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Contextualizing the categorical imperative: Category linkages, technology focus, and resource acquisition in nanotechnology entrepreneurship

Tyler Wry [a,*], Michael Lounsbury [b]

[a] Management Department, The Wharton School, University of Pennsylvania, 2031 Steinberg-Dietrich Hall, 3620 Locust Walk, Philadelphia, PA 19104-6370, United States

[b] University of Alberta School of Business and National Institute for Nanotechnology, 4-30E Business Building, Edmonton, Alberta, Canada T6G 2E7

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A B S T R A C T

This paper examines the role of category affiliations in entrepreneurial resource acquisition. Pace existing studies, we suggest category spanning will cause firms to be overlooked or discounted because evaluators assume that they have less expertise than their category-focused competitors; a phenomenon known as the 'categorical imperative'. We suggest, however, that categories can be related both vertically and horizontally, and that this has important implications for understanding how the actors that span between them are evaluated. Studying startup ventures in nanotube technology, we show that venture capital investments were affected by a firm's position across patent classes that were related at both of these levels of analysis and that the interaction between them had implications for which firms received the largest investments.

1. Executive summary

Recent years have witnessed a wellspring of interest among organizational scholars in the study of categories and categorization. Mirroring the strategic literature on relatedness, this work focuses on the organizational consequences of affiliating with many versus few categories. Rather than focusing on internal efficiencies, however, the emphasis is on the role of categories in shaping how an organization is perceived by external audiences. In this regard, there is a consistent finding that an unfocused, category spanning, position creates ambiguity about what 'type' an organization is, leading to perceptions of diffused expertise and discounted evaluations; Zuckerman (1999) coined this effect 'the categorical imperative'.

Examining the full population of startup firms in field for nanotube technology – one of the most prominent and well-defined domains of commercial nanotechnology – between 1992 and 2005, we examine how category affiliations affect the perceptions of one key audience, venture capital investors. Based on evidence that technology focus is a key consideration for equity investors, we examine the consequences for patenting across multiple United States Patent and Trademark Office (USPTO) classes — a type of category that distinguishes between different types of inventions. Pace existing arguments, our baseline hypothesis is that venture capitalists will perceive firms with diffused patent portfolios to be less attractive than their more focused counterparts, making investment less likely.

However, drawing on insights from cultural sociology and cognitive psychology, we argue that perceptions of relatedness are not necessarily static or uni-dimensional. Rather, categories may be linked horizontally and/or vertically and these linkages may shift as a field evolves. Reflecting this, we suggest that the detrimental effects of category spanning on venture capital investment will be attenuated when firms patent in USPTO classes that build on common types of knowledge (a type of horizontal link) or when they limit their patenting to classes associated with either scientific advance *or* commercial product development (a type of vertical link).

* Corresponding author.
E-mail address: twry@wharton.upenn.edu (T. Wry).

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Using hazard rate and tobit regression models, we find considerable support for our arguments. Although patenting across USPTO classes had a detrimental effect on the overall likelihood of receiving venture capital, our results suggest that this effect masks considerable nuance. As hypothesized, patenting across horizontally related classes (those that share underlying knowledge) significantly moderated the detrimental effects of category spanning. Further, over the years of our analysis, we observed the convergence of knowledge among patent classes associated with scientific discovery and commercial product development. When this happened, firms were able to stake out positions that bridged these category-groups while still conveying focused expertise. Indeed, in the later years of our analysis, firms with patents in classes that were associated with scientific discovery *and* in classes associated with product development became the most likely to receive large investments. As such, we show that relatedness is not necessarily an intrinsic property of two entities. Rather, it is embedded in shifting cultural frameworks. Moreover, we suggest that the evolving interaction between horizontal and vertical category linkages can facilitate the emergence of new and highly valued category combinations. In essence, the effects of category spanning depend on which categories are spanned, and when. This has a number of implications for the literatures on categories, relatedness, and entrepreneurial resource acquisition.

2. Introduction

Attracting resources from external providers is critical to the survival and growth of an entrepreneurial venture (Aldrich, 1999; Brush et al., 2001; Shane, 2003). Yet, gaining positive attention from audiences such as customers, ratings agencies, potential employees, and investors is a difficult task. Without an established track record, reputation – or even product in some cases – there is considerable uncertainty about a new venture, and this makes resource providers reluctant to invest (Brush et al., 2001; Shane, 2003; Stinchcombe, 1965). This is amplified in nascent high technology industries where products may have revolutionary potential, but require years of development before this is realized (or not) (Benner and Tripsas, 2012; Powell and Sandholtz, forthcoming). In such contexts, assessments of the technology that a firm is developing, and its ability to bring it to market successfully, are key considerations for resource providers such as venture capitalists (Chen et al., 2009; Fried and Hirsch, 1994; Martens et al., 2007). However, we have limited understanding about the factors which affect these assessments.

To date, studies examining the relationship between a firm's technology and its ability to attract external resources have been at a very broad level of analysis. The typical finding is that nascent firms with many technology patents are attractive to investors because they are viewed as more innovative (Baum and Silverman, 2004; Kortum and Lerner, 2000; Lerner, 1994). However, this finding overlooks potentially important variance with respect to the composition of a firm's technology profile. Firms may be more or less focused in the technologies that they are developing – taking out patents for a narrow range of technologies or pursuing a broader array of developments – and this may affect investor reactions (Anderson, 2011; Lux Research, 2006; Waitz and Bokhari, 2003). Indeed, rich literatures in organization theory and strategy suggest that a firm's focus has implications for how it is perceived and how it performs (Hsu, 2006; Hsu et al., 2009; Miller, 2006; Palich et al., 2000; Rao et al., 2005; Robins and Wiersema, 1995; Zuckerman, 1999). While this work has yet to be extended to nascent ventures, we argue that it may be an important consideration.

In advancing our argument, we draw primarily on insights from the categories literature in organization theory (Hsu, 2006; Hsu et al., 2009; Rao et al., 2005; Zuckerman, 1999). From this view, actors rely on categories to simplify thought and understanding by lumping similar things together and distinguishing them from others (Zerubavel, 1997). There is a growing consensus that firms which span multiple product or market categories are viewed less favorably because audiences have difficulty understanding them and assume lower levels of expertise in each as compared to more focused firms (Hsu, 2006; Hsu et al., 2009; Zuckerman, 1999). While this general finding is mirrored in the literature on strategic diversification (e.g., Palich et al., 2000; Robins and Wiersema, 1995), the underlying theoretical mechanisms are different: the categories literature concentrates primarily on audience perceptions rather than internal efficiencies generated through focus. In this way, it offers a more culturally informed view and suggests that firms are affected by interpretations of their expertise and efficiency, regardless of whether or not these are accurate (Lounsbury and Glynn, 2001; Navis and Glynn, 2011). Given the information asymmetries that typically exist between nascent ventures and external resource providers (Aldrich and Fiol, 1994; Graebner, 2009; Zott and Huy, 2007), this approach is well suited to studying the effects of focus in entrepreneurship.

Although technology categories – as reflected in United States Patent and Trademark Office (USPTO) patent classes – are somewhat different than the product and market categories featured in extant studies, we posit that they will similarly affect external evaluations of a firm. However, in making this extension, we suggest that a firm's focus may not be assessed against a backdrop of stable, discrete, and equidistant categories. Although this is a common assumption in the literatures on categories and strategic focus, evidence suggests that more nuanced forms of relatedness may be relevant (e.g., Miller, 2006; Rosch and Lloyd, 1978; Stimpert and Duhaime, 1997). Building on this, we argue that the relational structure of categories at the field level may affect how category spanning firms are evaluated (Rao et al., 2005; Ruef and Patterson, 2009). Notably, we provide evidence that categories may be related in multiple ways and that these may have independent and joint effects on how focus is assessed. We further show that category relationships may shift, making such assessments temporally contingent.

Our research context is the field for carbon nanotube (CNT) technology; a prominent domain of nanotechnology spawned by the discovery of a new form of carbon (C60) in 1985 (Meyyappan, 2005). CNTs are nano-scale structures with hexagonally arranged carbon atoms wrapped into a cylindrical shape. They are very strong and light, and are excellent thermal and electric conductors. Commercialization efforts began almost immediately after CNTs were discovered and the first patents were issued in the early 1990's. While this activity was initially led by scientists patenting their discoveries and firms developing CNT enabled products, new ventures began to emerge in the mid-90's. By 2005 there were over 60 CNT startups. As with cognate fields like biotechnology and semiconductors (Aldrich, 1999; Martens et al., 2007) venture capital was an important resource that helped these firms take applications from the lab to market (Jurvetson and Waters, 2005; Lux Research, 2006; Waitz and Bokhari, 2003).

To assess how the technology focus of entrepreneurial firms affects their likelihood of attracting venture capital, we examine the USPTO classes where they have patented. USPTO classes are a type of category that is used to group inventions according to their primary attributes and functions and there is a general consensus that they capture meaningful distinctions among areas of technological development. Reflecting this, they are widely used to distinguish between related and unrelated technologies in academic studies (Gilsing et al., 2008; Katila, 2002; Rosenkopf and Nerkar, 2001) and venture capitalists use them to help assess a firm's focus when they conduct their pre-investment intellectual property reviews (Bradley, 2007; Lux Research, 2006; Waitz and Bokhari, 2003: 5–7).

Our study makes a number of contributions to the literatures on categories, relatedness, and entrepreneurship: 1) We add considerable nuance to extant understandings about the relationship between technology and venture capital investment in startup firms. Specifically, we show that this relationship importantly relies on assessments of technological focus. 2) We bridge cognate literatures in organization theory and strategy that have proceeded largely independent of each other, despite a shared interest in categories and their organizational effects. In particular, we show that insights about relatedness can enrich organizational theory perspectives on category effects, while insights about audience perceptions enable the extension of strategic focus arguments to contexts where the outcomes of internal efficiencies are difficult to assess. 3) We show that multiple forms of relatedness may be concurrently relevant for how a firm is evaluated and that such assessment can take place against a dynamic backdrop. Thus, we provide novel insight into the relationship between categories, firm focus, and audience assessments, showing how these processes are embedded in shifting cultural frameworks.

Our argument proceeds as follows. We begin with a review of the literature on categories and audience perceptions, arguing that insights about product and market categories have explanatory purchase for understanding technology focus as well. We develop hypotheses that relate category focus to resource acquisition and suggest ways that this relationship might be moderated by different types of inter-category linkages. Next, we provide details about the CNT field and the new ventures that emerged within it. We analyze venture capital investments reported in the Zephyr database from 1994 (when the first CNT firm emerged) through 2005 using hazard rate and tobit regression models and conclude by discussing the implications of our findings for the literatures on entrepreneurial resource acquisition, categories, and relatedness.

3. Categories, audiences, and venture capital investments

Every firm must make decisions about the breadth of its product, market, and technology portfolio (Rumelt, 1974; Siggelkow, 2003). These decisions are far from banal and may have consequential performance implications. Reflecting this, a prominent line of strategy research examines the relationship between focus and organizational outcomes. Typical studies in this milieu examine the dispersion of a firm's business units across market categories and argue that focus leads to internal efficiencies and higher performance (Huckman and Zinner, 2008; Miller, 2006; Palich et al., 2000; Robins and Wiersema, 1995; Siggelkow, 2003). This work has yet to intersect the entrepreneurship literature, however. This is understandable because startup firms rarely create multiple business units and performance metrics are not readily available (Aldrich, 1999; Shane, 2003). Further, many nascent firms do not have established products or customer bases – especially in high tech industries (Benner and Tripsas, 2012) – making discussions of internal efficiencies secondary to the assessments of external evaluators who provide the resources necessary to bring products to market. As such, the categories literature – with its focus on audience assessments (see Negro et al., 2010b) – is useful for studying the relationship between the focus of a nascent firm and its ability to secure external resources.

Sociologists view categorization as a ubiquitous social process where actors group like things together. Through this act of grouping, categories set boundaries and create shared understandings about what appropriately falls within them (Douglas, 1986; Zerubavel, 1997). Because of these properties, product and market categories shape perceptions by providing audiences with a comparison set and specifying evaluation criteria for category members. By corollary, audiences have difficulty understanding where category spanning firms fit on the organizational landscape. Accordingly, such firms are less likely to receive attention from relevant audiences and, when they do, it is more likely to be negative because spanning conveys impressions of dispersed expertise relative to more focused competitors—a phenomenon that Zuckerman (1999) termed 'the categorical imperative'. This basic finding has been replicated across a range of contexts. For example, firms that operate in multiple industries are less likely to receive positive evaluations from securities analysts who have difficulty understanding what 'type' a firm is or where its expertise lays (Zuckerman, 1999). There is also evidence that actors who are associated with specific film genres have difficulty finding work outside of their 'home' genre and receive lower evaluations when they do (Zuckerman et al., 2003). Sellers with products in multiple categories on eBay and French Chefs who combined ingredients and preparation techniques from Haute and Nouvelle cuisine similarly faced penalties because audiences had difficulty reconciling their multi-category positions and assumed lower levels of expertise in each (Hsu et al., 2009; Rao et al., 2005).

Although the categorical imperative appears to be robust across diverse contexts (see Hannan, 2010), there are some important differences between the patent classes that we examine and the product and market categories featured in most studies. Patents from multiple classes may be required for a single product (Kennedy et al., 2010), firms may take out patents for inventions which never materialize in products, and patent classes may have applications across industries (Miller, 2006; Silverman, 1996). Despite these differences, there are also some important similarities which suggest that patent classes may affect audience evaluations in ways that mirror market and product categories. As with other types of categories, patent classes group items in a meaningful way (Benner and Tripsas, 2012; Benner and Tushman, 2002) and are widely used as a tool to distinguish between related and unrelated technologies (Katila, 2002; Rosenkopf and Nerkar, 2001). Further, nascent firms convey their identities in large part through the technologies they develop (Zucker and Darby, 1997) and resource providers look to this when making investment decisions (Fried and Hirsch, 1994; Martens et al., 2007). This is particularly important in the context of our study because venture capitalists conduct intellectual property reviews when making investment decisions and tend to view focused patent portfolios more favorably than dispersed ones (Bradley, 2007; Lux Research, 2006; Powell and Sandholtz, forthcoming). Reflecting this, Waitz and Bokhari report that:

> *IP [intellectual property] has been a central issue to every nanotech startup that we have looked at… One common pitfall…was lack of focus. This is an important issue with investors such as VC's… Frequently investors just pass on companies that have defocused [technologies]. One example of this that we saw was a nano startup that was having trouble raising capital. The firm [had patents for] memories, logic, displays, and batteries.* (2003: 5–7)

Based on the similarities between patent classes and the categories used in previous studies, our baseline hypothesis is that investors will have difficulty understanding the identities of firms with patents that are dispersed among classes, creating ambiguity about their expertise and thus reducing the likelihood of investment.

Hypothesis 1. Entrepreneurial ventures will be less likely to receive venture capital when they have an unfocused technology portfolio comprised of inventions that span multiple patent classes.

4. Contextualizing category effects

Although we agree that an organization is likely to be viewed less favorably when its category affiliations create ambiguity about its identity and expertise, we suggest that this is moderated by the relationships between the categories being spanned. In this regard, the categories literature in organization theory lags strategy research. Although many strategy studies measure diversification with concentric and entropy indexes derived from SIC classes (see Robins and Wiersema, 1995, 2003), others have sought deeper understanding about how these categories are related. For example, building on insights about mental maps, studies have shown that managers perceive market categories to be related in a variety of ways not captured in official classification schemes (Pehrsson, 2006; Stimpert and Duhaime, 1997). Others have shown that SIC classes are linked through common types of technological knowledge and that this deeper form of relatedness is associated with firm performance (Miller, 2006). While the specific linkages among categories are context dependent, this work suggests that the detrimental effects of category spanning may be attenuated when categories are seen as fitting together.

We extend this insight by drawing on studies in cultural sociology and cognitive psychology which suggest that categories can be related in various ways and levels and that this affects how their contents are understood. Examining this literature reveals two basic approaches; those which focus on 'horizontal' category linkages and those related to 'vertical' linkages. Examining categories at a common (horizontal) level of analysis, studies have shown that boundaries can be variably clear or fuzzy, with the result that certain categories are perceived to be more or less similar to each other (Kovács and Hannan, 2010; Negro et al., 2010a; Rao et al., 2005). Categories can also be linked vertically in a 'stem and branch' type hierarchy where higher level categories encompass a series of lower level ones. When lower level categories are associated with a higher level aggregate, audiences may perceive them as being meaningfully linked (Rosch and Lloyd, 1978; and see also Porac and Thomas, 1990). We suggest that when patent classes are linked in these ways, the penalties for spanning between them may be attenuated. To be clear, we are not suggesting that patent classes stop capturing meaningful differences among technologies, or are seen as irrelevant. More modestly, we claim that the distinctions actors make between classes are shaped by broader cultural frameworks where certain classes are viewed as fitting together—much like managers who see meaningful distinctions in SIC classes even as they perceive deeper relations among them (Pehrsson, 2006; Stimpert and Duhaime, 1997).

4.1. Category linkages at a superordinate level

Most studies of category spanning assume that categories are rigidly bounded, stable, equidistant, and discrete (but see Rao et al., 2005; Ruef and Patterson, 2009 for exceptions). This flat topography suggests that the meanings associated with each category are similarly potent. However, studies show that categories can be arranged hierarchically; for example, the category 'automobile' encompasses lower level categories for sports cars, sedans, trucks, SUVs, minivans, etc. (Rosch and Lloyd, 1978; Rosch and Lloyd, 1978; Wry et al., 2011a,b). This approach importantly notes that categories are variably useful for guiding cognition and action: high level categories may not provide meaningful enough distinctions, while low level ones may be too fine-grained to be practically useful. 'Basic' level categories sit somewhere between these solitudes and convey the types of distinctions that are relevant for actors as they make assessments about firms and their products (Porac and Thomas, 1990; Rosch and Lloyd, 1978; Rosch et al., 1976).

Although extant studies tend to assume that they are working with basic level categories, this is not assured. Relevant distinctions may sit at higher or lower levels of analysis and this is subject to change, especially for category systems in emerging or dynamic fields (Ruef and Patterson, 2009). In this context, one possibility is that categories may cohere in configurations that are associated with a higher level aggregate. When this happens, the higher level grouping may become more important for evaluative purposes than the lower level categories which comprise it (Porac and Thomas, 1990; Rosch and Lloyd, 1978; Rosch et al., 1976). This may take a variety of forms. For instance, Porac and Thomas (1990: 229) presented evidence that cognitive strategic groups in the Scottish knitwear industry were comprised of lower-level organizational categories such as 'knitwear, fashion knitwear, and fully fashioned knitwear' providers. Lounsbury (2007) similarly showed that Boston and New York money managers worked to create linkages among categories of mutual funds that they associated with *conservative* versus *aggressive* investing strategies and actively accentuated the differences between these higher-level groupings. Likewise, evidence suggests that the emergence of new product categories is related to the creative assemblage of existing ones (Kennedy, 2008; Kennedy et al., 2010) and that actors from disparate social categories can come together to form new, and widely recognized, collective identity categories (Wry et al., 2011a,b).

We extend this basic insight to patent classes. One possibility in this regard is that audiences may see a meaningful distinction between classes associated with scientific discovery versus those that are oriented toward product development. Studies show that development in high technology fields, such as nanotechnology, tends to be bifurcated between the basic science focus of university scientists and the product development efforts of corporations (Dasgupta and David, 1994; Hicks, 1995; Narin et al., 1995). Evidence also suggests that this distinction is replicated in the types of patents that these actors take out (Powell et al., 2005; Trajtenberg et al., 1997; Zucker et al., 1998). While there is inevitably some overlap – some university scientists invent end-stage products and some firms patent basic science discoveries – the distinction between these domains is widely documented (Dasgupta and David, 1994; Powell and Snellman, 2004). Reflecting this, patents for scientific discoveries and applied products are expected to cluster in different classes, largely mirroring the distinction that venture capitalists make between "composition of matter patents, process patents, and application patents" (Waitz and Bokhari, 2003: 10; and also see Lux Research, 2006).

Although our understanding of entrepreneurial behavior at the interstices of basic science and commercial activity remains incomplete (e.g., Nelson, 1986, 1989), studies suggest that startup firms tend to cluster around one pole or the other (Powell et al., 2005; Zucker et al., 1998). As such, spanning between patent classes that are associated with scientific discoveries may convey impressions that a firm is focused on scientific applications – and perhaps pursuing a technology licensing strategy (see Waitz and Bokhari, 2003: 10) – while spanning between classes associated with consumer products may lead to perceptions that it is focused on product development. Based on this, we expect that venture capitalists will perceive a clear identity and focused expertise for startups whose patents are diffused among classes associated with either science *or* product development, thus reducing the detrimental outcomes of category spanning. In contradistinction, studies have shown that it is difficult to transcend the gap between science and product development because each is associated with distinct actors and competencies (Dasgupta and David, 1994; Hicks, 1995; Nelson, 1986, 1989). As such, spanning between patent classes at this higher level of aggregation may convey a confusing identity and exacerbate perceptions that a firm has unfocused expertise. Thus,

Hypothesis 2a. The detrimental effects of category spanning on venture capital investment will be reduced when a firm is focused in patent classes that are associated with either scientific discoveries *or* commercial product applications.

Hypothesis 2b. The detrimental effects of category spanning on venture capital investment will be amplified when a firm is focused in patent classes that are associated with scientific discoveries *and* in classes associated with commercial product applications.

4.2. Category linkages through common knowledge

The mechanisms leading to discounted evaluations for category spanners might also be conditioned by the similarity of the inputs associated with the categories being spanned. While studies typically assume that the knowledge and skills required to compete effectively in one category are distinct from others (see Hsu, 2006; Siggelkow, 2003), this need not be the case. Within many classification systems, there are categories which are more and less similar (Kovács and Hannan, 2010; Negro et al., 2010a, 2010b; Rao et al., 2005). As such, while categories may be associated with distinct outputs – such as different products or technologies – there can be various degrees of overlap in the inputs that these build on. For example, there is growing agreement among organizational scholars that 'institutional theory' and 'social movements' research categories share a number of underlying similarities, even as they pursue different types of research questions (Campbell, 2005; Schneiberg and Lounsbury, 2008).

Moreover, category relationships are not static; they can evolve as actors build bridges, borrow across boundaries, and advocate for the appropriateness of such blending. As consensus emerges about the similarity of various categories, the boundary between them becomes less potent, fostering perceptions that they fit together to some degree and thus attenuating perceptions that actors are diluting their expertise by spanning between them (Kovács and Hannan, 2010; Lamont and Molnar, 2002; Negro et al., 2010a, 2010b). Illustrating this more dynamic form of relatedness, Rao et al. (2005) showed that chefs who mixed techniques and ingredients associated with Haute versus Nouvelle Cuisine initially received lower evaluations from Michelin Guide critics than their more focused counterparts. However, as the practice diffused, critics began to see this type of mixing as appropriate and the distinction between the categories as less absolute. As a result, the penalties for spanning these categories largely disappeared. Similarly, Lounsbury and Rao (2004) showed that before the 1970's mutual fund providers were perceived to have expertise as either 'growth' or 'trustee' investors based on their affiliation with these orthogonal investment classes. Subsequently, the field began to evolve an array of product categories encompassing varying degrees of risk. This allowed firms to cultivate positions across multiple categories without conveying diluted focus or expertise (Lounsbury, 2007).

Extending this insight to technological knowledge, studies have shown that patent classes can be more or less similar with respect to the knowledge stocks that they build on (Hall et al., 2001; Jaffe et al., 2000). We anticipate that audiences will perceive similar classes to be more closely related to each other than to classes that build on different types of knowledge. Further, firms that bridge classes which build on similar knowledge may be perceived as more innovative by venture capitalists because they are able to leverage their core expertise in multiple ways. Staking out this type of positions may also make a firm more attractive because it provides a range of options that can be efficaciously pursued in emerging and uncertain markets, such as the one that we focus on (Chiles et al., 2010; Hannan et al., 2007). As such, we think that when the knowledge that is relevant for inventing in different classes becomes similar, venture capitalists may see focused expertise and a coherent identity in a patent portfolio which crosses multiple classes. Thus,

Hypothesis 3. The detrimental effects of category spanning on venture capital investment will be reduced when a firm is focused in patent classes that build on similar knowledge.

5. Data and method

Our empirical context is the field for carbon nanotube (CNT) technology. CNTs are nano-sized structures comprised of hexagonally arranged carbon atoms that are wrapped into cylinders. They are very small, strong, and light with novel thermal and electro-conductive properties (Harris, 1999; Meyyappan, 2005). CNTs are derived from a completely new form of carbon (C60) which was discovered in 1985 and rewarded with a Nobel Prize (Smalley, 1995). There has been considerable speculation about the commercial potential of CNTs, with some observers predicting that they will revolutionize areas such as nano-tools, optics, materials, energy, electronics, and healthcare (Berube, 2006; Lux Research, 2006). Patenting began almost immediately after Sumio Iijima (1991) illustrated CNT synthesis and the field has developed into one of the most prominent domains of commercial nanotechnology (Lux Research, 2006).

In the mid-1990's entrepreneurial firms began to emerge, pursing opportunities related to CNT production and CNT-enabled products. As Fig. 1 shows, only a handful of firms were active through 2000. However, this jumped considerably in subsequent years. By 2005 the field encompassed 62 startup firms, collectively accounting for almost 250 patents. However, while firms were working to develop next generation memory devices, microprocessors, solar cells, and medical sensors, applications were very much in their nascent stages (Anderson, 2011; Berube, 2006; Lux Research, 2006). Reflecting the relatively long commercialization timeline, government grants were an important funding resource for some firms. However, venture capitalists also made significant investments in the field (Lux Research, 2006; Waitz and Bokhari, 2003): between 1994 and 2005 there were 68 completed deals spread among 26 firms that totaled approximately $250 million. Notably, the average deal size ($6 m) was over 10× larger than a typical government grant (Lux Research, 2006; Zucker and Darby, 2007). Given that investments were made based on evaluations of nascent stage technologies – with focus being an important consideration (Waitz and Bokhari, 2003) – the CNT field provides an excellent site to study the relationship between category focus, audience assessments, and resource acquisition.

To identify nascent CNT firms, we started by gathering data on all CNT patents from Nanobank — an authoritative storehouse of nanotechnology patents, grants, and articles (Zucker and Darby, 2007). To identify CNT patents from this larger set, we searched for 'nanotube' and related terms such as 'fullerene', 'buckeyball', and 'carbon 60' (e.g., Harris, 1999; Meyyappan, 2005). This search yielded 1128 patents through 2005 (when the Nanobank data ends), the first of which was issued in 1992. To identify startup firms, we examined the assignee names listed on each patent and matched them against a list of nanotechnology ventures compiled from sources including the Lux Nanotechnology Report (Lux Research, 2006), the Nanotube Site (Tomanek, 2009), and Understanding Nano (Boysen, 2009). The Lux Report was particularly useful because it lists the type of nanotechnology that each firm works with (e.g., nanotubes vs. quantum dots). Given that Nanobank does not include patents that were applied for, but not granted, before 2005, the Lux Report was crucial for identifying firms that were not picked up in our original sample. In total, we identified 62 startup firms, the first emerging in 1994.

To ensure that we had comprehensive data for each firm, we did a supplementary search for their patents in the USPTO database. Interestingly, this search yielded a handful of non-CNT patents (12 patents from four firms). We tried to account for this in two ways: 1) as a distinct variable and 2) as another instance of category spanning, equivalent to spanning between USPTO classes with CNT

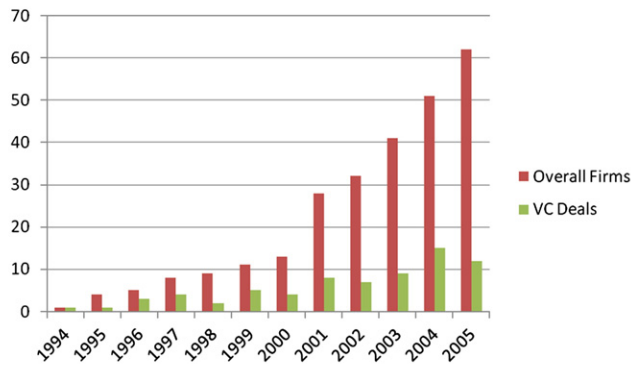

Fig. 1. CNT startup firms and venture capital deals per year: 1994–2005.

patents. The first was not significant in any model and neither approach affected the magnitude, direction, or significance of reported results. As such, we dropped these patents and confined our analysis to CNT patents.

5.1. Variable definitions

5.1.1. Dependent variable

Our dependent variable is venture capital investment. We track this in two ways. Primary analysis treats investment as a binary variable set to 1 for the year that a firm receives funding and 0 in all other years. This allows us to model the factors that help a nascent firm to secure investment. In supplementary analysis, we also explore differences in the level of funding which firms received. Here, venture capital is modeled as a continuous variable reflecting the amount of each investment in millions of dollars. Data is from Zephyr, a database tracking firms that received venture capital over the years of our analysis.

5.1.2. Independent variables

Category dispersion is calculated using a modified Herfindahl measure (where larger values reflect dispersion rather than concentration so as to match the direction of our hypotheses) that captures the extent to which a firm's patents are focused in a limited number of USPTO classes, or are spread out among many. The equation is written as:

$$H(\mu(x,y,t)) = 1-\sum\nolimits_{1p(t)}\mu^2_{i(l)}(x,y,t), \tag{1}$$

where $\mu i(l)(x, y, t)$ is the proportion of the firm's category memberships that come from l. Per the convention in patent studies, this variable is based on patent application dates (Hall et al., 2001).

Each patent issued by the USPTO is assigned into one of over 400 original (or primary) classes which group similar types of innovations together. Classification decisions are based on the claimed attributes and functions of an innovation. Expert examiners (typically with a PhD in a related discipline) review the claims listed on a patent application and follow an assiduously laid out protocol for determining which class it should be placed in (Hall et al., 2001; USPTO, 2009).[1] While the potential exists for a patent to be placed in a class not intended by its inventor(s), there is a general consensus that patent classes capture meaningful distinctions among the technologies that a firm is developing (see Benner and Tushman, 2002; Gilsing et al., 2008; Katila, 2002; Rosenkopf and Nerkar, 2001). Further, audiences such as venture capitalists use patent classes to map out innovation trajectories within a field and to assess the competitive position of various firms in this context (Harris and Harris, 2011; Lux Research, 2006). To wit, Jurron Bradley, Senior Analyst and head of nano-materials practice at Lux Venture Capital notes that "nanotech start-ups with technologies that are tailored to target one or two specific applications tend to be much more [attractive] than companies who develop a broad technology platform with no clear purpose" (Bradley, 2007).

Hypotheses 2a and 2b suggest that patent classes may be related at a higher level of aggregation – specifically as domains of scientific versus product innovation – and that this may affect the outcomes of category spanning among startup firms. Although we expect to observe a divide between patent classes at this level of aggregation, there is considerable variation in the specific classes that are relevant for development in different fields (Benner and Tushman, 2002; Hall et al., 2001; Katila, 2002) and there is no way to identify a field's science and product focused classes a-priori. As such, our first step was to determine which classes in the CNT field were focal points for development in these areas. To do this, we used the proportion of patents in a class assigned to high profile 'star' scientists and large corporations as a proxy of its science versus product focus, respectively. Our approach is based on evidence that the divide between scientific discovery and product development is replicated in the patent world (Powell and Snellman, 2004; Powell et al., 2005; Trajtenberg et al., 1997; Zucker et al., 1998) and we focus on star scientists and large corporations as the 'visible exemplars' of activity in these areas (Wry et al., 2011b; Zucker et al., 1998). We define star scientists as inventors with +1000 citations to their publications and large corporations as those with +500 m in yearly sales.

Notably, our data shows a low correlation between the proportion of star scientist and large corporation patents per class/year (.182) suggesting that there is minimal overlap in their patenting. We also note that the patents for each group tended to cluster in a different set of classes: across the years of our analysis, the top 10 classes for star and large corporation patenting accounted for .698 and .746 of the patents issued to these actors. Looking at the names of these classes offers a further degree of face validity for our operationalization: star scientists were most active in classes such as *#204: Chemistry*, *Electrical and Wave Energy* and *#423: Chemistry of Inorganic Compounds* while large corporations tended to cluster in classes like *#257: Transistors* and *#313: Electric Lamp and Discharge Devices*. Thus, we are confident that our measure taps a meaningful distinction among patent classes in the CNT field that are oriented toward scientific versus product innovation.

We used the average science and product focus scores for the classes where a startup firm had patented to determine the degree to which it was focused on *science* or *product* innovation. To test Hypothesis 2a – that the detrimental effects of category spanning will be reduced when a firm is focused in classes associated scientific discovery *or* product development – we created interaction terms for *category dispersion*×*science focus* and *category dispersion*×*product focus*. We tested Hypothesis 2b – that the detrimental effects of category spanning will be amplified when a firm is focused in classes associated with scientific discoveries *and* product applications – with a three way interaction term composed of *science focus*×*product focus*×*category dispersion*.

[1] In addition to examining official USPTO documents pursuant to classification, we conducted five interviews with patent examiners. Each told a consistent story of classification as a mechanistic process guided by the claims made in a patent application.

Hypothesis 3 argues that venture capitalists might perceive a coherent identity and focused expertise for firms that span classes which build on similar knowledge. To assess this, we began by examining the 'prior art' citations listed on the patents in each class per year. Similar to references in an academic article, each patent issued by the USPTO includes a list of related patents that it builds on (Hall et al., 2001). Patent classes that cite similar prior art are considered to build on like expertise (Hall et al., 2001; Jaffe et al., 2000). To formally assess the knowledge similarity among classes containing CNT patents, we began by creating yearly matrixes with citing classes in the rows and cited classes in the columns. Next, using Ucinet (Borgatti et al., 1999), we calculated joint affiliation data by multiplying each matrix by its inverse and then transformed the results into similarity scores using Pearson's correlation method. A firm's *category similarity* score is the average yearly knowledge similarity among the classes where it has patented. We tested Hypothesis 3 with the interaction between *category dispersion* × *category similarity*.

To be clear, we do not claim any discrete concordance between our similarity measure and the perceptions held by venture capitalists. Still, we anticipate that it is a reasonable proxy. USPTO classes communicate the types of inventions being pursued in a field – and the knowledge that is relevant to them – in a way that is readily accessible to interested observers. Although nanotechnology is a new and rapidly evolving field, many venture capital firms dedicate considerable resources to tracking its development. For example, Steve Jurvetson, Managing Director of Draper Fisher Jurvetson, is the founder of the Nano-Business Alliance (Jurvetson and Waters, 2005) and the Harris + Harris Group actively recruits scientists with specialized backgrounds to analyze nanotechnology investments (Harris and Harris, 2011). Thus, just as organization theorists tend to recognize that institutional and social movement literatures are converging (Campbell, 2005; Schneiberg and Lounsbury, 2008) and that institutionalism and economics are not (Roberts, 2008) without doing formal bibliometric analyses, we expect that interested observers in the venture capital community will perceive shifting linkages among patent classes in ways that reasonably approximate our formal measure.

5.1.3. Control variables

We include a number of controls related to the availability of venture capital and quality signals which might help firms access it. Certain regions may be more fertile for venture capital investments than others (Chen et al., 2010). For nanotechnology, commercial activity and venture capital are most prominent in Boston, Houston, and the San Francisco Bay area (Berube, 2006; Wry et al., 2010). We control for this by assigning a 1 to startups based in these *nano-regions*. Also, because venture capital funding often results in further financing (Lerner, 1994), we include a variable tracking the number of *investment rounds* that a firm has attracted. In our tobit regression models, we also include a control for *firm age* to account for potential life-course effects (this is directly integrated into hazard rate models as the temporal exposure condition). In addition, venture capitalists may be attracted to firms that target lucrative market segments, regardless of their underlying technology focus. To control for this, we consulted the Lux Research Nanotechnology Report (2006) which lists the primary market focus for each firm: these include nano-tools (9 firms), materials (19 firms), optics (8 firms), energy (6 firms), electronics (9 firms), and healthcare (11 firms). Based on this, we included a series of dummy variables tracking each firm's *market focus*, leaving out 'energy' as the comparison set.

Studies also suggest that resource providers look to signals about a firm's quality when making investment decisions (Sahlman et al., 1999; Zott and Huy, 2007). We controlled for four variables generally thought to reflect the quality of a high-tech firm: 1) intellectual property (IP); 2) IP value; 3) affiliation with established organizations; and 4) founder status (e.g., Martens et al., 2007; Stuart et al., 1999; Zucker et al., 1998). Our *IP* variable is the cumulative yearly count of patents owned by a firm or pending approval. *IP value* is the cumulative yearly sum of citations to a firm's patents in the prior art section of other patents; a widely accepted measure of quality and importance in the patent literature (Hall et al., 2001; Harhoff et al., 1999).[2] We also controlled for one important type of third-party affiliation—being a university or corporate *spinout* (Richards, 2009; Zahra, 1996). To control for the status of a firm's founder (or founding team), we include a dummy variable set to 1 for firms launched by a *star scientist founder*. Table 1 provides an overview of the variables used in our analysis.

5.2. Statistical method

We modeled the effects of category dispersion on the likelihood of receiving venture capital using Cox hazard rate analysis (Blossfeld et al., 2007; Cox, 1972). Unlike parametric models which make strong assumptions about the shape of a hazard rate, the Cox method controls for temporal exposure, but leaves the base hazard rate unspecified. The model is written as:

$$r(t) = h(t)\exp(A(t)\alpha) \tag{2}$$

where the transition rate, $r(t)$, is the product of an unspecified baseline rate, $h(t)$, and a second term specifying covariates, $A(t)$, expected to produce proportional shifts in the transition rate. Model estimation is based on the method of partial likelihood where $\mathrm{Y}i(\mathrm{t})$ indicates if actor i experiences an event at t, and $\mathrm{Y}k(\mathrm{t})$ specifies if actor k is at risk at t:

$$\prod_t \frac{\mathrm{Y}_i(t)\exp(A_i(t_i)\alpha)}{\sum_{=1}\mathrm{Y}_k(t)\exp(A_l(t_k)\alpha)}. \tag{3}$$

[2] Using patent citations is complicated somewhat, however, because more recent patents are cited less and patents in different years and categories are not equally likely to be cited (see Hall et al., 2001). To correct for this, we scaled the citations for each of a firm's patents according to the average yearly citations for all nanotechnology patents issued in the same category year (see Miller, 2006 for a similar approach). Citation rates were calculated based on Nanobank data.

Table 1
Variable descriptions.

	Variables	Mean	St. dev	Min.	Max.	Source
1.	VC (dummy)	.278	.449	0	1	Zephyr
2.	VC (millions)	6.37	2.58	0	24.10	Zephyr
3.	Nano tools	.118	.322	0	1	Lux Research
4.	Materials	.443	.399	0	1	Lux Research
5.	Electronics	.127	.333	0	1	Lux Research
6.	Optics	.114	.319	0	1	Lux Research
7.	Healthcare	.151	.359	0	1	Lux Research
8.	Nano region	.400	.491	0	1	Nanobank
9.	Investment rounds	.553	1.21	0	9	Zephyr
10.	IP (patents)	5.08	2.31	0	47	Nanobank/USPTO
11.	IP value	.734	2.03	0	22.21	Nanobank/USPTO
12.	Spinout	.052	.221	0	1	Nanobank/USPTO
13.	Star founder	.121	.327	0	1	Nanobank/Web of Science
14.	Category dispersion	.314	.321	0	.908	Nanobank/USPTO
15.	Product focus	.154	.141	0	1.00	Nanobank/Compustat
16.	Science focus	.193	.260	0	1.00	Nanobank/Web of Science
17.	Category similarity	1.41	1.27	0	3.49	Nanobank/USPTO

Firms enter our risk set the year that they apply for their first patent and leave when they are acquired or fail (as reported by Zypher). We include repeat observations in our analysis to model all instances of venture capital investment. We used STATA 11 for all models. After declaring our data as survival time with the *stset* command we created models using the *stcox* command. Finally, since our data contain repeat observations of individual firms, we used the *cluster* option with 'firm number' as the grouping variable to help account for unobserved variance at the firm-level. We controlled for temporal effects with year fixed effects. Presented results show coefficients rather than hazard rates for ease of interpretation.

In addition, based on results suggesting that some types of category spanning were more likely to result in venture capital investment, we constructed supplementary tobit regression models to explore which patent class combinations were associated with larger investments. Tobit regression is a non-parametric alternative to ordinary least squares regression and is typically used in cases where the dependent variable is continuous but skewed (or censored) on either side of the distribution. In our data, investment is bounded at zero – and is thus left censored – making tobit regression an appropriate estimation strategy. Also, since our data include repeat firm–year observations, we controlled for unobserved variance by estimating models with random effects using 'firm number' as the grouping variable. We controlled for unobserved temporal variance with year fixed effects. Models were estimated using the *xttobit* command in STATA 11. For all models, data is organized by firm–year and includes 336 observations between 1994 and 2005. Independent and control variables are lagged by 1 year.

6. Results

Table 2 provides variable correlations and shows that there are no collinearity problems. Table 3 reports the results of our hazard rate models. Model 1 is a baseline model with control variables. Models 3 to 8 add hypothesized variables and show improved fit over the baseline.

Table 2
Variable correlations.

Variables		2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1.	VC (dummy)	.83	.01	−.12	.17	.08	−.02	.08	.08	.19	.05	−.01	.11	.10	.11	−.02	.26
2.	VC (millions)	–	−.03	−.12	.22	.05	.00	.12	.04	.32	.11	−.04	.18	.14	.12	.01	.25
3.	Nano tools		–	−.40	−.14	−.13	−.16	−.12	.03	.02	.02	.25	−.14	−.12	−.01	−.17	−.10
4.	Materials			–	−.42	−.39	−.46	.16	−.01	−.05	−.08	−.14	.23	.21	−.31	.17	.10
5.	Electronics				–	.55	−.16	.10	−.01	.15	−.06	−.09	−.09	.02	.25	−.01	.01
6.	Optics					–	−.10	−.00	−.02	−.02	−.03	.08	−.13	−.03	.44	.02	−.07
7.	Healthcare						–	−.27	.01	−.06	.17	.09	−.05	−.06	.08	−.01	−.02
8.	Nano region							–	−.01	.12	−.02	.14	.41	.06	.23	.22	.33
9.	Investment rounds								–	.06	.24	.15	.02	.15	.15	.02	.05
10.	IP (patents)									–	−.01	−.01	−.08	.32	.19	.01	.07
11.	IP value										–	.08	.15	.10	.18	.08	.11
12.	Spinout											–	−.13	−.07	.15	−.11	−.11
13.	Star founder												–	−.19	.22	.53	.38
14.	Category disp.													–	.19	.08	−.05
15.	Product focus														–	.34	.27
16.	Science focus															–	.29
17.	Category sim.																–

Table 3
Cox hazard rate models of venture capital investment: 1994–2005.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nano region	1.085	1.35**	1.20**	1.26**	1.20**	1.25**	1.40**	1.56**
	(.505)	(.587)	(.560)	(.560)	(.549)	(.577)	(.631)	(.539)
Investment rounds	1.67***	1.92***	1.96***	1.99***	1.99***	2.03***	1.83***	1.86***
	(.251)	(.262)	(.251)	(.266)	(.279)	(.278)	(.280)	(.244)
IP (patents)	.031	.062**	.085***	.091***	.086***	.073**	.064**	.066**
	(.025)	(.024)	(.031)	(.029)	(.031)	(.034)	(.029)	(.032)
IP value	.092	.127	0.132	.130	.125	.116	.171	.184
	(.134)	(.131)	(.128)	(.109)	(.117)	(.117)	(.112)	(.115)
Spinout	.773	.951	.615	.632	.668	.720	.822	.919
	(.702)	(.638)	(.768)	(.934)	(.876)	(.888)	(.744)	(.837)
Star scientist founder	.401	.324	.557	.714	.555	.374	.280	.336
	(.711)	(.678)	(.692)	(.738)	(.681)	(.854)	(.729)	(.712)
Category dispersion		−1.43***	−1.90***	−1.68**	−2.03***	−1.84**	−2.13***	−2.97***
		(.431)	(.525)	(.842)	(.734)	(.916)	(.711)	(.764)
Science focus			−.608	−.979	−.764	−1.06		
			(.537)	(.884)	(.669)	(.777)		
Product focus			1.86**	1.47	1.63*	1.23		
			(.832)	(1.42)	(.928)	(1.04)		
Category similarity							.400***	.094
							(.103)	(.234)
Science focus × dispersion				−1.61		−.904		
				(1.98)		(1.73)		
Product focus × dispersion				.653		.865		
				(1.65)		(1.42)		
Science × product focus					.303	.318		
					(.552)	(.308)		
Science × product focus × dispersion						−.477		
						(.592)		
Similarity × dispersion								.524***
								(.193)
Market focus	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Log-likelihood	−387.43	−381.86	−376.55	−376.56	−376.07	−373.54	−373.47	372.47
LR X^2	115.70	137.51	135.42	135.24	160.82	133.12	197.91	189.06

Standard errors in parentheses; two-tailed tests.
** $p<.05$.
*** $p<.01$.
* $p<.10$.

Our first hypothesis argued that firms whose patents were dispersed among patent classes would be less likely to receive venture capital. The coefficient for *category dispersion* is negative and significant across most models, providing support for this hypothesis at a broad level of analysis. Hypothesis 2a suggested that this effect would be attenuated among firms that focused on patent classes associated with basic science discoveries or commercial product development. However, Table 2, models 3 and 4, show little support for this. There is some evidence that startup firms which focus in the same patent classes as large corporations are more favorably received, but this is not at a high level of significance and the effect disappears when category dispersion is introduced in model 4. Table 2, models 5 and 6, similarly fail to support Hypothesis 2b. Although the coefficient for the 3-way interaction between *science focus × product focus × dispersion* is in the expected direction, the effect is non-significant. Thus, the effects of dispersion do not appear to be amplified when a firm splits its focus among product and science classes. It is important to note, however, that while we fail to support the influence of these higher-order groupings when considered alone, we delved further into the relationship in supplementary models and found that they are actually quite important for understanding venture capital when considered in tandem with knowledge similarity.

Hypothesis 3 argued that venture capitalists would react favorably to firms that bridged classes where similar knowledge was relevant, making investment in these firms more likely. We find considerable support for this hypothesis. Table 2, models 7 and 8, show that firms with patents that built on a coherent knowledge base were more likely to receive venture capital and that this significantly moderated the penalties associated with having a dispersed patent portfolio.

6.1. Supplementary analysis: Category configurations and deal sizes

Given that firms which spanned between related patent classes were the most likely to receive venture capital, we decided to look more deeply to see if certain combinations were seen as more valuable, resulting in larger investments. Also, we were struck by the moderately high correlation between the scientific and product focus of CNT firms (.342), and that this was higher among funded firms (.556) – something that is counterintuitive to the logic of Hypotheses 2a and 2b. As such, we deepened our investigation, examining in more detail the role played by similarity as well as by the science or product development focus of a class.

As a starting point, we created maps detailing the patent portfolios of each firm, noting deal sizes as well as activity in classes where star scientists and large corporations were most active. Given the generally low activity of CNT startups leading up to the millennium, Figs. 2 and 3 show patent class affiliations for 2001 and 2005. For illustrative purposes, the figures distinguish between the top 10 classes where star scientists were active and the top 10 where large corporations were active as a way to visually map the most prominent scientific versus product classes. As previously noted, although there were +100 classes with CNT patents in our analysis, the top 10 for star scientists and large corporations captured a considerable portion of their patents: stars: 2001 = .746, 2005 = .720 and large firms: 2001 = .698, 2005 = .715.

To map the evolving knowledge similarities among classes, we created non-metric multi-dimensional scaling (MDS) plots that include every USPTO class where there were CNT patents in a given year. Fig. 4 plots the evolving relationships among these classes in three well-spaced panels: 1997, 2001, and 2005. MDS plots provide a visual representation of inter-class similarity based on Euclidean distances in 2-dimensions (Kruskal and Wish, 1978). When classes are close together they share similar citation patterns, otherwise they are far apart. We marked the top ten star scientist and large corporation classes on these plots, (eight on the 1997 plot because of the smaller number of categories with CNT patents at that time).

Taken together, Figs. 2–4 provide an illuminating picture of category focus as it relates to basic science and product classes and to deal sizes. As Figs. 2 and 3 indicate, there was a fairly clear divide between scientific and corporate development across the years of our analysis. The former concentrated in classes related to CNT synthesis and basic materials applications (e.g., *#204: Chemistry*, *Wave and Electrical Energy*, *#423: Chemistry of Inorganic Compounds*, and *#252: Compositions*). The latter concentrated on commercial applications; initially for conductive structures and basic imaging applications (e.g., classes #257, #430) and moved toward display devices (e.g., classes #313, #315), computers (e.g., classes #257, #438) and energy transmission (e.g., class #250) in the post millennium years. At a deeper level of analysis, however, it is clear that the underlying knowledge similarities among these classes changed dramatically. Fig. 4 shows that, through 2001, very different types of knowledge were relevant for scientific versus commercial product innovation. By 2005, however, this schism had largely disappeared. While a full account of the reasons for this convergence is beyond the scope of this paper, it is clear that the knowledge which was relevant to these classes became much more similar.

The evolving knowledge dynamics among scientific and product classes appears to have played an important role in both category spanning among nascent CNT firms and in the level of investment that they attracted. Looking at Fig. 2, it is striking that up to 2001 only two of 21 firms spanned between science and product classes and neither attracted venture capital. As such, it appears that the knowledge divide among these groupings may have presented a strong barrier to both spanning and to venture capital investment; a finding that lends a degree of support to Hypothesis 2b. By 2005, however, very different dynamics are apparent. Concurrent with the convergence in knowledge among scientific and product innovations, nascent firms began to span between these classes at a much higher rate. Moreover, as Fig. 3 shows – while some firms that affiliated with star science *or* product classes attracted funding – many large deals were for firms that straddled these areas.

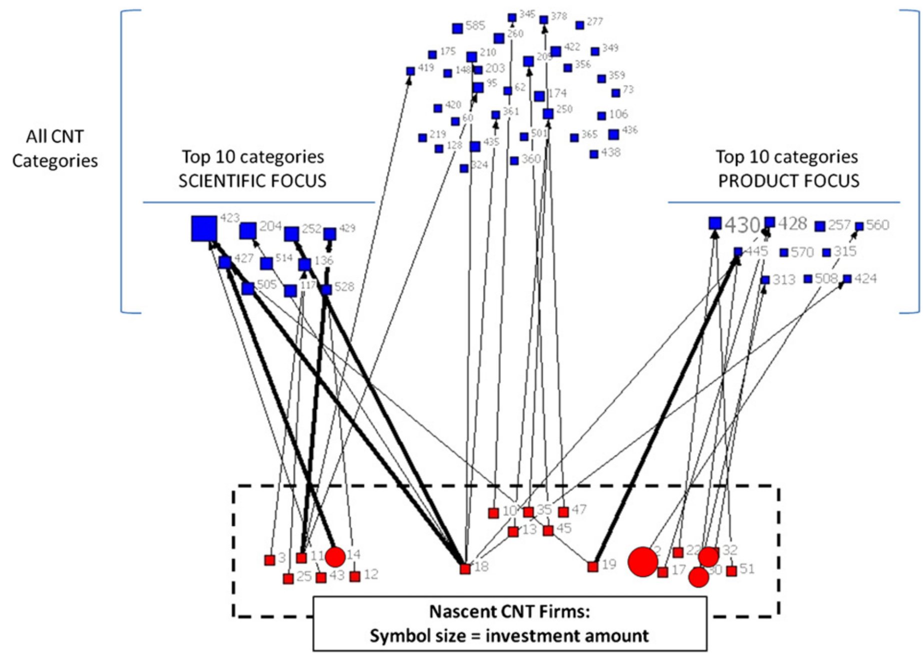

Fig. 2. Category affiliations and venture capital investments: 1994–2001.

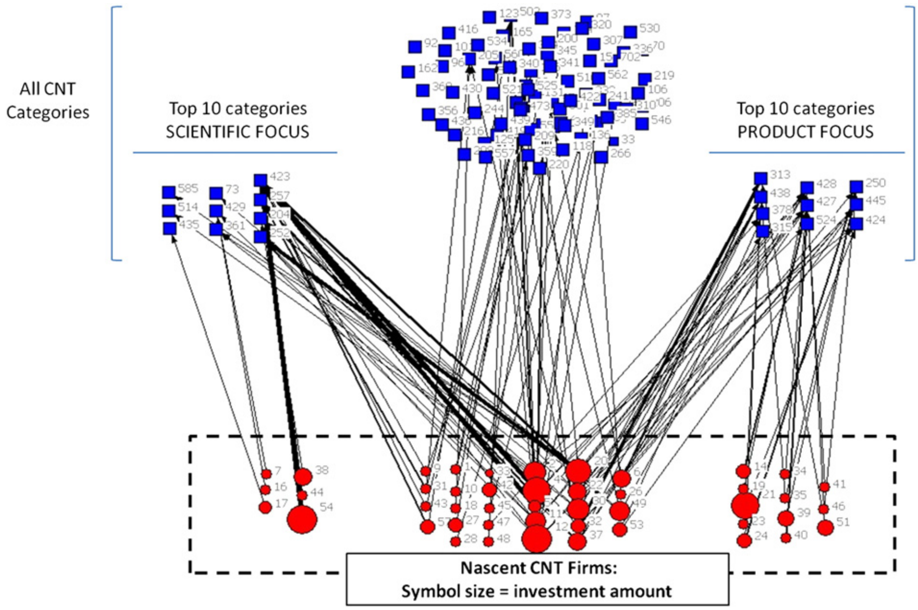

Fig. 3. Category affiliations and venture capital investments: 2001–2005.

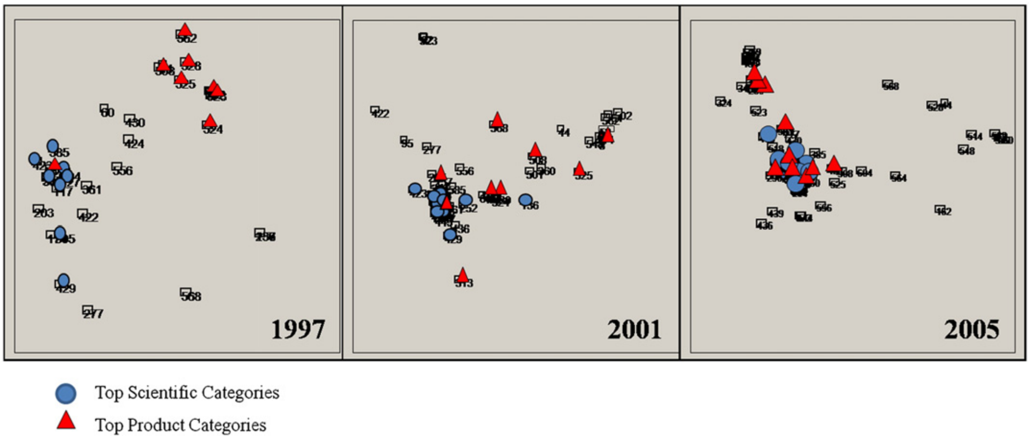

Fig. 4. Multi-dimensional scaling plots of CNT category similarities.

To see if this pattern was statistically significant, we constructed a series of periodized tobit regression models with 'deal size' as the dependent variable: Table 4. We used 2001 as a temporal divider because it is apparent that the dynamics of category focus and venture capital investment began to change around this time. Table 4 shows that, other than *category similarity* which has a positive influence across all models, there were a number of differences among the factors predicting deal sizes in the early and late periods. Most notably, models 3 and 4 show that the effect of splitting focus between classes for scientific and product innovation was opposite. Prior to 2001 (when these classes drew on different expertise) such firms were viewed less favorably, as reflected in significantly smaller deal sizes. However, as the underlying knowledge among these classes converged in the later period, firms that focused in both areas were significantly more likely to attract large investments, especially when they spanned between the most similar of them.

Overall, our supplementary analysis suggests that evolving relationships among patent classes enabled firms to successfully stake out positions that focused on scientific *and* product innovation. As such, a group of nascent firms created a unique space between the CNT field's most prominent players. As per arguments that firms are most attractive to investors when they stake out positions that resemble – but are distinct from – a field's existing players, our results suggest that this type of category spanning was quite lucrative (Lounsbury and Glynn, 2001; Navis and Glynn, 2011), but only when firms drew on like knowledge to do so.[3] Thus, while the knowledge distance between classes for scientific and product innovations made them a bridge too far

[3] We also investigated the influence of a firm's position vis-à-vis other firms. Results were not significant: a finding that is not terribly surprising considering that firms with the biggest deals shared a similar orientation bridging between science and product categories.

Table 4
Periodized tobit regression models of venture capital investment size (millions): 1994–2001(A) 2002–2005(B).

Variables	(1)		(2)		(3)		(4)	
	A	B	A	B	A	B	A	B
Constant	−2.035	−17.534	−2.019	−14.316*	−1.596	−10.614	−2.381	−12.661
	(2.259)	(9.134)	(2.520)	(8.418)	(2.430)	(9.065)	(2.624)	(9.256)
Firm age	−.492	.084	−.511	.100	−.707	.087	−.548	.045
	(.982)	(.374)	(1.106)	(.404)	(1.089)	(.379)	(1.111)	(.086)
Nano region	.281	.514	.487	.503	.779*	1.308	.680	.999
	(.429)	(1.986)	(.435)	(1.937)	(.432)	(1.900)	(.453)	(.856)
Investment rounds	.609	2.761***	.721*	1.575**	.652*	1.785**	.897*	2.141**
	(.482)	(1.015)	(.426)	(.923)	(.306)	(.944)	(.519)	(.979)
IP (patents)	−.119	.595**	−.160	.341	−.093	.329	−.572	.166
	(.166)	(.233)	(.165)	(.226)	(.161)	(.216)	(1.63)	(.221)
IP value	−.235	.363	−.234	.199	−.233	.313	−.219	.311
	(.467)	(.357)	(.463)	(.354)	(.451)	(.344)	(.447)	(.342)
Spinout	1.163	.707	.147	−.877	−.518	−.350	−.499	−.967
	(1.076)	(.991)	(1.271)	(.967)	(1.143)	(.840)	(1.672)	(.865)
Star scientist founder	.244	.783***	.658	.632**	1.358*	.784**	1.486**	.767**
	(.542)	(.247)	(.738)	(.302)	(.750)	(.312)	(.749)	(.313)
Category dispersion			−.627	.608	−.373	1.451	−.966	1.374
			(.747)	(1.350)	(.725)	(1.283)	(.812)	(1.067)
Science focus			.195	−.186*	.508***	−.806**	.551***	−1.397***
			(.164)	(.098)	(.153)	(.317)	(.184)	(.465)
Product focus			−.119	.617**	−.127	.457*	−.152	1.057***
			(.106)	(.269)	(.103)	(.264)	(146)	(.393)
Category similarity			2.256**	2.672***	1.684**	2.819***	2.420**	3.001***
			(1.175).	(.784)	(.806)	(.765)	(1.281)	(.842)
Science × product focus					−.463***	.076***	−.450	.105**
					(.158)	(.026)	(.354)	(.048)
Science × product focus × similarity°							−.145	.075*
							(.245)	(.040)
Market focus	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Log-likelihood	−156.69	−430.21	−154.94	−421.27	−147.87	−419.79	−146.65	−417.32
LR X^2	10.25	21.80	14.29	30.13	24.02	34.37	27.49	40.48

Standard errors in parentheses, two-tailed tests.
°All composite 2-way interactions are included in model estimation, but excluded for parsimonious presentation.
* $p<.10$.
*** $p<.01$.
** $p<.05$.

prior to 2001, their evolving similarities appear to have facilitated perceptions that spanning between them was a coherent and highly valued position in the post-millennium years.

6.2. Robustness checks

Given that we included all instances of venture capital funding in our models, we performed a series of robustness checks to make sure that our results weren't picking up systematic bias where venture capitalists invested in a firm, prodded it toward a more pointed focus, and then made additional investments. First, we re-constructed each of the reported models using a dataset where firms exited after their first investment. The magnitude and direction of the obtained results were consistent with those in our reported models. However, reflecting the reduced sample size, some findings were at lower levels of significance. To further validate our findings, we also ran generalized least squares regressions with firms' category similarity scores as the dependent variable. There was a modestly positive, but non-significant, relationship between venture capital investment and subsequent changes in a firm's category similarity ($\beta = .270$, $p = .176$, when controlling for market focus, age, geographic location, IP, and IP value). As such, we have confidence that our reported results capture hypothesized outcomes.

7. Discussion and conclusion

In this paper we investigated how the category affiliation(s) of nascent CNT firms affected their likelihood of attracting venture capital. Pace existing arguments about the categorical imperative, we suggested that firms would be less attractive to venture capitalists when their intellectual property was diffused among patent classes because this would lead to perceptions of unfocused expertise (Hsu, 2006; Hsu et al., 2009; Rao et al., 2005; Zuckerman, 1999; Zuckerman et al., 2003). While our findings show some support for this, results suggest that such broad analysis misses important nuance in the relationship between technology focus and venture capital in the CNT field. Some nascent firms with widely dispersed patents were less likely to attract investment, but this effect was significantly moderated when a firm bridged similar classes. Further, we showed that as the knowledge being used for basic science advances and corporate product development began to converge, firms that spanned between these areas were the most likely to attract large investments. Thus, dispersion was both rewarded and punished, depending on which classes were spanned and when.

Our findings contribute to the literatures on entrepreneurship, categories, and relatedness. In particular, we add significant nuance to extant findings about the relationship between patenting and venture capital investment (Baum and Silverman, 2004; Lerner, 1994). Although the number of patents that a firm has is a significant predictor of investment in some of our models, we show that additional considerations are relevant. This also contributes to the broader literature on entrepreneurial resource acquisition (Martens et al., 2007; Zott and Huy, 2007) while extending arguments about firm focus to a novel domain (Palich et al., 2000). In particular, we show how both can be bound up in broader, field-level, dynamics where assessments of firms and their potential are made based on understandings about which categories fit together, when, and why. We thus provide further evidence of the cultural embeddedness of entrepreneurship as it applies to individual firms (Lounsbury and Glynn, 2001; Navis and Glynn, 2011).

Our findings also have implications for the organizational literature on categories. Taking inspiration from the strategic literature on relatedness (Miller, 2006; Pehrsson, 2006; Stimpert and Duhaime, 1997), we advocated for an approach that accounts for deeper relationships among categories and the effects that this has on assessments of focus. In particular, we showed that patent classes in the CNT field were embedded in a system of shifting relationships; this facilitated specific patterns of category spanning and shaped how firms were perceived by resource providers. For example, key areas of CNT development such as those related to nanotube synthesis (e.g., class *#423: Chemistry of Inorganic Compounds*) and flat panel displays (*#313: Electric Lamp and Discharge Devices*) are associated with very different outputs. Yet, as they began to share elements of underlying knowledge, nascent firms were able to span between them without conveying unfocused expertise. As such, our findings offer further evidence that category systems evolve over time while showing the consequences that this can have for organizations (Rao et al., 2005; Ruef and Patterson, 2009).

Moreover, we showed that the relationship between category focus and organizational outcomes is specific to particular times and contexts. Our study thus contributes to discussions of focus in the strategy literature by showing that multiple forms of relatedness may be concurrently salient, but that they may not act in similar ways over time. Indeed, it appears as though the value of technological positions that spanned scientific and product classes were differently evaluated in the early and later periods of our analysis. As such, temporal shifts may be an important consideration when analyzing focus in dynamic industries where ongoing innovation brings some categories into close relation and pushes others apart on a continual basis (Brown and Eisenhardt, 1997; Kennedy et al., 2010). This also has implications for the organization theory literature on categories. Specifically, we identify an important scope condition for the categorical imperative and warn against assuming equivalent effects across categories, fields, and time periods: empirical investigation is required on a case-by-case basis.

We also show that evolving relationships among categories can facilitate the emergence of highly valued combinations. This is a novel finding in the categories literature and also suggests that different types of related diversification may be more valuable than others. In particular, our evidence suggests that when a field is composed of groups with divergent foci, but who draw on common knowledge, this may facilitate the emergence of fertile niche spaces. Firms that span between established domains may be able to cultivate unique positions that are distinctive, yet readily comprehensible and highly valued. Indeed, unlike category systems where individual categories become more distinctive over time (e.g., Ruef and Patterson, 2009), the CNT field saw progressively deepening inter-category relationships which appears to have enabled perceptions that certain combinations fit together. While it is speculative at this point, such dynamics may play a role in the emergence of higher order categories such as new organizational forms if combinations are repeated over time and become institutionalized among important audiences (McKendrick et al., 2003; Ruef, 2000).

7.1. Future research

Despite the strength of our findings, this research has some limitations that point to avenues for further research. For one, it is likely that some firms in our sample were not actively seeking venture capital. Results should be interpreted with this general data limitation in mind and future studies should engage this heterogeneity directly. It is also possible that venture capitalists utilize additional categories when evaluating CNT investments. While our results show strong evidence that the classes – and the relationships between them – which we focus on have consequential implications for investment decisions, we make no claims that they are exhaustive. A more robust picture of venture capital investments in nanotechnology may be gleaned by identifying further relevant categories. Our approach also overlooks potential variance in the degree to which venture capitalists attend to the CNT field, their relative knowledge about the relatedness of technological developments, and the emphasis which they place on a firm's focus (Gupta and Sapienza, 1992). Each is a potentially valuable research direction that may significantly enrich our understanding of the venture capital community and the various approaches taken when investing in nascent industries (Fried and Hirsch, 1994).

In addition, our findings should be explored in different contexts. The CNT field is very dynamic (Meyyappan, 2005) and USPTO classes are a specific type of category. It would be useful to investigate if similarity affects the categorical imperative in fields with different levels of dynamism and different types of categories. Such investigation may also help to illuminate factors that lead some category systems to trend toward similarity and integration, while others become more rigidly segregated over time (Ruef and Patterson, 2009). Further, venture capitalists are one audience and others may perceive firms differently (Hsu and Hannan, 2005). Attending to the perceptions of manifold audiences may help to provide a more robust understanding of the relationship between category focus, external evaluations, and resource acquisition.

We also foresee possibilities to build on our findings through qualitative research. While a quantitative approach is typical for category studies like ours (e.g., Hsu, 2006; Zuckerman, 1999), it required that we infer the perceptions of venture capitalists from their investments. Future research should examine these perceptions directly. Along these lines, it would also be useful to investigate how audience perceptions are affected by the narratives that firms use to describe their category affiliations. While it is generally assumed that audiences react to category focus in an unmediated way, such judgments are unlikely to take place in a vacuum (Lounsbury and Glynn, 2001; Wry et al., 2011a,b). Category spanners can advocate for the appropriateness of their position and this may affect how they are perceived as well as paving the way for others to follow (Rao et al., 2005). As such, category effects may be shaped by the interaction between the categories being spanned and the social skill of the actor doing the spanning (Fligstein, 1997).

In sum, we find that category affiliations have a significant effect on entrepreneurial resource acquisition. However, our results suggest that there is folly in assuming that all types of categories and category systems are alike. While we find support for arguments about category focus at a broad level of analysis, it masks important nuances that only become apparent when considering the deeper relationships that develop between categories. Thus, while some nascent firms are punished when they affiliate with multiple categories, those which bridge similar categories fare much better. Moreover, when a field is characterized by evolving relationships that bring constellations of categories together dynamically over time, it appears to lay the groundwork for highly valued combinations to emerge. In such cases, a narrow category focus may be more of an impairment than an imperative.

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