science-based populations come from? While we know much about how new science and technology are discovered and transmitted within and across existing firms, we have limited understanding about how new science and technology impact de novo firm formation and new industry emergence. Drawing on institutional and ecological theory, we test hypotheses about the impact of new science, technology, and human resources on the birth rate of dedicated de novo nanotechnology organizations from 1970-2004. We found that growth in scientific knowledge increases the birth rate and the effect is curvilinear (inverted U-shape). In contrast, technical knowledge growth as patents, decreases birth rates. Human capital availability is a significant factor with growth of nano scientists increasing but growth of nano patent authors decreasing birth rates of de novo dedicated nanotechnology firms. Fifty percent of the de novo population was founded before institutional legitimacy for the field was achieved. We discuss implications for theory and managerial and policy applications.

### Introduction and Theoretical Background

We have learned a great deal about how technology and innovation processes operate within existing firms and across organizations and industries. This includes for example studies of in-house research, technology alliances, organizational networks, and acquisition of innovative firms (e.g. Utterback, 1971; Utterback et al., 1988; Brown & Eisenhardt, 1997; Eisenhardt & Schoonhoven, 1996; Rosenkopf et al. 2001; Tushman, 2004; Gulati, 2007). However we have limited understanding about how new populations of science-based organizations emerge from theoretical breakthroughs and scientific research about the new science. We do not know how scientific knowledge growth combines with the availability of human resources to impact new population emergence. In this paper we investigate these questions by drawing from ecological and institutional theory to predict the birth of de novo dedicated nanotechnology organizations from 1970 to 2004.

Ecological theory has contributed substantially to research on organizational foundings. Several scholars have built on Stinchcombe's (1965) theoretical article analyzing the social,

political, and economic conditions associated with the rise of new organizational forms (Aldrich, 1979; Brittain and Freeman, 1980; Marrett, 1980; Pennings, 1982). With articulation of the organizational ecology perspective (Hannan & Freeman, 1977), the effects of prior foundings and population density on the arrival process of new organizations were worked out in studies of new Argentine and Irish newspaper organizations, local newspapers in the US, and national labor unions in the US, (Delacroix & Carroll, 1983; Carroll & Huo, 1986; Hannan & Freeman, 1987), respectively.

Between 1975 and 2009, seventy papers on organizational foundings or birth rates were published (Kim, 2010), and their theoretical bases are primarily in population ecology, community ecology, and occasionally institutional theory. A conceptual analysis of these reveals that the two largest clusters of birth rate research exist at the level of the external environment. Many focus on the role of population density on births where overtime, increasing population density has a curvilinear effect on birth rates. Increasing density first signals greater population legitimacy which in turn creates greater population competition and a decrease in birth rates. The second cluster of research examines the effects of environmental munificence on birth rates, with effects dependent on the specific indicator of munificence addressed. For example, industry concentration decreases the birth rate, but market concentration and resource availability increase birth rates. Unfortunately, only six of the seventy studies of birth rates touch upon the roles of science, technology or innovation.

In the next sections of this paper we review this limited literature base and develop a set of testable hypotheses about the effects of science and technology on the emergence of a de novo science-based population. We describe the discrete-time hazard model used to assess the population emergence process, present descriptive data, and graph major events in emergence of the dedicated nanotechnology population. To foreshadow results of the statistical analysis, we found that between 1970 and 2004, the accumulation of scientific knowledge stocks increase the birth rate of dedicated de novo nanotechnology organizations, with an inverted U-shaped curvilinear effect. However technology growth rates (as patents) have a negative effect on the birth rate. As the pool of potential entrepreneurs grows, growth in *scientific* human resources required to launch an entirely new population, the greater the birth rate. However increases in patent authors, the *technical* human resources required, decrease the birth rate. We introduce the concepts scientific and technical knowledge productivity, and find that these constructs interact for a negative effect on births. The models control for venture capital fund availability, prior de alio entrants, prior de novo foundings, and period effects for the date when nanotechnology was recognized by the U.S. government according formalized institutional legitimacy.

## Theory and Hypotheses

### The Role of Scientific Knowledge in New Population Emergence

In this paper we argue that de novo science-based populations emerge from two types of new knowledge: theoretical, academic knowledge as well as technical, practical knowledge. The first, theoretical and academic knowledge, can be characterized by the overall body of knowledge that develops over time, as captured by the growth rate of published scientific articles in the realm. The second, technical, practical knowledge, can be characterized by the accumulation of patent applications in the defined scientific realm. That is, technical knowledge as patents, accumulates such that products and services can potentially be created and sold commercially based on the technical knowledge contained within the patents. Hence, a major distinction between scientific knowledge and technical knowledge is the time lag that follows

new scientific knowledge creation before it is operationalized for potential commercial products and services for the market.

Before an identifiable population of organizations emerges dedicated to a new scientific realm, scientists in universities, government labs, and existing organizations investigating basic questions are creating a science base on which to build potentially patentable technology for commercialization. Specifically the relevant organizational sources for de novo population emergence will be a scientific community residing across multiple institutional settings creating theoretical knowledge within a delineated scientific realm. Scientific knowledge is freely shared among members of a scientific community through published journal articles and conferences that can be cited but which do not have the legal standing of protected intellectual property. While typically theoretical and not directly commercializable, scientific knowledge is nonetheless a critical building block for its eventual practical application in organizations. For example Feynman's (1959) theoretical claim that nano-dimension particles exist empirically was the building block which launched the fields of nanoscience and nanotechnology.

Zucker, Darby, and Brewer (1998) studied new biotech subunits in existing (de alio) biotechnology firms and new entrants. They found that the timing and location of both new entrants and new biotech subunits of incumbents are explained by when and where star scientists publish scientific articles about genetic-sequence discoveries in academic journals. "Star scientists" are defined as the 327 outstandingly productive scientists who represent only three quarters of one percent of the *GenBank* (1990) scientific authors, but account for almost 22 times as many articles as the average scientist. Zucker and colleagues focused on star scientists because they believed that for the first years of a new industry, knowledge held by an initially small group of discoverers would be critical to new industry launch. They found that star scientists' *locations* helped predict the locations of new divisions of existing biotech firms and new biotech organizations. From the perspective of large-scale data collection and manipulation, (i.e. otherwise collect data on all 200,000+ scientists and their locations), focusing only on a small proportion of the scientific population makes sense. However, this research leaves open the broader question about how the development of new science as a body of knowledge is related to emergence of an exclusively de novo population of organizations, independent of geographic location and independent of an existing corporation's stable support.

Next, focusing on nanotechnology publications and new entrants, Darby and Zucker (2003) expected high impact academic articles to have a significant impact on the county *location of new entrants* (2003: 19). Again, focusing on only a small proportion of the most cited articles (according to the ISI high-impact database), each is linked to the US *county location* of the article author(s). They defined "firm entry" as the first year a given organization's employees publish a nanotech article in an academic journal - essentially using date of first published scientific article to proxy for date of birth. The problem with this definition is that firms doing the publishing may well be existing organizations, as de novo firms require time beyond their founding dates (typically 12-36 months, Schoonhoven, Eisenhardt, & Lyman, 1990) to develop new technology. Darby and Zucker (2003) do not report organizational age of these firms when they publish their first nanotech article and they do not distinguish between de alio (extant) and de novo organizations.[1] Hence, the findings regarding our dependent variable, the

[1] In a prior 1998 study of biotechnology firms, Zucker, Darby, and Brewer did distinguish the two sources of new biotech organizations; 68% of their sample of 751 biotechnology firms were new entrants or de novo organizations in our terminology.

founding of dedicated de novo organizations, are confounded. They found that the county location of highly cited academic articles have a positive and significant effect on the county location of nanotechnology firm "entry", as first publication. They also found that regional research funding (in millions of dollars allocated to the top-100 universities in the US,) has a significant positive impact on the county location of a firm publishing its first article (i.e. entry) on nanotechnology in the US.

In contrast to Zucker and colleagues' emphasis on star scientists' locations and high impact publications, we argue that it is the body of scientific knowledge that accumulates *in toto* over time that will be influential in the founding of de novo organizations in a given population. That is, it is the knowledge stock created by multiple scientists in a community rather than just the exceptionally productive, star scientists and their high impact publications that will be related to new firm formation over time. Indeed, in their star scientists paper, Zucker and Darby (1996) noted that the stars accounted for less than one percent of all authors who published in *GenBank*, the data source for biotech science articles.

We expect that there will be a non-monotonic effect of growth in scientific publications on new firm formation. That is, initially growth in scientific publications will be positively related to the rate of de novo firm foundings, however over time growth in scientific publications will be associated with a decrease in the number of new firms formed. With the increase having a decreasing effect, this basically places a limit on the (expected) positive effects of growth rates in scientific knowledge on birth rates. We expect an upper limit on the utility of new scientific knowledge as the knowledge ages. Therefore we hypothesize:

- *$H_1$ There will be a curvilinear effect of growth in scientific knowledge on the founding rate of dedicated nanotechnology organizations: initial knowledge growth will have a positive effect followed by a negative effect over time.*

**The Role of Technical Knowledge in New Population Emergence**

In addition to scientific knowledge, new organizations founded in new realms of science require information about how to apply it. Practical applications are often developed in-house in the initial R&D stage of new organizations, or perhaps by licensing the technology of others. A license may be granted (for a fee typically) if the knowledge is patented by another. Many studies have used the attributes of patent applications to measure a variety of constructs related to technology transfer (see Bozeman, 2000 for a review). However few have linked patented technology to de novo population formation. Two small scale studies by Shane (2001a & b) link patents to new firm formation. Focusing on technology regimes, he found that the technical field's age, market segmentation, patent effectiveness, and complementary assets (regime dimensions) influence the likelihood that a given patent will be exploited through firm formation (2001b). In the second study, he conceptualized patents as technological "opportunities" for exploitation. He found that more radical patented inventions, more important patents, and patents with broader scope were more likely to be commercialized by new firms (2001a). So in these two small-scale studies based on MIT patents, individual patents were linked to the probability of being exploited by new firm formation. These patents are not viewed as "knowledge stock" to use Zucker & Darby's phrasing, but rather as opportunities for exploitation. Furthermore, the causal links in Shane's studies are between individual patents and individual firms (the organizational level of analysis), rather than between technical knowledge stocks and new population formation.

In a large scale study, Calabrese, Baum & Silverman (2000) conceptualized incumbent biotech's patenting activities as attempts to stabilize and control potential competition. They found that increases in the level and concentration of incumbents' patents discouraged foundings. In the empirical setting of our study, the first nanotechnology patent was filed in 1970. Early patents were filed exclusively by existing organizations like IBM (Woolley, 2007) because the first de novo founding did not occur until 1982 as data collected for the current study demonstrate, to follow.

Whether the patent filing organization is an incumbent or a de novo firm, we expect that the accumulation of practical nanotechnology knowledge will play a negative role in de novo population emergence. Following Calabrese and colleague's (2000) findings, we hypothesize:

- *$H_2$ The growth of nanotechnology technical knowledge (patents) will have a negative effect on the founding rate of dedicated nanotechnology organizations.*

**Human Resources: Pool of Potential Entrepreneurs**

We expect that the pool of potential nanotechnology entrepreneurs will be drawn from both scientists and engineers who have acquired scientific and technical knowledge through their education and work experience, which can be tapped via their publications and patents. There is substantial literature that shows that composition of the start up and top management teams in new science-based organizations are drawn from individuals with work experience and scientific training in related industries (Eisenhardt & Schoonhoven, 1990; Schoonhoven, Beckman, & Rottner, 2011; Low & MacMillan, 1988). In the case of an emergent, de novo population, the relevant pool will be drawn from individuals with related experience and relevant education. Related experience is defined as education or work experience in a field tangential to the focal industry (since it is just emerging). For example, employees in the semiconductor industry frequently leave it to start up companies in the related software industry, because a great deal of computer programming is required for semiconductor devices to behave as designed. Hence, this is related experience applicable in the software industry, which has higher profit margins.

In the context of nanotechnology start up firms, nanoscience is applicable across a broad range of existing industries. Hence, individuals experienced in the plastics and paint industries could start a firm in the nano materials industry, since some industrial coatings have now been reduced to nano size particles. Related experience is also found in individuals who do research on nano phenomena. These may be scientists who reside in industrial laboratories and universities. These may also be engineers who apply the basic science to create devices and materials suitable for commercialization – typically embedded in existing companies, which in turn patent their knowledge. Therefore, we have two hypotheses about the requirement of human resource pools for emergence of de novo populations.

First, we expect that scientists who publish journal papers on nanoscience will be members of the potential pool of entrepreneurs. Zucker and Darby (2002, 2003b) demonstrated the importance of star scientists in the founding of new science-based industries. We build on their findings but argue that it is the body of scientists working in a focused scientific arena rather than simply the very small proportion of "star scientists" who play a significant role in the formation of a de novo population. In this analysis, we view scientists as an independent pool of human resources. Therefore we treat these two populations of potential entrepreneurs separately and hypothesize:

- *$H_3$ Growth in the pool of individuals with scientific knowledge about nanotechnology will have a positive effect on the founding rate of dedicated de novo nanotechnology organizations.*

- *$H_4$ Growth in the pool of individuals with technical knowledge about nanotechnology will have a positive effect on the founding rate of dedicated de novo nanotechnology organizations.*

**How do Knowledge and Human Resources Interrelate?**

We expect that knowledge growth and human resource growth will interact to influence the founding of de novo nanotechnology organizations. Ideally we would like to simultaneously take into account the effects of scientific knowledge and the pool of scientists, as well as the effects of technical knowledge and the pool of technically trained individuals. As described later in research methods, when growth rates for these variables are calculated, the statistical advantage is to reduce autocorrelation and potentially biased estimates and thereby enhance reliability of the construct's measure. In contrast, an alternative conceptualization of knowledge and human resource pools is cumulative knowledge, which tends to increase systematically as the number in a given time period is added to the previous time period's value, in turn inducing autocorrelation. Furthermore, these four variables are observed over the same time period, 1970 to 2004, potentially triggering time-based multicolinearity of the four. To avoid this problem and to extend our theoretical conceptualization, we introduce the constructs *scientific knowledge productivity* and *technical knowledge productivity*. These constructs are borrowed from demographic research (Hinde, 1998) which speaks of fertility rates, defined as the propensity of women in a population to bear children. We define scientific (or technical) knowledge productivity as the propensity of human capital (scientists or engineers) to create or codify new knowledge (scientific or technical). In the absence of prior research to guide our hypothesis but with an expectation that the two productivity constructs are related in a complex manner, we propose a general interaction hypothesis:

- ***$H_5$: There will be an interaction effect of scientific knowledge productivity and technical knowledge productivity on de novo nanotechnology birth rates over time.***

First, we will test the basic hypothesis above. If it is statistically significant, we will then plot the interaction to gain greater knowledge of complexity of the relationship, acknowledging the exploratory nature of any additional analyses.

**Controls**

As we are seeking to understand the emergence of the dedicated nanotechnology population, the relevant unit for analysis can be the whole economy or an organizational community, referred to as sectoral analysis (Carroll & Hannan, 2000: 104). In the empirical research reported below, we control statistically for several factors shown in prior research to affect the environmental carrying capacity for the new population. We assume that environmental carrying capacities are stable over time, net of the following controls. We control for population density defined as extant competitors, prior foundings, and availability of Venture Capital funds in the US. Hannan & Freeman (1987) found that birth rates (of labor unions) depend on nonmonotic population density and prior births. To capture changes in the US economy's carrying capacity for de novo organizations, we control for the amount of Venture Capital available for investment for each year.

Last, scholars have written about the necessity for new organizations in a de novo populations to attain socio-political legitimacy (Stinchcombe, 1965). One theoretical paper posits agency action by entrepreneurs to promote socio-political legitimacy of an emerging population (Aldrich & Fiol, 1994). This theory, however, assumes the presence of both entrepreneurs and new organizations in the new population. However, our focus is on population *emergence* and in $T_0$, when no de novo organizations exist in the future population as yet**.** While individual agency may play a part at some point in attainment of socio-political legitimacy, the early new population entrepreneurs themselves will be too time and cash starved to pursue collective rather than more immediate goals of establishing a new company. Hence, our focus is on environmental conditions, essentially institutional conditions which may promote socio-political legitimacy of an emerging population.

We expect that the attainment of socio-political legitimacy will play a part in new population emergence, but only after the first organizations have been founded in the de novo population. We distinguish between the early establishment of population legitimacy signaled by increases in the first de Novo firms formed (Hannan & Freeman, 1977) and socio-political legitimacy, signaled by actions taken by social institutions like governments, universities and scientific associations. We expect that attainment of socio-political legitimacy during the emergence process will accelerate the founding rate. Specifically, in the year 2000, the National Nanotechnology Initiative (NNI) was created in the US. Based on institutional arguments, Lounsbury et al. (2009) referred to the NNI creation in 2000 as a shift from a science-based professional logic to a commercial logic, because it focused attention and increased funding for nano scale development. We expect that foundings will accelerate after the NNI, attributable to both the legitimacy which the national initiative accords to nanoscience and to the government budget allocated for nanoscience research in subsequent years. Hence the logic for this expectation is based on institutionally created population legitimacy whose effect is enhanced by the government's financial commitment accompanying creation of the NNI.

## Data

Data were drawn from a larger proprietary study (Schoonhoven, 2009) of the first generation of de novo firms dedicated to commercializing nano-science, to capture the early years of industry emergence and how new organizations founded to develop high risk new technologies survive and prosper. Several challenges exist when identifying new firms in an emerging set of industries or populations. First, how are the science and technology underpinning the new industry characterized? The *definition* of "nano" is that it is a unit of measure indicating ten to the minus ninth power, or one-billionth of a meter. "Nanoscience" refers to scientific activity that occurs within the range of 1-100 nanometers (Shea, 2005:186). "Nanotechnology" is defined as the development and use of products of a size less than 100 nanometers, requiring manipulation of single molecules, atoms and structures on the nano scale. The second challenge is to identify *when* to expect new organizations to form based on the new science. The "theory" about existence of the nano molecular level was first articulated in 1959 by the Nobel Prize-winning physicist, Richard Feynman. However, substantial theoretical and technological development was required before Freynman's ideas could be operationalized, including development of instruments to study nano scale phenomena and instruments to manipulate nano-scale matter. In 1981, the scanning tunneling microscope (STM) was invented by G. Binnning and H. Rohrer at IBM. Critical to commercialization of nanotechnology, it was

the first instrument to enable scientists to empirically view particles on the nanoscale.[2] Hence, the window of time for identifying new, dedicated nanotechnology firms begins in 1981.

We identified dedicated nanotechnology organizations consistent with Hannan and colleagues' (2007: 37) discussion of audience and producer roles in a domain: new organizations typically announce goals (directly or indirectly) which associate it with the role of producer, essentially claiming competence for membership. We identified de novo dedicated nanotechnology organizations through multiple sources seeking both audience and producer information: press releases (PR Newswire), Lexis-Nexis, investment reports (Forbes and Lux Research), an industry association, the NanoBusiness Alliance, sec.gov (Edgar) for IPO prospectuses, the National Venture Capital Association's data base, and PriceWaterhouse Coopers investment reports. We also obtained a list of firms from Lux Research, an audience member in the domain, with retrospective data published in 2007.

The problem with market research firms, investment houses, and others who collect industry data for sale to others is that they *do not begin to collect data until a market for the information exists*, typically years after the first new firms are founded. Hence the earliest years of a new industry are chronicled by the firms themselves through their press releases and web sites rather than by commercial databases. The first dedicated nanotechnology firm was founded in 1982 to manufacture Fibril nanotubes from high purity low molecular weight hydrocarbons. We confirmed that all organizations included meet the population membership criteria: they are dedicated nanotechnology de novo organizations with no prior organizational existence (Carroll & Hannan, 2000:41); their *first product or technology* is derived from nano-science; they do not produce any other product or technology in any domain other than nanotechnology at founding; and they are private, independent de novo start ups. Excluded are organizations whose starting events were the result of mergers or former corporate divisions or businesses spun-off from an existing organization.

## Measurement Section

### Dependent Variable

***De Novo Dedicated Nanotechnology Firms*.** Consistent with the description above about how we identified the de novo population of dedicated nanoscience organizations, for each organization we collected the founding year and (when available) the month the firm was founded. This is a proprietary data set collected by the authors (Schoonhoven, 2009). The analysis is conducted on a quarterly basis: when a given firm was founded in a given quarter-year it is coded 1; 0 otherwise.

### Covariates

Data for the covariates, Growth Rate of Scientific Knowledge, Growth Rate of Technical Knowledge, Growth Rate of Human Capital as Scientists, and Growth Rate of Human Capital as Engineers were derived from the NSF-funded *NanoBank d*ata set housed at UCLA[3]. We started with the raw data files which list all the scientific articles and their authors, and all patents and their authors, and we created a database appropriate for our analyses. That is, variables were summed to create values for each year. Hence, each of these variables was first measured as the cumulative number of scientific articles (or patents, or article or patent authors) about

[2] Woolley (2007) traced nanoscience history from 1956 through 2005.
[3] See http://www.nanobank.org/ for details on collection of basic data used in this analysis.

nanoscience published in major journals between 1970 and 2004. We summed the number of scientific articles by quarter and over time (or the number of patents, patent authors and article authors). Variables constructed as cumulative values tend to increase systematically because the number of scientific articles (or patents or human resources) generated at each period of time is added to the previous time period's value. Thus, numbers so calculated are not randomly distributed over time, leading to potentially biased estimations. We need to control for the possibility that the previous level of knowledge can determine its current level. In this study, we calculate growth rates over time from quarter to quarter, an alternative measure of knowledge (or human capital) which reduces the autocorrelation bias. Therefore, the growth rate measures are used in equations to test our hypotheses.

***Growth Rate Measures (scientific knowledge, technical knowledge, human resource pools of scientists & engineers)*:** The growth rate is operationally defined as the level of *flow* in a focal time interval. Borrowing the distinction made about stocks and flows of assets (Dierickx & Cool, 1989)[4], we understand that the growth rate of knowledge is considered a desired change in accumulated knowledge (e.g. Griliches, 1990). That is, the flow helps to predict the level of stock at a next period of time. To compute flows of knowledge, we assume that knowledge stock is depreciated at a constant rate over time. We assume a conventional value for depreciation of 0.20 as Darby & Zucker (2006) did by adopting Griliches's argument (1990). This measure is the growth rate of knowledge, calculated as:

$$GR_t = \frac{S_t - S_{t-1}}{\Delta t} \qquad \text{(Eq.1)}$$

where $GR_t$ is growth rate at time t; $S_t$ is the discounted stock at time $t$; $S_{t-1}$ is the discounted stock at time $t-1$. Note, that a lower growth rate thus does not indicate lower levels of knowledge accumulation. Human capital is measured slightly differently: confining human capital to the U.S., we measured article authors and patent authors as arrival rates. We counted 1 for the arrival rate of article authors at time $t$ when an author published his/her first article at time $t$. In other words, additional publications by an author post-time t, are not counted. Patent authors are measured in the same way. With these count measures, we computed the growth rate of each human capital indicator above as Equation (1) describes.

**Knowledge Productivity.** Since knowledge is created by individuals, we investigated how the amount of new knowledge produced by a given individual affects new firm emergence. "Knowledge Productivity" is derived from demographic studies where, for example, the fertility rate is defined as the propensity of women in a population to bear children (Hinde, 1998). Analogously, knowledge productivity is defined as the propensity of human capital (scientists or engineers) to create or codify new knowledge, or the extent to which knowledge is produced by pre-existing human capital. Since knowledge is classified as scientific or technical here, we calculate two independent knowledge productivity measures: *scientific knowledge productivity* and *technical knowledge productivity*. By definition, productivity is computed with the following equation.

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[4] *Flow* is the current knowledge or human capital and *stock* is accumulated knowledge or human capital

$$P_t = \frac{K_t}{H_{t-1}} \qquad \text{(Eq.3)}$$

where $P_t$ denotes knowledge productivity at time *t*; $K_t$ represents knowledge growth rates at time t; $H_{t-\Delta}$ is human capital growth rates at time *t-1*.

**Controls**

**VC Funds.** The amount of venture capital available for investment was collected for each of the years of the study (in billions). It has been demonstrated that venture capital plays a significant role in the formation of new firms and the creation of wealth via stock market initial public offerings (NVCA, 2007). The data source is *Venture Economics*, with data supplied by the national Venture Capital Association. Other measures of financial resources, like the Congressional allocation to nanoscience in 2001 and beyond as well as GDP, are highly correlated with venture capital availability.

**Prior Foundings**. The number of prior foundings is defined as the number of de novo firms, dedicated to nanotechnology, founded in the quarter before the focal quarter of a de novo firm's birth.

**Prior Entry of *de alio* Firms**. Since our dependent variable is *de novo* firm births, we need to control for the role of *de alio* firms in the emergence of new firms. *The de alio* population is identified by the presence of a nanotechnology patent application filed between 1970 when the first nanotechnology patent was awarded to 2004, end of our observation period. De alios are existing technology firms patenting nanotechnology from their R&D. Thus, the number of *de alio* entrants is measured as the number of firms to file a nanotechnology patent application in the quarter before the focal quarter of a de novo firm's birth.

**Legitimacy.** Legitimacy is defined as a set of period effects. Based on historical data, we created four periods: 1970-1982, 1983-1997, 1998-2000, and 2001-2004. The number of nanotechnology firms began to increase after 1983, and according to Hannan & Freeman (1997) and Aldrich & Ruef (2006), increasing births signal legitimation of the nanotechnology form. The second and third legitimacy indicators are the establishment of institutions. In 1998, the Interagency Working Group on Nanotechnology (IWGN) was formed under the National Science and Technology Council to investigate state of the art in nanoscale science and technology and to forecast possible future developments (www.nano.gov). This organization encouraged establishment of the National Nanotechnology Initiative (NNI). Created in 2000, it was the first federal acknowledgement of the promise and significance of the field of nanoscience in the US and an indicator of institutionalized legitimacy. From this year and beyond, annual amounts were allocated by Congress for nanotechnology research to agencies like the National Science Foundation (NSF).

We expect that attainment of socio-political legitimacy to promote the founding of more dedicated nanotechnology organizations. As seen in Figure 1 a steep upward curve in the number of births had already been created between 1986 and the year 1999. Hence, the growth of nanotechnology de novo firms is not the result of the scientific field attaining institutional legitimacy, at least not in the United States. However, as Figure 1 shows, post-2001, there is an increase in the rate of de novo foundings.

## Model and Analyses

### Model: Discrete-Time Hazard Model

To investigate effects of scientific and technological conditions on a de novo population's founding rate, we take the population is the unit of analysis and organizational foundings are events in a point process[5] for the population. Organizational births can be treated as an arrival process (Hannan & Freeman, 1987) frequently modeled under assumptions of a Poisson process (e.g. Hannan & Freeman 1987, 1989; Delacroix & Carrol, 1983; Ruef, 2000; Audia, Freeman, Reynolds, 2006; Staber, 1989). The Poisson model treats event counts in an interval as a dependent variable, assuming that the probability of an event is constant over time and that the probability of an event in the interval is independent of the history of the previous arrivals. However, those assumptions have limitations in treating time dependent variables (Amburgey & Carroll, 1984). In effect, founding rates may instantaneously vary depending on the cumulative number of foundings, which would violate the Poisson assumption that the rate of arrival is independent of previous arrivals. For this reason, other studies adopt negative binomial models, which take into account over-dispersion due to unobserved heterogeneity in entry rates (e.g. Hannan et al., 1995; Ranger-Moore, Banaszak-Holl & Hannan, 1991; Lomi, 1995). While the negative binomial model has produced consistent results in founding rate studies (e.g. Delacroix & Carrol, 1983; Ruef, 2000; Audia, Freeman, Reynolds, 2006; Staber, 1989), we need to explicitly model time dependence in our analysis. Since event count models explicitly or implicitly include time-varying variables (Amburgey, 1986), Amburgey & Carroll (1984) suggested using Poisson models with relaxed assumptions, and they recommended the Weibull distribution for time dependence. The parametric approach seems useful to explain time dependence, but if time dependence is due to omitted variables in the model, (i.e., if we cannot specify time dependence with a variable), time dependence should be treated as a nuisance function to be removed from the analysis (Amburgey & Carroll, 1986: p. 50). To deal with time dependence as a nuisance function, they suggested the proportional hazard model developed by Cox (1975), which assumes that covariates affect proportionally as an arbitrary unspecified baseline rate. While the parametric approach to time dependence needs to specify the baseline rate, the proportional hazard model does not require an explicit baseline rate because the baseline rate is mathematically cancelled out when parameters are estimated. Thus, the proportional hazard model has been widely used to investigate state transitions.

However, this model assumes event occurrence is recorded in continuous time. Hannan & Freeman (1989) used Poisson models when they have only yearly count data for events, but for fine-grained event data, they used the Cox model. Their modeling strategy implies that in many cases, it is not easy to determine the exact point of time of event occurrence. The fact that many studies on organizational foundings used the negative binomial model (e.g. Hannan et al., 1995) is evidence for this. It may be possible to define time intervals in which event occurrences may take place. Yet, the time intervals allow tied observations. Techniques exist to treat ties in the proportional hazard model, and partial likelihood functions have been developed (e.g. Tuma & Hannan, 1984; Breslow, 1974). However the model is still vulnerable to tied events: as the number of ties increases, the estimation yields severely biased estimates (Blossfeld, Hamerle, & Mayer, 1989: p. 105). Although we have quarterly data for foundings (i.e. smaller time period

[5] Point process models explain "the situations where discrete "point" events occur in a one-dimensional continuum, usually time" (Amburgey, 1986: p. 191)

than yearly data), there are many ties in many time intervals. As we collected data for predictors in discrete time, this study cannot assume continuous event occurrence.

As a consequence, **discrete time hazard models** are more suited for the analysis of event occurrence data (Singer & Willett, 2003; Blossfeld et al., 1989). Instead of using the Cox proportional hazard model, the discrete-hazard model typically uses an odds ratio, defined as the probability that an event will occur in any time period given that it has not occurred in earlier periods (Singer & Willett, 2003). Taking the natural logarithm of the odds, referred to as a logit transformation, we can use the conditional probability as a dependent variable. In addition, while the Cox models assume that the population is homogeneous, the discrete-time hazard model can introduce the possibility that the population is heterogeneous, i.e. different organizations have different hazard functions for organizing, called observed heterogeneity (Singer & Willett, 2003). Thus, **discrete-time hazard models calculate the probability that a population will experience a firm-emergence event in that time period,** conditioned on no prior event occurrence and particular values for the predictors in that time period.

Adopting the logit discrete-time hazard model in specifying the observed heterogeneous population and considering the dependence of the history of previous events and the current state of the population, our basic model holds that

$$\log\left(\frac{\lambda_t}{1-\lambda_t}\right) = X_{t-1}\beta + Z_{t-1}\pi + \gamma D + \varepsilon \qquad \text{(Eq. 2)}$$ [6]

where $\lambda_t$ denotes the probability of *de novo* firm foundings at time *t*; $X_t$ is a matrix of covariates, which are growth rates of technological knowledge, scientific knowledge, and human capital for technology and science, productivity measures, and $\beta$ is a vector of their coefficients; $Z_t$ is a matrix of control variables[7] and $\pi$ is a vector of their coefficients; *D* denotes a set of time indicators for period effects and $\gamma$ is a vector of their coefficients. The probability of *de novo* firm foundings is estimated with logit transformation of observations of whether a firm is founded at a certain time. To estimate our model above, we need to specify the baseline founding rates. As Singer & Willett (2003) specified, the **baseline for discrete-hazard models** is a function whereby the value of all substantive predictors **is 0**, and thus we focus on shifting this baseline function by a constant amount in each time period per unit difference in the predictor (p.370). Therefore, we can easily fit the discrete-time hazard model and estimate its parameters by using a maximum likelihood method.

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[6] This equation resembles a logistic regression model with correlated data, but its data structure is different. Correlated data in discrete-time hazard models is truncated when the main event occurs (a founding event here), whereas logistic regression models have no truncation rule (Singer & Willett, 2003).

[7] For controls of prior foundings and prior entry, we calculate rate dependence rather than density dependence (Hannan & Freeman, 1987; 1989). Although density dependence is widely used (Hannan & Freeman, 1989), some populations, especially newly formed populations (e.g. McKendrick & Carroll, 2001), will not have non-monotonic effects on firm emergence. Because early in population growth mortality is rare but also the number of firms plays a role only for legitimation (McKendrick & Carroll, 2001). Mortality is also very low within our observation window. Furthermore, the density measures are highly correlated with other predictors, because we treat time-dependent variables. In this situation, we believe rate dependence is more valid for the early period of population growth; therefore we adopt the concepts of stock and flow.

## Results

Figure 1 graphs the time span of major events in emergence and growth of the population of de novo dedicated nanotechnology organizations, from 1956 to 2004. In 1956 Feynman first articulated his theory about the existence of nano scale elements. Twenty-six years transpired before the first dedicated nanotechnology organization was founded in 1982, so the time span between first theory articulation and first firm founding is a quarter of a century for this population. Fifteen years later, in 1997, the first 25% of the dedicated de novo firms had been founded, and by the year 2000 (44 years later), 50% of the de novo population already existed, before any institutional recognition or support was allocated for nanotechnology research and development in the U.S. However, the effect of the NNI was a belated acceleration of the founding rate: two years later, by 2002, 75% of the population had been founded, and by 2004, the end of our observation period, the first wave of dedicated de novo nanotechnology organizations was complete.

---

Insert FIGURE 1 about here

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Moving next to statistical analyses, Table 1 has descriptive statistics and Table 2 *(deleted for submission)* reports bivariate Pearson correlations.

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TABLE 1 Descriptive Statistics about here

TABLE 2 Correlation Matrix *deleted for submission*.

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As discussed earlier, cumulative values tend to be correlated with one another over time but growth rates less so. The correlation between number of patents (stock) and growth rate of patents (flow) is -.40, indicating a successful distinction between stocks and flows for each of the variables noted above. Table 2 *(deleted for Academy)* shows a pattern of diminished correlations between measures for articles, patents, authors of patents and authors of scientific articles, and their growth rates.

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TABLE 3 Discrete-Time Hazard Models about here

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Table 3 reports results for Discrete-Time hazard models predicting the birth rate of de novo dedicated nanotechnology organizations. First, we control for the effects of Venture capital availability, prior de alio entrants and prior foundings (both expressed as curvilinear values with their squared terms included). Because GDP and US government NNI funding are highly correlated with one other and venture capital, they are excluded from the analysis. The five controls included in each equation are located at the top of each column reporting coefficients for statistical findings, by equation.

Each hypothesis is analyzed separately and corresponding results are reported in Models 2 through 5 for growth of scientific knowledge, technical knowledge, scientific human capital, and engineering or technical human capital, respectively. We see in Model 2 the effects of scientific knowledge and its square are statistically significant with the main effect positive and

its square negative, as expected. These results support Hypotheses 1. Recall that a depreciated value of knowledge was calculated and despite this, the impact on births is still curvilinear.

Model 3 reports the effect of (discounted) technical knowledge measured as growth of patent applications in the nanotechnology arena, and as expected, technical knowledge growth has a negative effect on de novo birth rates. Results support Hypothesis 2.

In Model 4 are results for effects of scientific human capital measured as growth in the number of scientists who authored (or co-authored) an article published in a major nanotechnology scientific journal. These are the first of two relevant pools of potential nanotechnology entrepreneurs. As expected, the greater the growth rate of scientists, the greater the founding of de novo nanotechnology firms (Hypothesis 3).

In Model 5 we test Hypothesis 4 regarding the effects of available technical personnel on the founding of nanotechnology firms. Results do not support our hypothesis, and we find that growth in technical personnel has a negative effect on birth rates rather than our anticipated positive effect. We will consider these unexpected findings in the discussion section, later.

Model 6 contains results for the full model where hypothesized effects are pitted against one another, along with controls. We find the same results in the full model as we did in the constrained models, such that Hypotheses 1, 3 and 4 are supported once more, but as before, results for Hypothesis 5 are the opposite of our prediction. The variance inflation factors (VIF's) for coefficients in Model 6 are all below 6.5, which is within the range indicating absence of multicolinearity.

In Hypothesis 5 we expected an interaction between scientific knowledge productivity and technical knowledge productivity. While we anticipate a complex relationship between the four variables, there is however, little *a priori* knowledge available from current theory or research on which to base a more detailed hypothesis. In Model 7 we find a significant interaction between the two productivity constructs, as expected, so these results support Hypothesis 5. However the interaction itself is negative. To explore these and results for Hypothesis 1, a curvilinear expectation, Figures 1 and 2 plot the curvilinear effect of discounted scientific knowledge flow on firm births and the interaction between scientific and technical knowledge productivity on firm births, respectively.

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Insert FIGURES 1 and 2 about here

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**Interpreting the curvilinear and interactive results.**

We hypothesized an inverted U-shaped, curvilinear effect of scientific knowledge growth on de novo nanotechnology birth rates. Figure 1 shows that limited scientific knowledge flow and high knowledge flow depress the founding rate of de novo firms. However the highest rate of new foundings is relatively early in the flow of scientific knowledge: ***only 25% of the eventual science that accumulates is sufficient to generate the greatest proportion of new firms.*** Despite the fact that scientific knowledge is discounted by a factor of 20%, there is nonetheless a clear inverted U-shaped curve.

Figure 2 graphs the interaction effect of scientific and technical knowledge productivity on de novo firm births. When scientific knowledge productivity is low to moderate, the probability of firm births increases slightly as low and moderate technical knowledge productivity increase slightly. However as scientific knowledge productivity increases, lower technical productivity is more likely to accelerate the probability of firm births than when

technical knowledge productivity is moderate or high. That is, *even though the absolute value of technical knowledge created is still low, nonetheless as the patents filed per author increase, the rate of new firm births escalates exponentially as scientific knowledge productivity increases.*

All models in Table 3 contain controls as period effects for the extent of the US government's recognition of nanotechnology as a legitimate science, with periods beginning 1970, 1983, 1998, and 2001. For the periods 1970-1997, results are negative but primarily insignificant. The only positive and significant effects are from 2001 to 2004, but only for the baseline model and the models (2 and 4) containing growth of scientific knowledge and scientific human capital variables. As noted earlier, there was already a strong significant increase in the number of nanotechnology de novo firms by 1999, before the NNI was inaugurated in 2001. The primary impact of the NNI's symbolic, socio-political legitimation of the scientific field is to increase the birth rate toward the very end of our observation period for a short period of time.

Venture Capital availability has no significant effect on nanotechnology firm births in any of the models. Last, the most consistently significant controlled effects are for prior de alio entrants and prior foundings, and their curvilinear expressions are also significant, as predicted by theory (Delacroix & Carroll, 1983; Hannan & Freeman, 1987).

We also calculated marginal effects and conducted a robustness check via bootstrapping (using clustered standard errors). Although *not included here* because of space constraints, nonetheless the marginal effect results (Table 4.) are perfectly consistent with results in Table 3. In the robustness check (Table 5.) for coefficient stability (compared to Table 3), results for the two analyses are consistent, with no indication of coefficient instability. In all three tables (3, 4, and 5) the model that best fits the data is the one containing the equation with the Scientific and Technical Knowledge Productivity Interaction.

## Discussion

This paper has investigated the scientific origins of a de novo population focused on nanoscience. We hypothesized that growth in new scientific knowledge, as well as growth in the availability of scientifically experienced and in technically educated potential entrepreneurs would have positive effects on the birth rate of de novo firms. We also hypothesized that patents would create a barrier to de novo foundings and decrease the founding rate. We introduced the concepts scientific productivity (number of published scientific articles per scientist) and technical productivity (number of patent applications per patent author), hypothesizing an interaction between the two as their joint impact on de novo firm births.

We found that initially, growth of scientific knowledge stock has a positive, significant effect on births up through the first twenty-five percent of new scientific knowledge published during the time span of our observations. After the first twenty-five percent of new scientific knowledge is published, the birth rate turns negative, with births decreasing as scientific knowledge continues to grow. These results demonstrate that the publication of new scientific knowledge is critical to the initial emergence of a new science-based population. Scientific publications are *the significant factor* in new population formation, decades – twenty years in fact – before the new scientific paradigm achieves socio-political legitimacy. This means that entrepreneurs did not wait until knowledge about this new scientific field, nanoscience, had crystalized, been formalized, or been acknowledged by a prestigious professional organization as an accepted scientific paradigm. It is they who jumped in and founded companies early to mid-point in the new knowledge's development. The nanoscience entrepreneurs are the true risk takers in this field. Nor is it venture capital investors either; they had literally no significant

effect on new firm emergence in nanoscience over the entire thirty-four year period of observation. Nor did U.S. government money targeted for nanoscience have an effect until twenty years after the first new nano firms were founded when the NNI introduced Congressional allocations for nanoscience.

We hypothesized that the availability of trained and productive nano scientists creates a pool of potential entrepreneurs. Although research has shown that a very small proportion of scientists in the life sciences, in particular, transition from university employment to working full time in newly founded firms (Stuart & Ding, 2006) nonetheless their very existence for consultation, perhaps, or for membership on technical advisory boards, for example, apparently renders their existence a significant resource for new science-based firms. As expected, we found that growth in the number of scientists publishing nanoscience articles also has a significant positive effect on the new firm formation rate Therefore the available pool of human capital is also critical to the formation rate.

It is important to note in this context, that it is the entire growing pool of publishing nano scientists that has this positive effect on births. It *is not* only the exceptionally small proportion of high impact "star scientists" or their geographic locations that are of consequence here. Independent of the individual scientist's productivity or their location, new nanoscience firms benefit from the new knowledge scientists create through their research and publications. This means that entrepreneurs do not require a star scientist in order to successfully found a new nanotechnology firm. Since "star" scientists represent only .0075 of one percent of published scientists in biotechnology (Zucker & Darby, 1996), the probability of gaining access to these rare individuals for technical advice is low. So this finding works in the interests of entrepreneurs, who have one less challenge in founding a new nanotechnology firm. While entrepreneurs need to understand the underlying science and technology, scarce star scientists are not a necessary condition for starting a new nanotechnology firm.

Consistent with expectations, existing patent filings had a negative effect on new firm formation. Patent filings played a clear anti-competitive role in the formation of new nanoscience firms. These results are consistent with Calabrese, Baum & Silverman (2000) findings for the biotechnology industry in Canada. These findings add to the growing literature that shows that the formation and emergence of two new science-based populations – biotechnology and nanoscience - were deterred by the filing of patents. Since both Calabrese et al.'s study and ours are both large scale and quantitative, these results suggest that in general, patenting has the intended legal effect of decreasing competition from de novo firms when de alio firms file the patents in science-based industries.

We conceptualized nanotechnology patent authors as another potential pool of entrepreneurs for staffing de novo firms. To our surprise, growth in nanotechnology patent authors had a negative effect on the birth rate, rather than a positive one, as hypothesized. In the absence of other information, we can speculate as to why this might be true. It is quite likely that employees of existing science-based firms, i.e. those writing the patents, have signed legally-binding non-disclosure agreements as a condition of employment in companies with engineering, research and development (Radack, 1994). It is probable that the short life span of new technologies and products along with perceived inadequacies of patent protection may have induced companies to require the signing of non-disclosure agreements. While no data on pervasiveness of this practice could be located, expert informants in the emerging industry suggested that this might be a reasonable explanation for the negative finding.

Last, we hypothesized and found an interaction between scientific knowledge productivity and technical productivity in predicting the de novo firm formation rate. Recall that knowledge productivity is defined as the propensity of human capital (scientists or engineers) to create or codify new knowledge (scientific or technical). When measured, the two constructs take into account four variables: scientific knowledge as publications and the number of scientists, and technical knowledge as patents and the number of engineers. Specifically we found that as scientific knowledge productivity increases from low to a moderate level and when technical knowledge productivity is low, the rate of new firm birth increases exponentially. This means that a relatively low threshold of both knowledge and human capital is sufficient to increase the rate of de novo firm births substantially. The implication for potential entrepreneurs is that they do not need to hesitate to found a new firm during the scientific knowledge discovery process – as long as they understand the science and technology. And given the very late creation of the NNI and the large proportion of new firms already founded when it was created, neither do entrepreneurs need to wait for socio-political legitimacy to be bestowed on the new scientific realm or for the new scientific realm to have entirely crystalized before founding a de novo firm.

We found that relative to patents, as patent growth increases, fewer entrepreneurs found firms. This suggests that potential entrepreneurs need to attend to the extent of patent saturation in a field. The successful anti-competitive effect of patents makes it likely that one may not be able to create a viable firm when there is already extensive protected intellectual property.

Last, when a new scientific realm emerges, entrepreneurs cannot depend on venture capital as a source of equity to fund their firms. The VC's simply did not take substantial risks by investing in the entirely new realm of nano scientific inquiry. Even though technical knowledge as patents applications had begun to increase – a sign that the new scientific knowledge was being translated into technical innovations, nonetheless VC resources had no significant effect on growth of nano ventures. The same is true of government money. In the U.S. at least, the government was belated in recognizing the economic potential of this emerging scientific fields: nanoscience is the driver of an entirely new industry, new ventures, and new jobs. Very little government money was available until after 2001 to fund either scientific research or the founding of new firms. In a separate analysis, we found that it was not until about 2000 that any grant money was allocated by the U.S. government for nanotechnology scientific research.

If the government wished to increase the founding rate of de novo science-based organizations and to speed up the founding rate to an earlier historical point, then allocating grant money for scientific research earlier in time could be a reasonable strategy.

Shifting to institutional effects, there are two theoretical implications of this research. First, in 2001 the NNI established formal socio-political legitimacy for the new nanotechnology scientific paradigm, consistent with Aldrich & Fiol's (1994:748) definition as acceptance by key opinion leaders and government officials. However, the NNI was established nineteen years after the *first de novo nanotechnology organizations* were founded and when fifty percent of the new population already existed. The only period with a significant effect on birth rates, albeit negative, was 1983 to 1997 when the very first firms were founded. These results suggest the theoretical nuance that socio-political legitimation may not be a significant factor in the *early to mid-years of science-based population emergence.*

The second theoretical issue is that in nanotechnology, there is no evidence that founders mobilized to take collective action to gain sociopolitical approval (Woolley, 2007), as Aldrich and Fiol (1994) argued. Rather it is their individual agency in founding the de novo firms

themselves that is significant in population emergence. This latter point is consistent with Hannan's (1986) argument that it is increasing size of the new population that helps legitimate the form. The strong direct effects of prior de novo foundings on births in our results support this interpretation.

Last, we controlled for several constructs shown in prior research to play a part in new population formation. Availability of venture capital funds in billions of dollars had no significant effect in de novo population emergence in nanotechnology, despite findings to the contrary in a number of other science-based industries. These results are consistent with Darby and Zucker's (2003) findings that the past level of *regional* venture capital activity was not significant in the formation of new *local* entrants. Our findings provide some insight into the timing and effectiveness of venture capital investments in new populations.

## Conclusion

This paper has demonstrated the important role that new scientific knowledge plays in the emergence of a science-based de novo population. The paper has also revealed that early growth in the number of scientists, a pool of potential nanoscience entrepreneurs, is a significant contributor to the formation of this de novo population.

Whereas high growth rates of scientific knowledge are associated with lower foundings, this demonstrates that in the United States, at least, there is a substantial pool of scientific knowledge that awaits practical application. Last, this study reinforces the importance of including institutional theory arguments in studies of new population emergence.

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**TABLE 1: Descriptive Statistics**

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| Births by quarter | 2.10 | 4.14 | .00 | 22 |
| Time to Birth since 1970 | 30.57 | 3.00 | 13.75 | 34.5 |
| VC funds (in billion dollars) by quarter | 2.97 | 7.07 | 0.00 | 47.70 |
| Prior founding (*de alio only*) by quarter | 1.42 | 3.48 | 0.00 | 22.00 |
| Prior founding (*de novo only*) by quarter | 0.77 | 1.98 | 0.00 | 13.00 |
| Discounted scientific knowledge flow by quarter | 0.44 | 0.64 | -0.14 | 2.77 |
| Discounted technical knowledge flow by quarter | 0.16 | 0.33 | -2.46 | 1.04 |
| Growth rate of human capital (article author) by quarter | 1.29 | 1.31 | 0.00 | 4.46 |
| Growth rate of human capital (patent author) by quarter | 0.78 | 0.66 | 0.01 | 2.37 |
| Productivity of scientific knowledge by quarter | 1.62 | 1.52 | 0.05 | 11.15 |
| Productivity of technical knowledge by quarter | 1.73 | 0.42 | 0.70 | 2.81 |
| Period Effect (1970-1982) | 0.42 | 0.49 | 0.00 | 1.00 |
| Period Effect (1983-1997) | 0.39 | 0.49 | 0.00 | 1.00 |
| Period Effect (1998-2000) | 0.05 | 0.22 | 0.00 | 1.00 |
| Period Effect (2001-2004) | 0.03 | 0.18 | 0.00 | 1.00 |

## TABLE 2: Correlation Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Births | 1 | | | | | | | | | | | | | | | |
| 2. VC Funds | 0.14 | 1 | | | | | | | | | | | | | | |
| 3. Prior foundings (de alio) | 0.18 | 0.70 | 1 | | | | | | | | | | | | | |
| 4. Prior foundings (de alio)$^2$ | -0.11 | -0.30 | 0.00 | 1 | | | | | | | | | | | | |
| 5. Prior foundings (de novo) | 0.23 | 0.67 | 0.52 | -0.44 | 1 | | | | | | | | | | | |
| 6. Prior foundings (de novo)$^2$ | -0.03 | -0.26 | -0.23 | 0.12 | 0.00 | 1 | | | | | | | | | | |
| 7. Discounted scientific knowledge flow | 0.14 | 0.31 | 0.32 | -0.26 | 0.50 | -0.25 | 1 | | | | | | | | | |
| 8. Discounted scientific knowledge flow$^2$ | 0.14 | 0.22 | 0.23 | -0.24 | 0.44 | -0.19 | 0.94 | 1 | | | | | | | | |
| 9. Discounted technical knowledge flow | -0.14 | 0.25 | 0.14 | 0.00 | 0.00 | -0.27 | 0.13 | -0.02 | 1 | | | | | | | |
| 10. Growth rate of human capital (articles) | 0.06 | 0.34 | 0.37 | -0.29 | 0.34 | -0.29 | 0.77 | 0.57 | 0.43 | 1 | | | | | | |
| 11. Growth rate of human capital (patents) | 0.11 | 0.63 | 0.60 | -0.32 | 0.62 | -0.34 | 0.68 | 0.51 | 0.46 | 0.82 | 1 | | | | | |
| 12. Scientific knowledge productivity | 0.27 | 0.58 | 0.62 | -0.33 | 0.78 | -0.16 | 0.54 | 0.49 | -0.19 | 0.36 | 0.59 | 1 | | | | |
| 13. Technical knowledge productivity | 0.12 | 0.52 | 0.54 | -0.29 | 0.54 | -0.22 | 0.45 | 0.33 | 0.27 | 0.55 | 0.64 | 0.47 | 1 | | | |
| 14. Year dummy (1970-1982) | -0.08 | -0.33 | -0.34 | 0.25 | -0.33 | 0.21 | -0.53 | -0.40 | -0.27 | -0.72 | -0.69 | -0.36 | -0.53 | 1 | | |
| 15. Year dummy (1983-1997) | -0.06 | -0.15 | -0.15 | -0.04 | -0.24 | 0.06 | 0.15 | 0.09 | 0.15 | 0.41 | 0.17 | -0.17 | 0.07 | -0.67 | 1 | |
| 16. Year dummy (1998-2000) | 0.04 | 0.39 | 0.32 | -0.10 | 0.26 | -0.39 | 0.29 | 0.22 | 0.14 | 0.27 | 0.46 | 0.31 | 0.29 | -0.20 | -0.19 | 1 |
| 17. Year dummy (2001-2004) | 0.26 | 0.17 | 0.40 | -0.24 | 0.64 | 0.28 | 0.29 | 0.30 | -0.50 | 0.08 | 0.22 | 0.69 | 0.31 | -0.16 | -0.04 | -0.05 |

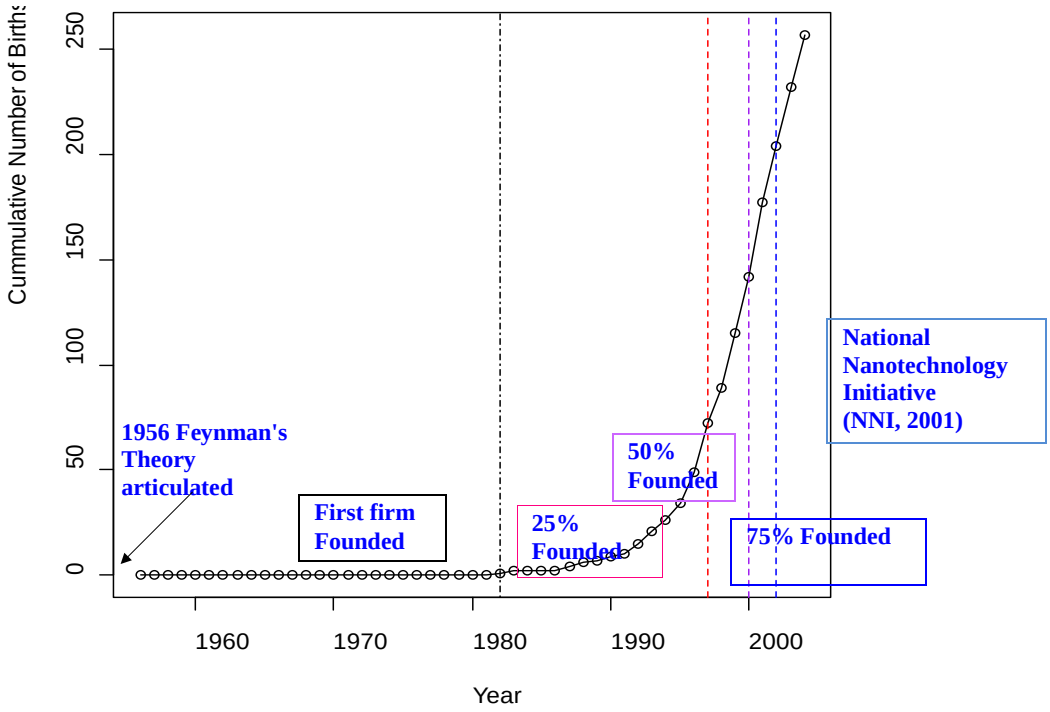
## TABLE 3: Tests of Primary Hypotheses

| | **Model 1 Baseline** | **Model 2 Sci. Knowledge (Disc'd)** | **Model 3 Tech. Knowledge (Disc'd)** | **Model 4 Human Capital (Article)** | **Model 5 Human Capital (Patent)** | **Model 6 Full(disc. sci. & tech. knowledge)** | **Model 7 Productivity Interaction** |
|---|---|---|---|---|---|---|---|
| ***Intercept*** | -6.349$^{***}$ (.236) | -6.402$^{***}$ (.246) | -6.306$^{***}$ (.239) | -7.126$^{***}$ (.392) | -5.948$^{***}$ (.283) | -6.721$^{***}$ (.462) | -6.902$^{***}$ (.331) |
| ***CONTROLS*** | | | | | | | |
| *VC Funds (in billions)* | -.014 (.009) | -.007 (.010) | -.011 (.009) | -.009 (.009) | -.014 (.009) | -.002 (.010) | -.011 (.009) |
| *Prior Entry (de alio)* | .963$^{***}$ (.131) | .921$^{***}$ (.128) | 1.018$^{***}$ (.133) | .874$^{***}$ (.129) | 1.180$^{***}$ (.166) | 1.154$^{***}$ (.158) | .791$^{***}$ (.172) |
| *Prior Entry (de alio)$^2$* | -.576$^{***}$ (.129) | -.506$^{***}$ (.130) | -.679$^{***}$ (.137) | -.439$^{***}$ (.125) | -.803$^{***}$ (.170) | -.719$^{***}$ (.161) | -.499$^{***}$ (.131) |
| *Prior Foundings (de novo)* | 1.013$^{***}$ (.156) | .846$^{***}$ (.176) | .945$^{***}$ (.160) | .915$^{***}$ (.153) | 1.099$^{***}$ (.161) | .782$^{***}$ (.179) | .427$^{*}$ (.194) |
| *Prior Foundings (de novo)$^2$* | -.426$^{***}$ (.099) | -.370$^{***}$ (.102) | -.362$^{***}$ (.101) | -.365$^{***}$ (.095) | -.443$^{***}$ (.102) | -.248$^{*}$ (.100) | -.122 (.095) |
| *Period Effect (1983-1997)* | -.710$^{\dagger}$ (.419) | -807$^{\dagger}$ (.424) | -.692 (.421) | -1.211$^{**}$ (.452) | -.726$^{\dagger}$ (.450) | -1.512$^{**}$ (.467) | -.451 (.454) |
| *Period Effect (1998-2000)* | .159 (.236) | -.032 (.249) | .368 (.246) | -.249 (.257) | .474$^{\dagger}$ (.274) | .096 (.280) | .275 (.257) |
| *Period Effect (2001-2004)* | 1.085$^{***}$ (.264) | 1.345$^{***}$ (.288) | .287 (.400) | 1.417$^{***}$ (.282) | .596$^{\dagger}$ (.348) | .304 (.416) | -.026 (.392) |
| ***HYPOTHESIZED EFFECTS*** | | | | | | | |
| ***Growth rate of Discounted Scientific Knowledge*** | | .383$^{*}$ (.169) | | | | .387$^{*}$ (.189) | |
| ***Growth rate of Discounted Scientific Knowledge$^2$*** | | -.254$^{*}$ (.106) | | | | -.322$^{**}$ (.116) | |
| ***Growth rate of Discounted Technical Knowledge*** | | | -.477$^{**}$ (.180) | | | -.508$^{*}$ (.223) | |
| ***Growth rate of Human Capital*** *(Scientific Article Authors)* | | | | .507$^{**}$ (.154) | | .610$^{***}$ (.180) | |
| ***Growth rate of Human Capital*** *(Patent Authors)* | | | | | -.541$^{*}$ (.238) | -.707$^{*}$ (.302) | |
| ***Scientific Knowledge Productivity*** | | | | | | | 1.279$^{***}$ (.222) |
| *Technical Knowledge Productivity* | | | | | | | 1.106$^{**}$ (.382) |
| ***INTERACTION EFFECTS*** | | | | | | | |
| ***Scientific Knowledge Productivity *Technical Knowledge Productivity*** | | | | | | | -.648$^{***}$ (.147) |
| **Deviance** | 1477.7 | 1470.3 | 1470.7 | 1466.7 | 1472.4 | 1441.4 | 1419.9 |
| **Δ Deviance ($\chi^2$)** | - | 7.46$^{*}$ | 7.07$^{**}$ | 11.02$^{***}$ | 5.32$^{*}$ | 36.39$^{***}$ | 21.60$^{***}$ |
| **AIC prediction error** | 1495.7 | 1492.3 | 1490.7 | 1486.7 | 1492.4 | 1469.4 | 1443.9 |
| **Firm-quarter: 23726, # of firms: 194, time periods: 138** | | | | | | | |

†$p$ <.1 * $p$ <.05 ** $p$ <.01 *** $p$ <.001

**TABLE 4: Marginal Effects and TABLE 5: Robustness Check with Bootstrapping (Clustered Standard Errors) are *eliminated to conserve space.* Please see text for results.**

**FIGURE 1: Births of de novo Firms over time, 1956-2004**




| Event | 1st firm founded | 25% founded | 50% founded | 75% founded |
|---|---|---|---|---|
| Year | 1982 | 1997 | 2000 | 2002 |
| Duration since 1956 | 26 yrs | 41 yrs | 44 yrs | 46 yrs |

**FIGURE 3: Interaction of Scientific and Technical Knowledge Productivity on Firm Births**

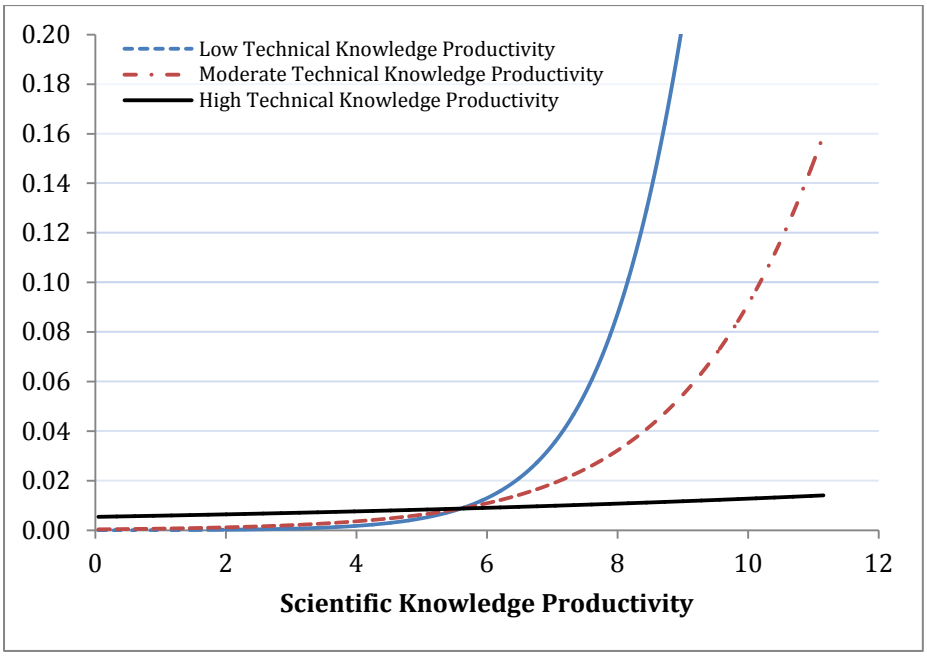


**FIGURE 3: Interaction of Scientific and Technical Knowledge Productivity on Firm Births**