# Construing Novelty: Category Boundaries and Venture Capital Investment in Entrepreneurs' Recombination

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**Abstract**

Research in economics and sociology points to recombination as the source of novel social and economic developments. Most systematic studies of this thesis investigate whether recombination is associated with the creation of high-impact technologies. This study looks at novelty in markets, investigating the association between recombination and venture capital investment. Acknowledging that people use different categories in different contexts, the author argues that the evaluator's categorical system is foundational to what is recognized and rewarded as recombination. Supporting this view, findings show that venture capitalists are more likely to invest in software entrepreneurs that engage in recombination across *market categories*, but standard measures of recombination across technological categories (based on patent classes) are not associated with investment. In addition, whether a person values recombination depends on his orientation toward disrupting the status quo. In line with this, it is high and low status VCs who are more likely to invest in firms that engage in recombination. In syndicates comprised of middle status investors only, the direction of the effect reverses. Findings suggest that the evaluator role is fundamental to the concept of recombination and the construal of novelty in a domain.

Schumpeter's insight that novelty emerges from "the carrying out of new combinations" spawned a large and diverse literature (Schumpeter, 1934: 66). "Recombination," or new combinations of existing elements, is widely accepted as the primary antecedent for novel developments. Recombination is reified as the "ultimate source of novelty" (Fleming, 2001: 118; Schoenmakers 2010), and "the 'holy grail' of innovation research" (Gruber, Harhoff and Hoisl, 2013: 837).

Researchers' prolonged interest in the subject arises from the idea that recombination is the source of new developments that transform the economy and society. For Schumpeter (1942), new combinations of existing elements are what "incessantly revolutionizes the economic structure," (p. 83). Nelson and Winter (1982) write, "The creation of any sort of novelty in art, science, or practical life - consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence," (p. 130). Weitzman (1988) proposes that novelty, "new configurations of old knowledge," is the determinant of long-term growth (p. 359). Scholars show that important inventions resulted from new combinations of existing elements (Tushman and Anderson, 1986; Henderson and Clark, 1990; Hargadon and Sutton, 1997). Systematic studies of patents and academic publications find that technical developments that combine distant elements are highly cited (Fleming, 2001; Nerkar, 2003; Schoenmakers and Duysters, 2010; Uzzi, Mukherjee, Stringer and Jones, 2013; Foster, Rzhetsky and Evans, 2015; Leahey, Beckman and Stanko, 2016). But it is still an open question whether recombination leads to the types of market transformations that have sustained the interest of researchers and practitioners alike.

Much research on recombination studies patents and academic papers and presumes that a particular institutional classification (patent classes and journal disciplines) defines boundaries over which recombination can occur. This paper questions that assumption. Recognizing that people use different categories in different contexts (Hsu, 2006; Hannan, 2010; Durand and Paolella, 2013; Goldberg, Hannan and Kovács, 2016), I propose that recombination—and thus novelty—is relational, depending not only on characteristics of the object, but also on the relevant categorical system used by the evaluator. This has important implications in markets, where firms and products are often classified using

either technology categories or market categories. Whereas previous studies of recombination take a technology perspective and study how recombination affects citations, here I ask whether recombination is valued on the market and investigate venture capital (VC) investment in entrepreneurial firms.

Drawing on the literature that links recombination with novelty, I propose that VCs will invest in firms that engage in recombination. This provides the first systematic study of which the author is aware showing that recombination is a source of novelty in markets. But simply linking VCs to the idea of recombination is not enough: it is critical to determine what is a recombination. Traditionally, scholars have conceived of new combinations as bringing together elements from different technology categories (Fleming, 2001; Nerkar, 2003; Wezel, Kovacs and Carnabuci, 2014). But, because the categorical system VCs use is based on market classification, I argue that VCs invest in firms that combine elements across *market category boundaries*, and that combining technology categories does not capture novelty for VCs.

Recombination across market categories does not necessarily reflect recombination across technology categories. For example, in 2007 NVIDIA leveraged its Graphics Processing Unit (GPU), originally created to transform a 3D image into 2D for gaming, for general-purpose programming of large amounts of data in parallel. This innovation drew on their existing technology grounded in one technology category, but combined market categories: graphic display and parallel processing. In the 1990s, collaboration software emerged as a new product that allowed people to work remotely. It combined video, microphones, graphics, and mathematical algorithms; novel on the market but not a radical technology advance. Both examples combined elements across market categories and led to the disruptive change that VCs seek. But in terms of technology categories, neither were new combinations.

This study suggests that recombination cannot be defined by the object only; the evaluator affects whether recombination is recognized and rewarded. First, it is necessary to know the relevant categorical system before recombination can be defined. Second, recombination is not universally sought, but is valued by people who are interested in transformational changes. Ideas are investigated using a unique data set of 3,298 software firms in their entrepreneurial phase, that tracks VC financing, underlying

elements of technical advances (using patents), and classification based on either *market categories* or *technology categories*.

**Recombination and Boundaries**

Scholars have proposed that recombination is the ultimate source of novelty. Studies show that novel products and technologies are based on new combinations of existing components (Henderson and Clark, 1990; Hargadon and Sutton, 1997; Vilhena et al., 2014). Research in the categorization literature defines recombination as mixing features associated with existing categories (Montauti and Wezel, 2016). Such combinations are the foundation for new organizational forms and cultural developments (DiMaggio, 1991; Clemens, 1996; Rao, 1998; Phillips and Owens, 2004; Rindova and Petkova, 2007). Many of these studies take an *ex post* view (Eggers and Kaul, 2014), investigating a new development that became successful and tracing it back to its innovative roots.

Studies that take an *ex ante* approach investigate patents or journal articles. Both are tracked in archival data where citations are recorded. Backward citations measure the knowledge foundation of the patent or article, which indicates if it is based on recombination. Forward citations measure success. These data allow for systematic studies of the association between technology recombination and subsequent technical importance. Findings underscore the inherent uncertainty of recombination. Patents that build on similar elements are more useful on average, but those that combine distant components have variable outcomes, leading to breakthroughs or failure (Fleming, 2001). Journal articles show similar trends: novel bridges to other literatures are rare, but high impact papers have unconventional citation pairings (Uzzi, Mukherjee, Stringer and Jones, 2013; Foster, Rzhetsky and Evans, 2015; Rzhetsky, Foster, Foster and Evans, 2015; Leahey, Beckman and Stanko, 2016). This distinction maps to exploration and exploitation in the organizational learning literature. Exploiting local knowledge is reliable but predictable, while exploring distant knowledge is risky but has the potential to be revolutionary (March, 1991; Kogut and Zander, 1992; Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002; Nerkar, 2003; Beckman, Haunschild and Phillips, 2004; Dahlander, O'Mahony and Gann, 2016).

Previous studies recognize that recombination is partially based on social construction, even in technical domains (Fleming, 2001; Gruber, Harhoff and Hoisl, 2013; Wezel, Kovacs and Carnabuci, 2014). Scholars allow that technological boundaries change over *time* as technologies evolve: for example, a material based on sand and aluminum would have seemed strange to a scientist in the 1940s but is widely recognized as a semiconductor today (Fleming, 2001). But innovation researchers have not considered that at the same point in time people frequently use different category systems to interpret their environments. These systems will influence how recombination, and thus novelty, is construed.

Building on the literature on concepts and categorization, I argue that recombination is relational, depending on both the object being evaluated and the system of categories used by the evaluator. It is elements in different categories that are the "previously unconnected" components with the potential to create a recombination (Montauti and Wezel, 2016). Every domain has multiple classifications. For example, a person can be categorized by his occupation ("attorney," "doctor", "janitor"), marital status ("husband", "bachelor") or interests ("runner", "foodie"). Automobiles can be classified by their style ("economy", "family", "luxury") or engine type ("four cylinder", "V6"). Software can be classified by its underlying technologies or how it is marketed. For example, reporting software in the "relational technology" category is in different market categories: "business intelligence," aimed at presenting actionable information to executives, "customer relationship management," used to help an organization communicate with customers, or "enterprise resource planning," which maintains back-office functions. For a coder, "relational technology" is salient, but for a customer, market categories are relevant.

Studies in cognitive science show a person can shift between different categorical structures based on which is most relevant (Murphy, 2004). For example, a person may categorize all things "green," objects that are "buildings" or "things with windows" (Lupyan, Mirman, Hamilton and Thompson-Schill, 2012). A person's role—or more generally, his context—determines which categorical system is used (Barsalou, 1983; 1991). This is in line with recent sociological research on categorization that defines categories with respect to an audience (Hannan, Pólos and Carroll, 2007; Hannan, 2010; Pontikes, 2012). It has implications for recombination. For a person who uses market categorization, a

product that combines elements across these market categories will be a novel recombination. For someone that uses technology categories, the novel product combines elements over technical boundaries.

Consider the example of athletic clothing illustrated in figure 1. This shows two ways clothes can be classified: using materials or design. There are two objects, a "poly/merino shirt" and a "hit the trails skort." Whether the object is a recombination depends on the category structure. If default categorization is design, a shirt or skirt is squarely in one category, while the skort—a blend of shorts and skirts—is a recombination. But if the relevant category structure is materials, it is the poly/merino shirt that is a recombination. It is likely that most people would be able to recognize both category systems. What is important to the argument is that the category system most pertinent to an evaluator affects what is a novel development. Note that this argument does not assume that people have different, stable category systems. The role a person is in at a point in time determines the relevant category structure.

Previous research assumes that technology categories are a universal default (Fleming, 2001; Rosenkopf and Nerkar, 2001; Nerkar, 2003). But recombination based on patent classes will not resonate with a person for whom a different categorical structure is most important. Recombination, and thus the construal of novelty, depends on the categorical system of the evaluator.

**Recombination and VC investment**

What underlies interest in recombination is that novel developments are the source of value creation in the economy (Schumpeter, 1934; Nelson and Winter, 1982; Weitzman, 1998). Radical change destabilizes market structures, challenging established companies and providing opportunities for entrepreneurs (Abernathy and Clark, 1985; Tushman and Anderson, 1986). But systematic studies of recombination do not directly study whether recombination leads to these important changes in markets. Rather, the outcome variable is citations, either to patents or journal articles. The assumption is that highly cited patents are engines of productivity (Trajtenberg, 1990). Researchers have not directly investigated whether recombination is associated with novelty in a market. This study addresses this gap by investigating the association between recombination and VC investment.

VCs are high-status, high-risk investors who look for entrepreneurs that have the potential to create new markets (MacMillan, Zemann and Subbanarasimha, 1987; Hisrich and Jankowicz, 1990). They aim for their investments to become the next "new, new thing" (Lewis, 1999). Because mature markets typically are controlled by established companies, the VC strategy is to invest in companies that are poised to be leaders in new markets that are predicted to grow quickly. Such a company is often called "disruptive" (Pontikes and Barnett, 2015). Peter Thiel, co-founder of PayPal who became a prominent VC, advocates that rather than trying to take a piece of an established market, start-ups should do something entirely new. He writes, "The next Bill Gates will not build an operating system. The next Larry Page or Sergey Brin won't make a search engine. … If you are copying these guys, you aren't learning from them." (Thiel and Masters, 2014: 1). A VC I interviewed concurs, highlighting that s/he invests in counter-normative companies:

> you want to invest in those things, where you look at it and are like – that'll never work. But if it *does* – you know, dot, dot, dot. Like Airbnb. That'll never work. People will never go sleep in a kid's bedroom in someone else's house and pay a nightly rate. But if it did …

In this quote, "dot dot dot" refers to explosive growth, as was seen in the "sharing economy" in the 2010s. This idea is articulated by consulting firm Play Bigger Advisors, who assert that "category kings"—companies with the potential to quickly dominate a new market category—are the most valuable targets for VC investment, citing companies like Facebook, Twitter, LinkedIn, Dropbox, and Airbnb. They state, "Emerging Category Kings define a new space by conditioning the market to buy and consume new technology in a new way … they create a change in the … market with a 'different' approach," (Ramadan, Lochhead, Peterson and Maney, 2013: 19).

Another high-status VC I interviewed described their firm as employing a high-risk, high-return strategy through IPOs. They avoided companies that sought to achieve value through acquisition. Success in public markets is important for VCs to establish and maintain their reputations (Gompers, 1996; Lee and Wahal, 2004). The strategy of identifying big winners who will dominate a unique market and IPO, rather than be acquired, also resonates with Play Bigger's take (Ramadan, Lochhead, Peterson and

Maney, 2013). VC Paul Martino of Bullpen Capital echoes this sentiment, stating "Coming in second means nothing … there's an advantage of … backing something before it becomes obvious to others," (Goldfisher, 2014). Of course, such large wins cannot be precisely predicted. This is why VCs use a risky, high-variance strategy, where most investments result in losses, but a few generate outsized returns (Sahlman, 1990). VC investment indicates that the firm is in the "tails" of a performance distribution: VCs bet that a unique company will be especially successful, but risk that it might be a flop.

An open question is how VCs identify novel companies. Research points to recombination as the ultimate source of novelty, which suggests that VCs should invest in firms that engage in recombination. But this begs the question, what is recombination for someone in the role of VC? For VCs, transformative companies are those poised to dominate a market that fundamentally changes the customer experience. This indicates that VCs use market-based categorization when deciding how to invest.

The market novelty that VCs seek may not be captured by technology category recombination historically used in innovation research (e.g. Fleming, 2001; Nerkar, 2003; Schoenmakers and Duysters, 2010; Gruber, Harhoff and Hoisl, 2013). Certainly, technology is essential to the outstanding success of many VC backed start-ups. But the ultimate goal for VCs is to identify a novel market that will see explosive growth. The successful entrepreneurs that VCs want to emulate developed technological products. But companies like Facebook, Airbnb, and Uber's contributions are not groundbreaking technologies. Rather, these companies created new styles of communication that radically changed the way people interact in the marketplace. Drawing on the idea that recombination depends on the categorical system relevant to the evaluator, I propose that novelty for VCs is captured by recombination across *market categories*.

> *Hypothesis 1a*: Venture capitalists are more likely to invest in organizations that develop technologies based on high levels of market category recombination, compared to those with low levels of recombination.
>
> *Hypothesis 1b*: Recombination across market category boundaries is more predictive of VC investment as compared to recombination across technology categories.

To test the hypotheses, it is necessary to investigate outcomes based on whether the same elements are combined across boundaries of different category systems. The patent record is one of the few data sets that contains systematic information on inventive components (Fleming, 2001). This study uses the patent record to represent a firm's inventive developments, but is unique in that it can classify these patents either using market categories and technology categories (described in detail below).

A number of studies have investigated the relationship between patenting and VC investment in terms of whether VCs value patents as signals of quality (Stuart, Hoang and Hybels, 1999; Hall and Lerner, 2010). Both investors and entrepreneurs use patents as signals of technical expertise, branding, or differentiation (Lemley, 2000; Mann, 2005; Graham and Sichelman, 2008). Companies with patents raise more money (Baum and Silverman, 2004; Audretsch, Bönte and Mahagaonkar, 2012), and patents are most important when there are fewer alternative signals (Hsu and Ziedonis, 2013). Even in the software industry, some studies find that patent counts are correlated with investment (Mann and Sager, 2007).

But if the above arguments are correct, and venture capitalists invest in organizations that can revolutionize an industry, the number of patents a firm has may not be the most informative metric. To the extent that patents are used as a signal, VCs should value organizations with patents that have the potential to transform the market – those that engage in market category recombination.

*Valuing recombination: Middle status conformity among VCs*

VCs are high-status investors, which is consistent with their orientation toward risky investments that disrupt existing structures. The hypotheses above are predicated on such a novelty-seeking evaluator.

But not all people seek counter-normative developments. Much of the literature on market categorization shows that people typically prefer objects that conform to categories (Hsu, Hannan and Koçak, 2009; Negro, Hannan and Rao, 2010; Smith, 2011; Leung and Sharkey, 2013). At the same time, the appeal of categorical conformity depends on the audience: for example, whether a person values novelty and atypicality (Pontikes, 2012; Merluzzi and Phillips, 2015; Goldberg, Hannan and Kovács, 2016). Similar audience-based differences are found for whether inventors engage in recombination:

scientists generate more recombinatory patents than do engineers (Gruber, Harhoff and Hoisl, 2013). Such differences are also found among VCs: compared to the traditional private equity (PE) investor, corporate VCs invest in less risky syndicates (Dushnitsky and Shapira, 2010) and are less novelty seeking (Pontikes, 2012).

This is important because recombination and novelty—disrupting existing structures—is not always "better" than building on what already exists. Recombination leads to outsized rewards but not necessarily higher mean performance. Fleming (2001) finds that inventions based on distant combinations have lower citations on average, but higher variance. Scientists who engage in interdisciplinary research publish fewer papers, but those published have more visibility (Leahey, Beckman and Stanko, 2016). In biomedicine, innovative publications are less likely to reach publication, but once published garner higher citations (Foster, Rzhetsky and Evans, 2015). This reflects the trade-off between exploration and exploitation described in March (1991). Distant combinations are risky: resulting in breakthroughs or failure.[1]

If they succeed, novel developments are especially impactful. This is what led Schumpeter (1934;1942) to identify new combinations as the engines of economic development. It is also resonant with the way venture capitalists describe their process of selecting investments. Recombination should appeal to someone who is willing to risk great losses for a chance to reap an exceptional reward.

The quest to find new and different firms paints a picture of the prototypical, high-status VC. But there is variance among VC investors in terms of a status, which may be related to how much a VC values market category recombination. Seeking novelty is a contrarian endeavor, requiring a person to invest in companies that, at first glance, seem like they will "never work." Even though this is the ideal business model for VCs, sticking to a contrarian strategy runs against human tendencies to conform. As a result, many successful VCs write books and articles reiterating that investors should move against the crowd

[1] There is also evidence that the most successful developments are both novel and interpretable (Rindova and Petkova, 2007; Bingham and Kahl, 2013; Uzzi, Mukherjee, Stringer and Jones, 2013; Dahlander, O'Mahony and Gann, 2016).

(Marks, 1993; Thiel and Masters, 2014). Despite most VCs intending to invest in novel firms, consensus behavior among is rampant among them (Pontikes and Barnett, 2016).

Middle status VCs may be the most reluctant to embrace novel investments. As Philips and Zuckerman (2001) proposed with "middle status conformity," high-status actors, secure in their positions, feel free to deviate, and low-status actors have nothing to lose. They find middle status actors are most adherent to social conventions. This may be because they deliberately employ conservative strategies, but could also result from psychological factors. In a laboratory study, when subjects were manipulated to be middle status, they were less creative and more convergent (Duguid and Goncalo, 2015).

Status is important among VC investors (Stuart, Hoang and Hybels, 1999). Reputations help VCs raise capital and find investment opportunities (Gompers, 1996; Sorenson and Stuart, 2008). Status orderings are stable, indicating that middle status conformity applies in this setting (Phillips and Zuckerman, 2001). Together, these arguments suggest that whether recombination (across relevant categories) is valued, depends on the evaluator's willingness and ability to overlook social conventions.

*Hypothesis 2*: The positive effects of market category recombination on VC investment will be stronger for high and low status VC investors, as compared to those of middle status.

**Empirical Test**

These ideas are studied in the software industry, an innovative domain where both market categories and technology categories are important. Technology categories reflect how a product is created: for example, the type of code used, if it is object-oriented, its graphical integration, or how the software is optimized. Market categories are use-based, allowing customers, analysts, investors, and partners to understand what they can do with the product (Pollock and Williams, 2009; Wang, 2009; 2010). For example, "digital audio" software is used for recording, editing, and producing audio files, "enterprise resource planning" integrates applications that manage and automate back-office functions, "supply chain management" executes transactions and manages supplier relationships, "ETL (extraction, transformation, load)" software moves data from one system to another. A digital audio and supply chain management product

could use the same type of graphical interface and optimization system, making them similar from the technology category system. But they are different in terms of customer use, placing them far apart for market categories.

To test the hypotheses, it is necessary to investigate outcomes based on whether the same elements are combined across boundaries of different category systems. Patents provide a detailed historical record of a firm's inventions over time, including citations that uncover what an invention is built on. They are a good source of data for the underlying technical components used by software firms. These elements can be classified by technology categories using patent classes, as in many previous studies of recombination (Fleming, 2001; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Schoenmakers and Duysters, 2010; Gruber, Harhoff and Hoisl, 2013). This study is unique in that the data also allow for the same elements (patents) to be classified using market categories.

In software, a fair amount of invention can be tracked through patents. Although IP protection is not as important as in other industries, previous research shows that patents do influence venture capital financing, IPOs, acquisition, and market entry (Mann, 2005; Mann and Sager, 2007; Cockburn and MacGarvie, 2011). A problem with using patents in a software study is that laws in the United States historically did not allow software to be patented. In 1972, the Supreme Court ruled in *Gottschalk v. Benson* that software could not be patented. But through a series of cases this was overturned, and was effectively changed by 1994 – 1995 (Hall and MacGarvie, 2010; Cockburn and MacGarvie, 2011). Therefore, the time period analyzed in this study starts in 1995.

Another concern might be that immediately after software patenting was allowed, patent classification may not have adequately reflected technology categories. The USPTO has subsequently re-classified many software patents. To address this concern, recombination across technology categories is computed using both the original USPTO class, the current USPTO class, and IPC classification maintained by the World International Property Organization (WIPO). These three classifications should capture technology categories for patents issued by software companies during this time period.

VC financing is critical in software (Onorato, 1997; Mann, 2005), often more important than customers or revenue. VCs are known for aggressively trying to invest in the next revolutionary idea (Lewis, 1999). The importance of both technology and market categories, and the focus on novelty and VC investment, makes software a good context for this study.

**Data and Methods**

Hypotheses are tested using a unique data set of patents, venture capital financing events, and technology and market categorization for all software organizations that could be tracked in press releases. These data include organizations that do not receive funding, allowing for additional tests of receiving initial funding, which is unusual in research on patents and VC financing (Mann and Sager, 2007; Hsu and Ziedonis, 2013).

Market categories are extracted from press releases issued by software organizations between 1990 and 2002 (this study uses the period between 1995 and 2002). In almost every press release, a software company will state the market category they are in, so press release data provide a historical record of market category affiliations. Previous research shows that using self-affiliations is reliable classification (Hoberg and Phillips, 2010; Hoberg, Phillips and Prabhala, 2014; Hoberg and Phillips, 2015; Pontikes, 2012; Pontikes and Hannan, 2014). Patent portfolios were gathered from the NBER U.S. Patent Citations data file (Hall, Jaffe and Trajtenberg, 2001), which has been extended through 2006. Technology categories were based on USPTO and IPC patent classes gathered from NBER data the Patent Network Dataverse (Li et al., 2014).[2] Market categories were extracted from press releases. The risk set is comprised of all software organizations in their entrepreneurial phase (private and less than 15 years old in analyses of all VC financing rounds, and less than 10 years old for first round financing).[3]

[2] NBER data contain original and current class and subclass assignment for the patent's primary class. The Patent Network Dataverse contains multiple class and subclass assignments for the patent's current class only.
[3]Founding dates could not be located for some organizations, likely to be small, young firms that were not successful, and so excluding these might bias the results. Therefore, I also include private organizations where the founding date is unknown. Firms that IPO or turn 15 during the study period are removed from the risk set as a censored observation.

*Dependent variables.* The primary dependent variable is whether the organization receives venture capital financing in the current year. Because a subset of software organizations patent, separate estimations are run on the risk set of all organizations and for patenting organizations only.[4] There are 3,298 private organizations under 15 years of age for 9,049 organization-years between 1995 and 2002, and 1,403 VC funding events (734 organizations funded). For patenting organizations, there are 368 organizations over 1,057 organization-years, for which there are 174 VC funding events (103 organizations funded). Models are also run to estimate first round financing, on 2,322 firms under 10 years of age over 5,631 organization-years, with 260 first round funding events and 129 events of first round financing from private equity firms only.

VC funding events for high, middle, and low status VCs are computed using the LPJ reputation index (Lee, Pollock and Jin, 2011). Reputation scores are computed based on funds under management, number of start-ups invested in and amount invested, number of companies taken public, and the firm's age. Firm status is defined based on LPJ rank each year.[5] High-status firms rank 1 – 24, middle status 25 – 149, and low status 150 or higher.[6] Dependent variables used to test hypothesis 2 include whether a firm receives funding from a high, middle, or low status investor in the given year, or whether it receives funding from *only* high, middle, or low-status investors that year.[7]

*Independent variables.* Patent data are used to measure the components a firm's inventions are based on, using citations.[8] Recombination is measured for market categories and technology categories based on whether patents build on elements within or across boundaries of the respective classification. The underlying elements are the same (patents).

[4] Recombination and other patent-based measures are set to zero for organizations that do not patent.
[5] This measure is correlated with that used in Podolny (2001) at 0.7 (Lee, Pollock and Jin, 2011).
[6] These cut-offs were chosen such that status bands had approximately similar numbers of events for all organizations and for patenters only. Results are not sensitive to the thresholds.
[7] Not all VC firms are recorded in the Lee et al. (2011) reputation rankings. Receiving funding from "only high status" is defined as when there are high status investors in the round and no middle or low status investors. There may be investors of unknown status. "Only middle" and "only low" status are calculated in the same manner.
[8] All measures are timed by the application year of patents (only patents that were later granted are used).

Market category recombination: Market category recombination measures whether a firm's patents combine technologies across market categories it is not in. This is computed based on whether a firm's patents cite patents that are in other market categories. *Patent classes are not used in the construction of this measure*.

To compute market category recombination, patents must be mapped to market categories. This is done by first constructing an n-dimensional "knowledge space" based on the patent citation network of software patents (Podolny, Stuart and Hannan, 1996; Pontikes and Hannan, 2014). Knowledge space is built on all patents relevant to software (not just from organizations in these data). Similarity between two patents ($\sigma_{mn}$) is calculated by dividing the common citations by the total citations by the focal patent.[9] Areas of knowledge space are mapped to market categories based on the category of the organization that is assigned the patent. Market category recombination is based on whether an organization's patents draw on knowledge associated with a market category that it is not in. This is computed using the knowledge space similarity ($\sigma_{mn}$) between a patent *m* issued to organization *A* (*m* is in *A*'s portfolio $P_A$), and each patent *n* that is affiliated with a category organization *A* is not in: $D_A \in D: (\mu_A(D_A) = 0)$, where $\mu_A$ is *A*'s grade of membership in category $D_A$.[10] A patent *n* is affiliated with market category $D_A$ if it was issued to an organization *B* that is a member of $D_A$ ($\mu_B(D_A) > 0$), weighted by *B*'s grade of membership in $D_A$. The proximity to different categories ($D_A$) for each patent *m* issued to organization *A* is computed as:

$$prox_{m,D_A} = \sum_{(n \in P_B)} [\mu_B(D_A) \times \sigma_{mn}] \quad (1)$$

where $P_B$ is the patent portfolio of organization *B*. This is then summed over all categories that *A* is not in:

$$prox_{m,D} = \sum_{(D_A:(\mu_A(D_A)=0))} [prox_{m,D_A}] \quad (2)$$

Patent level proximities are aggregated to the organization level using an average. Because the distribution is skewed, the natural log is taken:

[9] Second degree similarity is also calculated between two patents with shared similarity to a third, by multiplying these similarities.

[10] Organizations in multiple market are weighted by their grade of membership, (the number of press releases in which organization *A* claims category *k*) divided by (the number of press releases in which it claims any category) in a given year, so they do not have an outsized effect on the measure.

$$(\text{Market category recombination})_A = ln\left(\frac{\sum_{m\epsilon P_A} prox_{m,D}}{npat_A}\right) \quad (3)$$

Develops within market categories: I also include a variable that measures the extent to which an organization builds on knowledge related to its own categories, as a control. This is computed identically to market category recombination (3), but measures an organization's knowledge space proximity to patents in its own categories, $S$, rather than different categories, $D$.

Technology category recombination: To test hypothesis 1b, recombination across technology categories is computed using patent classes from the USPTO and IPC classification. Previous studies use a number of different measures of recombination based on patent classes (see Gruber *et al* (2013) for a detailed review). Variants of two measures are used here:

1. Originality: a widely used measure of recombination is derived from a Herfindahl index based on the class assignments of patent *j*'s cited patents (Trajtenberg, Henderson, and Jaffe, 1997). I use the bias-corrected modification proposed by Hall (2005):

$$Orig_p = \frac{N_p}{N_p - 1}\left(1 - \sum_{k=1}^{K}\left(\frac{cite_{p,k}}{J}\right)^2\right) \quad (4)$$

Here patent $p$ has $J$ backward citations to $k = 1 \ldots K$ patent classes, and $cite_{p,k}$ is the number of $p$'s citations in class $k$. $N_p$ is the number of total classes patent $p$'s citations are in, and multiplying the Herfindahl index by $\frac{N_p}{N_p-1}$ corrects for bias when the total number of citations are small (Hall 2005). These analyses are at the firm level, so the measure is aggregated. It is plausible that VCs would look at either the originality of the entire patent portfolio or of one promising patent. Estimates test both average and maximum originality of the organization's patents, *P,* for a given year:

$$mean\_orig_A = \frac{\sum_{p=1}^{P} Orig_p}{P} \quad (5)$$

$$max\_orig_A = \max_{p \in P} Orig_p \quad (6)$$

Originality is calculated for original USPTO class, current USPTO class, and WIPO IPC class.

2. Breadth: The second measure counts the classifications to which a patent is assigned. This measure is used by Lerner (1994), and a similar measure is used by Leahey (2006). I use both the number of classes and subclasses assigned to a patent and calculate the average and maximum for each firm. Multiple class and subclass assignments are available from the Patent Network Dataverse only for the patent's current class and subclass.

There is a question of whether effects result from the different way market category recombination is computed. Supplementary analyses include a measure of technology category recombination that is computed identically to market category recombination, but using the current and original USPTO patent class. Using the same patent citation network, a patent's proximity to patents in different patent classes is computed as in equation (2), and aggregated to the firm level as in equation (3).

*Controls*. Estimations include the number of patents issued to the organization in the previous year.[11] Previous studies show that category ambiguity affects VC investment and so category fuzziness is included (Pontikes, 2012).[12] The number of other organizations in the same market categories (weighted by grade of membership) and the number of firms in the category that received VC funding (and its square, also weighted by grade of membership) are included to control for the popularity and competitiveness of the organization's market category. The number of acquisitions made by the organization, its tenure in the press release data, and a 0/1 indicator variable for whether it was ranked in *Software Magazine*'s Software 500 are included to control for firm size and quality. The number of previous rounds of financing is included in models run on all VC funding, to capture quality or a tendency for VCs to try to salvage an investment (Guler, 2007). Supplementary analyses include the total number of citations to the organization's patents in the eight years following its grant date as a control for the quality of the organization's patents. All independent and control variables are lagged by one year.

--- Insert table 1 about here ---

[11] Results are robust to including: number of citations, cumulative patents, cumulative citations, the natural log of these variables, average citations per patent, and whether the organization patented in the previous year.
[12] Measured as one minus the average grade of membership of organizations in the category.

Tables 1 contains descriptive statistics. Correlations are available upon request. There are high correlations between market category and technology category recombination, which could raise concerns of whether these capture different classifications.[13] Some organizations do not patent every year, which artificially inflates correlations. Patent level correlations are a better indicator, and patent-level correlations between market and technology category recombination are low, indicating that they are different classifications.

*Model and Estimation*

I model the hazard rate of receiving VC funding as a function of the independent and control variables:

$$r(t - t_n) = r_o(t - t_n) \cdot \exp(\beta_{ind} \cdot \mathbf{x}_{\boldsymbol{ind}} + \alpha_{control} \cdot \mathbf{x}_{\boldsymbol{control}} + \varepsilon) \qquad (7)$$

The rate is estimated using a piecewise exponential model using the routine in STATA. In models with repeated events, organizations that are funded exit and enter with a new ID, and standard errors are clustered by firm. Duration is the time since the organization was last funded or since it appeared in press releases. Estimations where the DV is investment by a type of VC are modeled as competing risks.

**Results**

Evidence for hypothesis 1a and 1b is evident by graphical inspection. Figures 2 and 3 plot the mean number of venture capital funding events by market category recombination and technical category recombination (average originality based on USPTO current class), respectively. The trends show a positive relationship with market category recombination, but the trend for technical category recombination is flat.

--- Insert figures 2 - 3 about here ---

Table 2 provides statistical tests of hypothesis 1a. Column (1) contains controls only. Column (2) tests hypothesis 1a by including market category recombination. The effect is positive and significant ($p < 0.05$), providing support for the hypothesis. Column (3) includes a control for the extent to which a firm's inventions develop knowledge from within its market categories to test if the effect is capturing

[13] There is also the concern that effects might arise from multicollinearity. Effects are similar in models run without highly correlated variables.

recombination or something about general citation patterns. With this control included, the effect of market category recombination becomes larger and the significance level increases ($p < 0.01$). The effect of developing within the firm's categories is non-significant, but the coefficient is negative across models. This may suggest a corollary of hypothesis 1a, where VCs are less likely to invest in firms that build incremental knowledge. Because only a subset of organizations in these data patent, column (4) tests the effect when run on the risk set of organizations that have previously patented. Results continue to support hypothesis 1a. A one standard deviation increase in market category recombination is associated with a 24% increased likelihood of receiving VC funding.[14] This is substantial: twice as large as the increased likelihood of being funded after having received a previous round (12%),[15] an effect that previous literature has shown to result in strong biases in favor of investment, even in the face of evidence that returns are declining (Guler, 2007).

--- Insert table 2 about here ---

Tables 3 - 4 contains tests of hypothesis 1b using technology category recombination metrics averaged across the firm's patents (e.g. equation 5).[16] Results are reported in estimations run on all organizations and for patenting organizations only. When included alone (table 3), none of the technology category recombination measures has a statistically significant positive effect on VC funding at the $p < 0.05$ level. The average number of classes has a marginally significant effect in models run on all organizations, but this disappears in models run on patenters only.

Table 4 includes market category covariates. Market category recombination continues to have a positive effect, at conventional significance levels ($p < 0.05$) in most models and marginal levels ($p < 0.10$) in all models. The coefficient size of market category combination remains steady, but the coefficients for technology category recombination substantially decrease. This provides additional evidence that recombination across *market category boundaries* is positively associated with VC

[14] This is computed using the estimate from table 3 column 4, and a standard deviation for market category recombination from table 2: exp(0.199 * 1.09) = 1.24.
[15] Computed from estimates reported in table 3 column 4: exp(0.109*1) = 1.12.
[16] Estimates using the firm's patent that yields the maximum level of recombination (e.g. equation 6) show similar results (available upon request).

investment. There is no evidence that recombination across *technology category boundaries* attracts venture capital financing. This provides evidence in support of hypothesis 1b.

--- Insert tables 3 - 4 about here ---

*VC Status*

Table 5 presents estimates that test hypothesis 2. In the first two sets of estimates the dependent variable indicates that a firm received funding in a round that included a high, middle, or low-status VC, run on all organizations and on patenters only. In the third set, the dependent variable indicates that a firm received funding from only a high, middle, or low status investor, run on all organizations (there are not enough events to run estimates for this dependent variable for patenters only). The positive effect of recombination is most stable for high-status investors, positive and significant at $p < 0.10$ in all models. There is also evidence that low-status VCs invest in firms that engage in market category recombination, positive and significant at $p < 0.05$ in models run on all organizations, though significance levels drop in models run on patenting organizations only.

--- Insert table 5 about here ---

There is no evidence that middle-status VCs invest in companies that engage in market category recombination. Effects are not significant in any model, and coefficients are negative in models run on all organizations. In all models of middle-status investors, the coefficient for developing technologies within market categories is positive, suggesting that they may have opposite preferences as compared to high or low status VCs. In the third set of models, effects are positive and significant for high and low-status investors, and negative and non-significant for middle status investors, and 90% confidence intervals do not overlap. Together, results provide weak support for hypothesis 2.

*Additional Tests*

A number of supplementary analyses were conducted to test the validity of the results. They are described below and models are available upon request.

There may be a concern that results supporting hypotheses 1a and 1b are due to the way market category recombination was computed. To test against this, technology category recombination was computed in the same manner. Using the patent citation network, each patent's proximity to patents of different classes were computed as in equation (2), and aggregated to the firm level as in equation (3).[17] This variable does not have a significant effect, and it does not change the effects of market category recombination reported above.

One question may be whether the effects of market category recombination are driven by VCs accurately predicting the technologies that will become important. Models test against this by including the *future citations* of the organizations' patents. Patent citations are the typical measure used to represent the impact of a patent (Trajtenberg, 1990).[18] It is unusual to include future events in a statistical model, but in this case the control provides a conservative test of the hypothesis. If causality is reversed and companies that are funded are more likely to have their patents cited, this biases results in favor of the control. Effects indicate that results reported above are not accounted for by VCs accurately predicting which patents will become important.[19]

Another concern might be that effects are picking up on organizations that are in particular categories. To test against this, 0/1 indicator variables were included to control for the categories each organization was in for a given year, for categories that had ten or more members.[20] Results are similar to those reported above.

These data allow for tests of first-round financing, when there is the most uncertainty around an investment. Estimates run on a risk set of organizations that have not previously received funding that are less than ten years old, for all first round funding and for funding events where all investors in the first

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[17] These measures have a similar distribution as compared to market category recombination: for patenters only, current class, $\beta$=1.9, standard deviation=1.8, maximum value = 5.6.

[18] Importance can reliably be measured *ex post*, but there are not reliable present-time indicators of the future importance of patents (Fleming, 2001). Most studies use recombination as the ex-ante measure.

[19] Effects of market category combination lose significance, $p = .105$ for all organizations and $p < 0.10$ for patenters only. Remember these are conservative models designed to test the alternative explanation that predicting patent importance accounts for the market category combination effect. Results do not support this alternative.

[20] Estimates run on patenting organizations would not estimate when this threshold was reduced. Estimates on all organizations show similar results when all category dummies are included.

round are private equity firms.[21] Results show that market category recombination is positive and significant for all round 1 investment ($p < 0.10$) and for round 1 investment from PE firms only ($p = 0.051$).[22] This provides additional support for hypothesis 1a. The coefficient for round 1 PE investment ($\beta = 0.485\ (0.249)$) is 2.5x larger than the effect using all rounds from column (3) in table 3 (($\beta = 0.196\ (0.0702)$). The trend suggests that patents may be most important as signals when there is the most uncertainty surrounding the investment (Hsu and Ziedonis, 2013).

An important concern in tests of hypothesis 1b might be that patent classification does not reflect technology categories in the software industry. To address this, estimations are run using three different classifications to calculate originality: the original and current USPTO class, and the WIPO IPC patent class. If the original USPTO class did not accurately reflect software categorization, either the IPC class or the current USPTO classification should capture technology categories.

I further test against this concern by testing whether technology category recombination for software organizations' patents has expected effects on future patent citations, the standard measure of patent importance. Negative binomial estimations are run on patent citations eight years after the grant date. This analysis focuses on effects of the dispersion parameter (alpha), as recombination is predicted to result in high-variance outcomes (Fleming, 2001).[23] Results show the expected effect for patent originality, the most commonly used measure for technology recombination (Gruber, Harhoff and Hoisl, 2013), when computed using the USPTO current class. Patents based on recombination across current USPTO technology categories are more likely to land in the tails of the distribution: either especially important or especially unimportant.[24] For comparison, the patent-level measure of market-category

[21] Previous research shows that in initial financing PE investors are especially novelty seeking (Pontikes, 2012).
[22] Round 1 models are run on all organizations, as the round 1 analysis is a substantial reduction in data. Further refining the data to patenters only results in small numbers of VC funding events (22 for all investment, 13 for PE only). Effects for round 1 funding should be interpreted as high values of recombination leading to higher rates of VC investment compared to both firms that patents and do not recombine and firms that do not patent.
[23] The above of effects on VC funding also investigate a high-variance outcome, since investing in high-risk, but potentially high-payoff companies – those in the tails of the distribution – is the VC business model.
[24] That the effect is restricted to recombination across current patent classes suggests that reclassifications provide more accurate technology categories. But note that models run on patents from all software organizations (including all ages and public firms) show a positive and significant effect on the dispersion parameter for all originality measures. The negative effect for market category recombination remains.

recombination (the natural log of equation (2)) was included in a separate estimation, and this has a *negative* effect on the dispersion parameter ($p < 0.001$). Technology category recombination has the expected effect on novelty for technical but not market evaluations. This suggests that results do not simply stem from market categories being a more precise classification.

*Effects of controls*

Number of patents does not have a significant effect on receiving funding. This may reflect that success in software is not predicated on IP protection. Category fuzziness has a positive effect on in models run on all organizations, but is insignificant in models on patenters only. For organizations that patent, combining elements across market categories may be a better indicator of novelty than being in a fuzzy category. The number of category members does not have a significant effect on venture capital investment,[25] and the number of market category members that received VC funding has a quadratic effect. Together, these results indicate that market category crowding does not have a competitive effect, perhaps because it indicates that demand is growing. Controlling for other effects (like previous funding rounds), older firms are less likely to receive financing. The number of previous funding rounds is positively associated with receiving a subsequent round.

**Discussion**

The idea that recombination is the ultimate source of novelty underlies research on technical, economic, and social change. This paper suggests that recombination is inherently categorical and depends on the evaluator. Findings support this view. Venture capitalists are more likely to invest in organizations that engage in recombination across market categories, but measures of recombination across technology categories do not significantly correlate with investment. This support the idea that recombination is a basis for novelty, but with an important caveat: recombination cannot be properly studied without knowing the categorical system the evaluator is using.

[25] Estimates were also run with a quadratic term for number of category members and effects reported are similar.

Previous research on recombination has given primacy to technology. Studies measure recombination across technology categories and also use a technical measure of importance: citations. They find that recombination across patent classes results in especially useful inventions. Findings here indicate that technology categories are not always the relevant classification and by no means are natural divisions that determine recombination. Many evaluators do not use technology categories, and as a result, recombination based on these categories does not reflect how novelty is construed. If one did not consider the categorical system for a VC, he might come to the erroneous conclusion that recombination is not associated with VC investment. But VCs do value firms that engage in recombination – if they combine elements across market categories. Recombination is defined with respect to the categorical system of the evaluator.

Findings also indicate that whether recombination is valued also depends on the evaluator. There are positive effects of market category recombination on investment by high and low-status VCs, but not for middle-status investors. There is directional evidence that middle-status investors shy away from recombinatory firms and prefer those that develop within-category technologies. This is consistent with research on middle status conformity (Phillips and Zuckerman, 2001). Evaluators that challenge conventions value recombination; those who are predisposed to support the status quo are repelled by it.

This study may help reconcile recent research that questions the link between recombination and novelty. Kaplan and Vakili (2014) analyze patent texts to identify when a patent originates a new topic. They show that both recombination across patent classes (using citations) and new topic formation (using text) result in high patent citations. But these effects are independent: recombination does not lead to new topic formation. They interpret these results as calling into question a whether recombination is the primary antecedent of novelty. Findings here suggest an alternative: perhaps text-based novelty and citation-based recombination rely on different categorical structures.

In these data, recombination is not measured for firms that do not patent, and so this study does not speak to whether VCs invest in firms that engage in non-patented versus patented recombination. But the weak effect of number of patents on VC financing does suggest that VCs are not prioritizing IP

protection in this context. What matters is the type of patenting a firm engages in. Results indicate that patents can be studied not only as measures of IP protection, but also to measure the types of technologies a firm develops. Patents do matter in contexts like software because they provide the basis for reliable measures of technological advancement – here market category recombination, which is strongly associated with VC investment. It may be fruitful for researchers to expand patent studies beyond investigating IP.

Previous research shows that patent counts have a positive effect on VC financing in industries like biotechnology and semiconductors with strong intellectual property protection (Baum and Silverman, 2004; Hsu and Ziedonis, 2013). VCs also seek novel organizations in these contexts. Positive effects of recombination on VC financing should be observed even when IP protection is strong, as an effect in addition to patent counts. Future research in this area will be informative.

This work has implications for research on categorization in markets. Much of this literature emphasizes how categories constrain individual action, reproducing existing structures (Zuckerman, 1999). More recently, scholars have focused on actors that challenge institutional boundaries and cause categories to change over time (Lounsbury and Rao, 2004; Rao, Monin and Durand, 2005; Pontikes and Hannan, 2014). This study lends additional support to the second line of inquiry. VC investment in companies that combine elements across market categories results in the blurring of boundaries, leading institutional structures to evolve (Negro, Hannan and Rao, 2011).

Findings also support an audience-based view of categorization (Hannan, Pólos and Carroll, 2007; Hannan, 2010; Pontikes, 2012; Goldberg, Hannan and Kovács, 2016). Different actors, or the same actor in different roles, use different categorical systems. Most contexts yield multiple classifications: how academics and practitioners classify research, the critic versus layman's categorization of music, technical versus use-based understanding of products. This study shows that recombination, a concept important to many literatures, is fundamentally dependent on these systems of classification.

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# Figures

Figure 1. Example of two types of recombination in athletic wear.

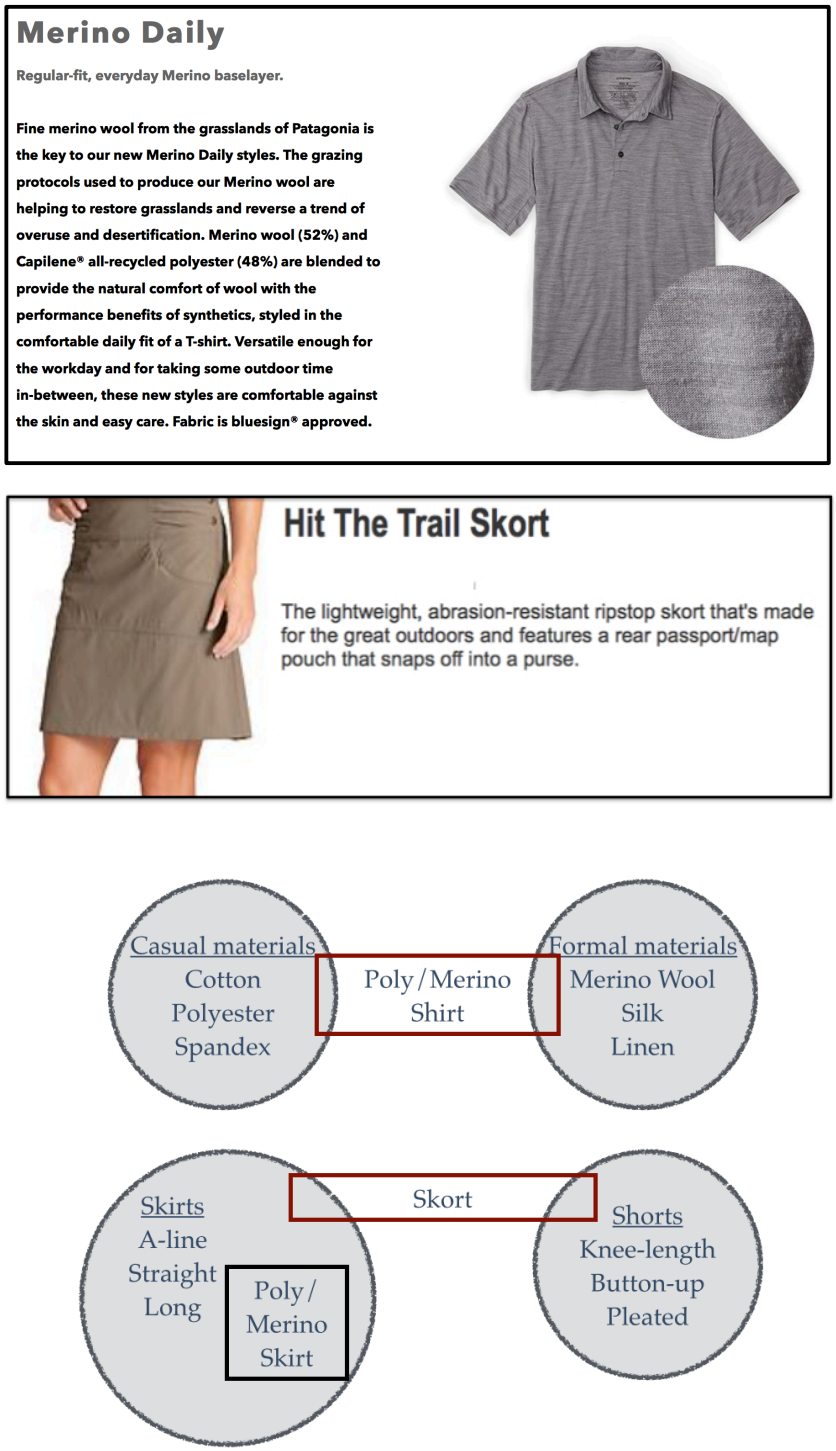


Figure 2. Mean VC funding events by market category recombination.*

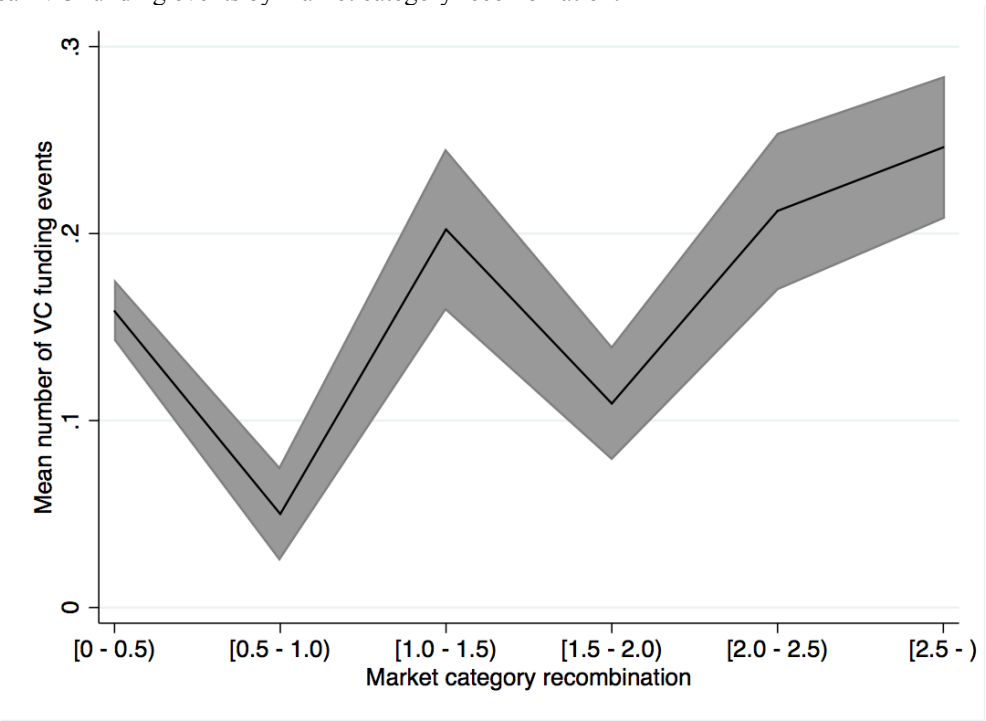
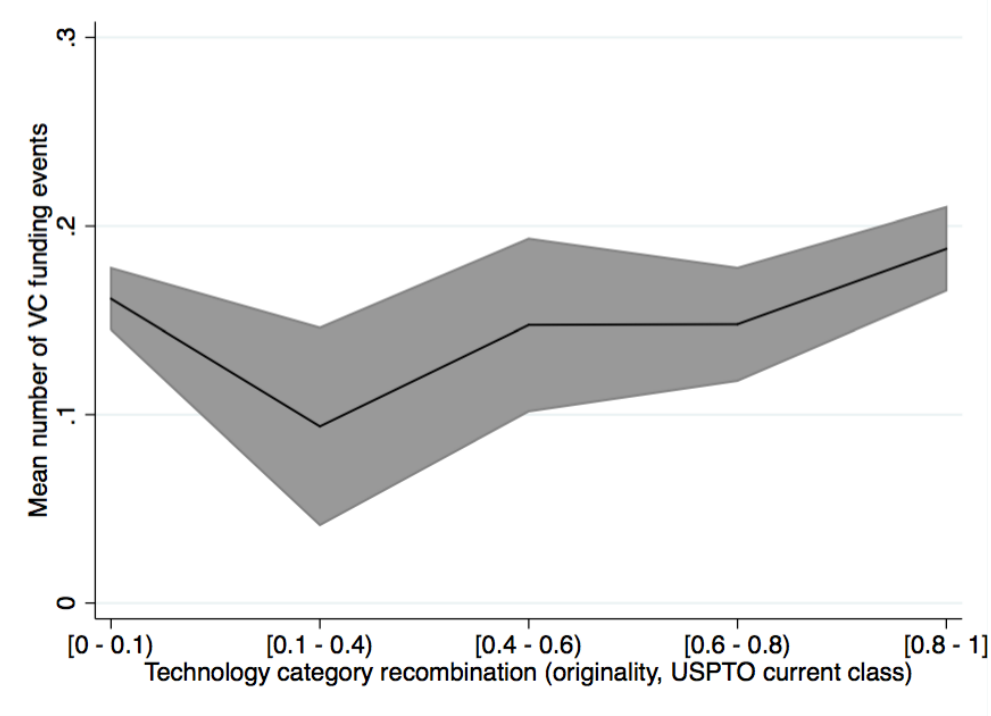



Figure 3. Mean VC funding events by technology category recombination (originality, USPTO current class).*




*Data include patenting organizations only.

## Tables

Table 1. Descriptive statistics (age < 15 years, 1995 - 2002).

| All organizations (N=9,049) | | | | | | Patenting organizations only (N=1,057) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Std. Dev. | Min. | Max. | | | Mean | Std. Dev. | Min. | Max. |
| Received VC funding | (1) | 0.1550 | 0.3620 | 0 | 1 | Received VC funding | (1) | 0.1646 | 0.3710 | 0 | 1 |
| Market category recombination | (2) | 0.1085 | 0.4775 | 0 | 3.962 | Market category recombination | (2) | 0.9292 | 1.0909 | 0 | 3.962 |
| Develops within market categories | (3) | 0.0124 | 0.0905 | 0 | 1.631 | Develops within market categories | (3) | 0.1061 | 0.2454 | 0 | 1.631 |
| Originality (USPTO original class) | (4) | 0.0461 | 0.1869 | 0 | 1 | Originality (USPTO original class) | (4) | 0.3944 | 0.4024 | 0 | 1 |
| Originality (IPC class) | (5) | 0.0354 | 0.1576 | 0 | 1 | Originality (IPC class) | (5) | 0.3035 | 0.3626 | 0 | 1 |
| Originality (USPTO current class) | (6) | 0.0469 | 0.1902 | 0 | 1 | Originality (USPTO current class) | (6) | 0.4016 | 0.4092 | 0 | 1 |
| No. subclasses | (7) | 0.0977 | 0.3842 | 0 | 2.773 | No. subclasses | (7) | 0.8367 | 0.8035 | 0 | 2.773 |
| No. classes | (8) | 0.0650 | 0.2558 | 0 | 2.303 | No. classes | (8) | 0.5561 | 0.5358 | 0 | 2.303 |
| No. future citations (8 years) | (9) | 0.2406 | 0.9641 | 0 | 7.568 | No. future citations (8 years) | (9) | 2.060 | 2.053 | 0 | 7.568 |
| Number of patents | (10) | 0.1670 | 0.9772 | 0 | 21 | Number of patents | (10) | 1.430 | 2.525 | 0 | 21 |
| Category fuzziness | (11) | 0.3785 | 0.2766 | 0 | 0.8332 | Category fuzziness | (11) | 0.5354 | 0.1194 | 0 | 0.7974 |
| No. members of categories (weighted; logged) | (12) | 2.432 | 1.964 | 0 | 6.549 | No. members of categories (weighted; logged) | (12) | 3.452 | 1.275 | 0 | 6.121 |
| No. category members received VC funding (weighted) | (13) | 3.133 | 4.126 | 0 | 25.07 | No. category members received VC funding (weighted) | (13) | 2.693 | 3.703 | 0 | 25.07 |
| No. category members received VC funding squared (weighted) | (14) | 26.84 | 70.44 | 0 | 628.8 | No. category members received VC funding squared (weighted) | (14) | 20.96 | 59.12 | 0 | 628.8 |
| Number of acquisitions | (15) | 0.0082 | 0.0971 | 0 | 4 | Number of acquisitions | (15) | 0.0255 | 0.1905 | 0 | 4 |
| Tenure in data | (16) | 1.823 | 2.028 | 0 | 13 | Tenure in data | (16) | 3.547 | 2.245 | 0 | 13 |
| Number of previous rounds of financing | (17) | 0.646 | 1.626 | 0 | 20 | Number of previous rounds of financing | (17) | 1.105 | 2.124 | 0 | 15 |
| Ranked in Software 500 | (18) | 0.061 | 0.239 | 0 | 1 | Ranked in Software 500 | (18) | 0.1003 | 0.3005 | 0 | 1 |
| Year | (19) | 1999 | 2.049 | 1995 | 2002 | Year | (19) | 1999 | 1.947 | 1995 | 2002 |

Table 2. Piecewise continuous models hazard rate models on likelihood to receive VC funding. Effects of market category recombination.[1]

| | (1)<br>< 15 years | (2)<br>< 15 years | (3)<br>< 15 years | (4)<br>< 15 years; patenters |
|---|---|---|---|---|
| Market category recombination | | 0.147* | 0.196** | 0.199* |
| | | (0.0604) | (0.0702) | (0.0953) |
| Develops within market categories | | | -0.408 | -0.422 |
| | | | (0.325) | (0.359) |
| Number of patents | 0.0243 | -0.0277 | -0.0274 | -0.0686 |
| | (0.0226) | (0.0344) | (0.0331) | (0.0446) |
| Category fuzziness | 1.368*** | 1.335*** | 1.288*** | 0.192 |
| | (0.240) | (0.241) | (0.246) | (0.857) |
| No. members of categories (weighted; logged) | 0.0396 | 0.0398 | 0.0465 | 0.0840 |
| | (0.0301) | (0.0303) | (0.0309) | (0.0646) |
| No. category members received VC funding (weighted) | 0.0377* | 0.0379* | 0.0383* | 0.0928+ |
| | (0.0182) | (0.0183) | (0.0183) | (0.0553) |
| No. category members received VC funding squared (weighted) | -0.00262* | -0.00264* | -0.00266* | -0.00650+ |
| | (0.00108) | (0.00108) | (0.00108) | (0.00378) |
| Number of acquisitions | -0.00333 | 0.0113 | 0.0158 | 0.680* |
| | (0.314) | (0.320) | (0.326) | (0.313) |
| Tenure in data | -0.0590* | -0.0645* | -0.0634* | -0.0421 |
| | (0.0287) | (0.0290) | (0.0291) | (0.0457) |
| Number of previous rounds of financing | 0.159*** | 0.160*** | 0.160*** | 0.109** |
| | (0.0287) | (0.0284) | (0.0284) | (0.0411) |
| Ranked in Software 500 | -0.195 | -0.199 | -0.198 | -0.679* |
| | (0.159) | (0.158) | (0.157) | (0.316) |
| Time piece: 0-1 year | -2.125*** | -2.123*** | -2.125*** | -1.281+ |
| | (0.146) | (0.146) | (0.146) | (0.687) |
| Time piece: 1-3 years | -3.876*** | -3.861*** | -3.862*** | -2.676*** |
| | (0.157) | (0.157) | (0.157) | (0.638) |
| Time piece: 3-5 years | -4.689*** | -4.661*** | -4.664*** | -3.474*** |
| | (0.229) | (0.230) | (0.230) | (0.673) |
| Time piece: 5+ years | -5.711*** | -5.663*** | -5.669*** | -5.023*** |
| | (0.434) | (0.434) | (0.433) | (0.954) |
| Year Dummies | Yes | Yes | Yes | Yes |
| Category dummies | No | No | No | No |
| Log pseudo likelihood | -3587.4 | -3584.7 | -3584.1 | -356.3 |
| Degrees of freedom | 20 | 21 | 22 | 22 |

+p<.10 *p<.05 **p<.01 *** p < 0.001

[1] For all organizations, there are 1,403 events for 3,298 organizations over 9,049 organization-years. For patenters only, there are 174 events for 368 organizations over 1,057 organization-years. Risk set restricted to organizations < 15 years old (or founding date unknown). All independent variables are lagged.

Table 3. Piecewise continuous models hazard rate models on likelihood to receive VC funding. Effects of technology category recombination.[1]

| | All organizations (age < 15 years) | | | | |
|---|---|---|---|---|---|
| | Originality (USPTO original class) | Originality (IPC) | Originality (USPTO current class) | No. subclasses | No. classes |
| Technology category recombination | 0.159 | 0.0732 | 0.283 | 0.133 | 0.230+ |
| | (0.181) | (0.231) | (0.180) | (0.0906) | (0.138) |
| Number of patents | 0.00182 | 0.0166 | -0.0173 | -0.0191 | -0.0252 |
| | (0.0319) | (0.0299) | (0.0344) | (0.0359) | (0.0369) |
| Log pseudo likelihood | -3587.0 | -3587.3 | -3586.1 | -3586.3 | -3585.8 |
| | Patenting organizations (age < 15 years) | | | | |
| Technology category recombination | -0.0286 | -0.265 | 0.133 | 0.0537 | 0.142 |
| | (0.198) | (0.234) | (0.212) | (0.105) | (0.151) |
| Number of patents | -0.0438 | -0.0290 | -0.0565 | -0.0560 | -0.0630 |
| | (0.0404) | (0.0375) | (0.0427) | (0.0428) | (0.0444) |
| Log pseudo likelihood | -358.2 | -357.7 | -358.1 | -358.1 | -357.9 |

+p<.10 *p<.05 **p<.01 *** p < 0.001

[1] For all organizations, there are 1,403 events for 3,298 organizations over 9,049 organization-years. For patenters only, there are 174 events for 368 organizations over 1,057 organization-years. Risk set restricted to organizations < 15 years old (or founding date unknown). There are 21 degrees of freedom in all models. All models include controls for category fuzziness, number of category members (logged), number of category members that received VC funding (and squared), number of acquisitions, tenure in data, number of previous rounds of funding, whether ranked in the Software 500, and year dummies. Time pieces are included for 0–1, 1-3, 3-5, and 5+ years. All independent variables are lagged.

Table 4. Piecewise continuous models hazard rate models on likelihood to receive VC funding. Effects of market and technology category recombination.[1]

| | All organizations (age < 15 years) | | | | |
|---|---|---|---|---|---|
| | Originality (USPTO original class) | Originality (IPC) | Originality (USPTO current class) | No. subclasses | No. classes |
| Market category recombination | 0.236* | 0.224** | 0.206* | 0.213* | 0.186+ |
| | (0.0939) | (0.0793) | (0.0990) | (0.102) | (0.0981) |
| Develops within market categories | -0.370 | -0.405 | -0.405 | -0.402 | -0.411 |
| | (0.311) | (0.321) | (0.320) | (0.320) | (0.324) |
| Technology category recombination | -0.195 | -0.216 | -0.0410 | -0.0360 | 0.0277 |
| | (0.264) | (0.270) | (0.266) | (0.143) | (0.205) |
| Number of patents | -0.0135 | -0.0128 | -0.0250 | -0.0217 | -0.0302 |
| | (0.0352) | (0.0345) | (0.0363) | (0.0376) | (0.0387) |
| Log pseudo likelihood | -3583.7 | -3583.7 | -3584.0 | -3584.0 | -3584.0 |
| | Patenting organizations (age < 15 years) | | | | |
| Market category recombination | 0.248* | 0.235* | 0.236* | 0.241* | 0.213+ |
| | (0.111) | (0.0953) | (0.112) | (0.114) | (0.113) |
| Develops within market categories | -0.377 | -0.409 | -0.411 | -0.412 | -0.419 |
| | (0.347) | (0.350) | (0.352) | (0.356) | (0.358) |
| Technology category recombination | -0.282 | -0.408+ | -0.160 | -0.100 | -0.0484 |
| | (0.253) | (0.248) | (0.251) | (0.139) | (0.196) |
| Number of patents | -0.0529 | -0.0471 | -0.0618 | -0.0565 | -0.0650 |
| | (0.0440) | (0.0429) | (0.0451) | (0.0450) | (0.0465) |
| Log pseudo likelihood | -355.7 | -355.1 | -356.1 | -356.1 | -356.3 |

+p<.10 *p<.05 **p<.01 *** p < 0.001

[1] For all organizations, there are 1,403 events for 3,298 organizations over 9,049 organization-years. For patenters only, there are 174 events for 368 organizations over 1,057 organization-years. Risk set restricted to organizations < 15 years old (or founding date unknown). There are 23 degrees of freedom in all models. All models include controls for category fuzziness, number of category members, number of category members that received VC funding (and squared), number of acquisitions, tenure in data, number of previous rounds of funding, whether ranked in the Software 500, and year dummies. Time pieces are included for 0–1, 1-3, 3-5, and 5+ years. All independent variables are lagged.

Table 5. Piecewise continuous hazard rate models on likelihood to receive funding from high, middle, and low status VCs. Effects of market category recombination.[1]

| | All organizations (age < 15 years) | | |
|---|---|---|---|
| | High status | Middle status | Low status |
| Market category recombination | 0.314** | -0.0355 | 0.254* |
| | (0.113) | (0.125) | (0.110) |
| Develops within market categories | -0.630 | 0.142 | -0.339 |
| | (0.550) | (0.543) | (0.454) |
| Number of patents | -0.0468 | -0.0721 | -0.0686 |
| | (0.0663) | (0.0675) | (0.0717) |
| No. events | 440 | 588 | 681 |
| Log pseudo likelihood | -1548.6 | -1928.3 | -2169.1 |

| | Patenting organizations (age < 15 years) | | |
|---|---|---|---|
| | High status | Middle status | Low status |
| Market category recombination | 0.276+ | 0.147 | 0.173 |
| | (0.151) | (0.175) | (0.144) |
| Develops within market categories | -0.480 | 0.311 | -0.135 |
| | (0.602) | (0.586) | (0.491) |
| Number of patents | -0.0869 | -0.126 | -0.0945 |
| | (0.0775) | (0.0885) | (0.0771) |
| No. events | 63 | 63 | 91 |
| Log pseudo likelihood | -178.3 | -181.3 | -236.6 |

| | All organizations (age < 15 years) | | |
|---|---|---|---|
| | High status only | Middle status only | Low status only |
| Market category recombination | 0.372+ | -0.419 | 0.411* |
| | (0.202) | (0.315) | (0.175) |
| Develops within market categories | -1.135 | 0.447 | -0.913 |
| | (1.225) | (1.509) | (0.830) |
| Number of patents | 0.00505 | -0.264 | -0.0300 |
| | (0.117) | (0.177) | (0.109) |
| No. events | 120 | 186 | 272 |
| Log pseudo likelihood | -582.4 | -848.7 | -1154.5 |

+p<.10 *p<.05 **p<.01 *** p < 0.001

[1] For all organizations, there are 1,403 events for 3,298 organizations over 9,049 organization-years. For patenters only, there are 174 events for 368 organizations over 1,057 organization-years. Risk set restricted to organizations < 15 years old (or founding date unknown). There are 22 degrees of freedom in all models. All models include controls for category fuzziness, number of category members, number of category members that received VC funding (and squared), number of acquisitions, tenure in data, number of previous rounds of funding, whether ranked in the Software 500, and year dummies. Time pieces are included for 0–1, 1-3, 3-5, and 5+ years. All independent variables are lagged.