Two Sides of the Same Coin: How Category Ambiguity Affects Multiple Audience Evaluations

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Abstract

Recent research indicates that when organizations are hard to categorize they will suffer in terms of external evaluations. Here, I suggest this depends on the type of audience that is evaluating the organization. Some audiences have little influence over organizations and look for products and services that fulfill particular requirements. They use classification systems as maps to navigate an organizational world and are put off by unclear categorical affiliations. Other audiences have a voice in shaping organizations and seek novelty. Members of these audiences are motivated to understand organizations that do not easily fit into a category structure. For the first type of audience, ambiguous categories make organizations *unclear* and less appealing. For the second type, the same ambiguity is *flexible* and more appealing. I test these ideas in the context of the software industry for audiences of consumers as opposed to venture capitalists. As predicted, organizations in ambiguous categories are *less* appealing to consumers, but *more* appealing to venture capitalists. Differences between category-level and organization-level measures of ambiguity, and implications for the emergence of category structures are discussed.

Researchers are becoming increasingly interested in how categorization affects organizations. Observers use categories to make sense of the organizational world, and categories help define what people should expect from an organization. Important performance outcomes are influenced by how organizations are categorized. Specifically, a consensus has been building that organizations that span multiple categories are hard to understand, and therefore are less likely to be successful on a range of outcomes, as compared to more focused competitors. This has been demonstrated in a number of contexts, from discounted valuations on the stock market (Zuckerman, 1999) to reduced sales on eBay (Hsu, Hannan, and Koçak, 2009), to lower ratings for feature films (Hsu, 2006). It seems that when organizations muddy their identities by spanning categories, they reduce the appeal of their offerings.

Yet, despite this organizations in many contexts continue to expand their offerings across categories. In addition, organizations also identify with ambiguous categories that have a relatively unclear social meaning. This is especially evident in the software industry where the category structure is a network of overlapping labels (see figure 2). In this industry, organizations frequently belong to more than one category, and many categories have ambiguous social meaning. If part of an organization's identity is derived from its category affiliation, and previous research that shows organizations suffer when they do not have clear identities, then how does a category structure like the software industry come to be?

I suggest that both affiliating with ambiguous categories and identifying with multiple categories can increase an organization's appeal to certain types of audiences. Previous research that documents hazards of spanning multiple categories takes the perspective of an audience that has little influence over an organization, such as a typical consumer. Members of this type of audience evaluate an organization depending on whether its products or services meet specific needs. Categories are used as cognitive structures that facilitate this goal. This kind of audience is not interested in spending cognitive energy trying to understand an organization that does not easily fit into a category. Organizations with ambiguous categorical identities may not come up when an individual is searching for a specific product or service. When people do evaluate the offerings of these organizations, they may use the wrong criteria and so the organization will come up short. As a result, this type of audience devalues organizations that claim to be in many different categories or those that are in ambiguous categories.

At the same time, studies also indicate that some groups are less put off than others by organizations that are hard to classify. Rather than advocating conformity, institutional entrepreneurs changed the default form for art museums (DiMaggio, 1991) and drew on previously unconnected cultural beliefs to create consumer watchdog organizations (Rao, 1998). Enthusiast users of an online review site did not devalue organizations in ambiguous categories as much as casual users (Kovács and Hannan, 2009). These findings indicate that when people are actively involved in a domain, they may not be as averse to organizations that are not coherently classified.

In this paper, I show that some audiences prefer organizations that do not have clear categorical identities. Audiences that have influence over an organization and that prize novelty will be motivated to spend time understanding organizations that are hard to classify. Therefore, organizations with unclear identities will not be devalued because they violate categorical expectations. Rather, they may benefit as a result of multivocality and brokerage. Organizations with ambiguous identities can adapt their offerings if there are unforeseen changes in an industry, and have the potential to appeal to many different tastes. Research in the network tradition suggests that multivocality – or the ability be interpreted in different ways by different audiences – is beneficial (Padgett and Ansell, 1993). Brokerage, or linking otherwise unconnected groups, is also advantageous (Burt, 1992). Thus, the way an organization with an unclear identity is regarded depends on the perspective of the person evaluating the organization. For an audience with little influence that is looking for specific functionality, categorical ambiguity makes organizations *unclear*. But for an audience with voice that is looking for the next "new thing," this same ambiguity is *flexible*.

This investigation contributes to extant literature on categorization in two ways. First, it reconciles two disparate views regarding whether it is more beneficial to have a clear identity that fits a well-defined category, or to cultivate a flexible identity that can fit multiple perspectives. Findings here show that the same category affiliations are evaluated differently depending on the audience. In this way, this study brings the relational nature of categories squarely into view. Theories of categorization emphasize the importance of defining a relevant audience for a particular set of categories (Zuckerman, 1999; Hannan, Pólos, and Carroll, 2007). However, previous literature does not explicitly examine when two different audiences will have opposing reactions to the same categorical claims. In this study, I show that unclear identities result in divergent evaluations by two distinct audiences.

Second, this study looks at both organizational- and category-level characteristics to examine how unclear identities affect evaluations. Much previous research uses category spanning to indicate whether an organization has an unclear identity, and assumes that the underlying categories have the same strength of meaning. Recent work indicates that category-level characteristics are also influential. All categories convey social meaning, but some are more ambiguous, lenient, and have fuzzier boundaries than others. This can impact member organizations. Spanning categories did not affect an organization's credit ratings when category boundaries were blurred, but those in ambiguous categories were consistently less likely to receive high ratings (Ruef and Patterson, 2009). In another study, users of an online review site preferred organizations in unambiguous categories (Kovács and Hannan, 2009). These studies indicate that an unclear organizational identity can arise from category and organizational factors. In this paper, both category ambiguity (category-level) and category spanning (organization-level) are used to indicate whether an organization has an unclear identity.

I investigate these ideas within the context of the software industry, for the time period from 1990 to 2002. Software companies classify themselves in meaningful ways in order to attract investors and customers. Boundary setting is one of the most important tasks for a software entrepreneur (Santos and Eisenhardt, 2009), and it continues to be critical as companies grow. Some organizations claim membership in well-defined categories to establish a clear and focused identity, while others affiliate with ambiguous categories. In some organizations, managers create an original label in an attempt to establish a new market for a new class of goods. The resulting classification structure is a network of overlapping categories used to classify organizations.[1]

There are two audiences that are vital to software organizations: consumers and venture capitalists. Consumers tend to have less direct influence and focus on finding a product or service that fulfills a specific goal. Venture capitalists have much more influence over the companies they are involved with, and they seek out innovative organizations that have the potential to change an industry. Below, I suggest that while affiliating with ambiguous categories

[1] Previous research on categorization distinguishes between *labels* for a class of organizations, and *categories*, which are schematized and have a consensual social meaning (Hannan, Pólos, and Carroll, 2007). The data in this study contain labels that organizations affiliate with to establish their identities. Many are categories by the above definition but others, especially those that are very ambiguous, are not. Because it is difficult to assign a threshold that distinguishes labels from categories, I use the term "category", and employ continuous measures to indicate whether categories are ambiguous.

and spanning multiple categories will *reduce* an organization's appeal to an audience of *consumers*, this same diluted identity will *increase* its appeal to *venture capitalists*.

Category Spanning, Ambiguity, and Audience Evaluations

Categorization is a natural human process that allows people to access large amounts of information with minimal effort (Rosch, 1978). Once a category structure is established, it influences evaluations (Osherson and Smith, 1982). Expectations that arise from categorization can be thought of as a set of codes to which organizations are supposed to comply (Hsu and Hannan, 2005; Hannan, Pólos, and Carroll, 2007). Category codes may be enforced explicitly, such as by critics who rate and classify organizations or gatekeepers who determine whether something is included in a consideration set. They also are enforced implicitly. For example, if customers expect that products in a category will have specific features (Rosa et al., 1999), or that some types of organizations will refrain from offering taboo services (Phillips and Zuckerman, 2001), organizations that do not meet expectations will not be as highly regarded.

Managers use categories to convey an organization's scope and its set of competitors. They affiliate with categories to place their organizations within a competitive landscape (White, 1981; Porac and Thomas, 1990), often responding to rivals through the media (Kennedy, 2005). Different categories are associated with different logics of competition (Barnett, 2008). There tends to be stronger rivalry among competitors that are members of the same category (Porac et al., 1995), and organizations that are experienced competing in one context may not be equipped to face rivals in another (Barnett and Pontikes, 2008). By conforming to category codes, rivals help define boundaries. At the extreme, two categories may be oppositional, so that an organization cannot legitimately belong to both (Carroll and Swaminathan, 2000). However, the more that rivals cross category boundaries, the more acceptable it becomes for others to do so (Rao, Monin, and Durand, 2005). By conforming or not conforming to categorical expectations, competitive rivals help to construct categories and maintain their boundaries.

Category Spanning

Once categories are established, what happens to organizations that do not conform to categorical expectations? Because observers use categories to make sense of organizations, those that do not neatly fit into existing categories are often ignored or devalued. Thus, analysts tend to overlook firms whose industries do not match their specializations (Zuckerman, 1999), actors that have worked in many different genres have a harder time finding employment (Zuckerman et al., 2003), films that span genres are less appealing to both critics and general audiences (Hsu, 2006), and category generalists do not receive as many auction bids as do category specialists (Hsu, Hannan, and Koçak, 2009). Niche-width theory suggests that organizations need to devote a fixed amount of resources towards "fitting in" to any particular category, and so organizations that span multiple categories have fewer resources to devote to any one (Freeman and Hannan, 1983; Dobrev, Kim, and Hannan, 2001). A similar resource-based argument is used in the literature on strategic management, which shows that widely diversified firms have lower average rents (Montgomery and Wernerfelt, 1988; Wernerfelt and Montgomery, 1988), an effect that is exacerbated when organizations diversify into unrelated markets (Berger and Ofek, 1996).

In resource-based explanations, it is possible that what drives the increased performance of specialists is underlying technical requirements for products and services associated with that category. But research also shows that category labels themselves can affect how an organization is evaluated. Increasing the number of categories that partition a set of products leads to increased satisfaction with a person's choice, even when the categories do not provide any information about the products (Mogilner, Rudnick, and Iyengar, 2008). Before the category for "minivans" emerged, a wide range of "minivan"-type automobiles were equally as appealing to consumers, but when the "minivan" category became defined by specific elements, models that did not fit the new expectations were less acceptable to consumers (Rosa et al., 1999). Indeed, the mere act of labeling an entity as spanning categorical boundaries can have harmful effects. On a peer-to-peer lending site, when individuals were labeled as members of multiple categories they were less likely to receive a bid. When labels were removed from customer view, the same boundary spanners suffered no penalty (Leung and Sharkey, 2009). Categories are helpful in that they allow people to reduce a space of infinite dimensions into one that is finite and comparable. At the same time, they can interfere with how people evaluate entities that bridge categorical boundaries.

Category Ambiguity

The research cited above investigates contexts where categories are well defined, and shows that when organizations span these categories audiences have difficulty making sense of their identities. Recent research indicates that category-level measures are also important. When categorization systems were in flux for credit ratings in 19th Century America, boundary spanning was not problematic, but in this same context organizations that belonged to ambiguous categories consistently suffered lowered ratings (Ruef and Patterson, 2009). When category boundaries in the Italian wine industry were blurred, returns to specialism were not as great (Negro, Hannan, and Rao, 2008), and restaurants in low-contrast categories were less likely to be favorably evaluated on an online review site (Kovács and Hannan, 2009). Category ambiguity also affects how classification systems evolve. When product categories become ambiguous, new categories are more likely to emerge (Lounsbury and Rao, 2004). On the other hand, because ambiguous categories present fewer constraints they are less likely to push out specific organizations. So, for organizations that develop a new technology, it is those that belong to low leniency categories that are more likely to start a new market category (Pontikes, 2008). Together, these studies suggest that category characteristics can lead to unclear identities for organizational members.

As a result I use ambiguity, a category-level measure, in addition to boundary spanning, an organization-level measure, to indicate the extent to which an organization has a clear or unclear identity. An ambiguous category may be widely recognized and adopted, but it does not have a well-defined boundary, broadly accepted social meaning, nor does it elicit strong expectations of what members should or should not do. These categories are not especially constraining and provide flexibility to organizational members. Examples of these in the software industry include "e-business applications," "enterprise," "platform," and "portal." Unambiguous categories are more constraining, have clearer boundaries, and elicit strong expectations about what a member will be. Examples of these in the software industry are "expense management," "entertainment software," and "digital imaging."

Audiences Without Voice: Consumers

The literature that documents the hazards of having an unclear categorical identity tends to take the perspective of audiences that interact with an organization as outsiders. They have little influence over the organization and tend to seek out products or services that meet a specific need. The studies cited above investigate consumers (Rosa et al., 1999; Hsu, 2006; Hsu, Hannan, and Koçak, 2009; Kovács and Hannan, 2009), critics and gatekeepers (Zuckerman et al., 2003; Rao, Monin, and Durand, 2005; Hsu, 2006), and stock market investors (Zuckerman, 1999). These audiences evaluate an entity either by choosing it or rating it, but do not anticipate having a voice in shaping it.

If an audience has little influence over an organization, it is unlikely that the organization will modify its offerings if they do not meet an audience member's expectations. For example, end-users cannot expect that Oracle will add desired features into its product; if a user chooses Oracle, she will expect to use the product as is. Because there is little opportunity to modify the offering after the fact, it is important to choose the right organization before hand. Organizations that are clearly categorized are easier to understand, place, and compare. These organizations will be more appealing to an audience without voice.

Further, an audience with the goal of finding a product or service that meets a specific need may find offerings that have the potential to be many things unappealing. There is evidence from social psychological research that when an individual is focused on a specific goal, he is less likely to favorably evaluate a multi-functional product. For example, once people are made aware that a pen can also be used as a laser pointer, they are less likely to use that pen for the purpose of writing (Zhang, Fishbach, and Kruglanski, 2007). Audiences with task-oriented goals tend to use categories as cognitive maps to find an organization that can satisfy these goals. If they were motivated to try and understand the social construction of a category structure then categorically unclear identities might not be a problem. However, decoding the category structure is not an appealing task for someone looking for a particular product. This type of audience member is not interested in becoming an anthropological expert of an industry; rather, she wants to find organizations whose offerings can meet her needs.

Therefore, organizations that are clearly categorized should be more appealing to an audience without voice that has the goal of finding an offering that meets particular requirements. Indeed, previous research which documents the hazards of spanning categories or being in ambiguous categories investigates contexts with these types of audiences. Consumers in the software industry are another example of such an audience. A consumer is one voice of many in terms of his influence over an organization. Consumers can request that an organization move in a certain direction, but except for cases where a small organization is reliant on one major client, they have little assurance that these appeals will be heeded. In addition, consumers tend to look for software products that meet a specific need. They use categories to understand the software domain, and so organizations with ambiguous identities are more likely to be confusing. As a result, the above arguments suggest that for an audience of consumers, organizations with clear identities are more appealing than those with unclear identities. Therefore, I expect:

H1a: Organizations that are members of *more ambiguous categories* will be *less appealing* to consumers, as compared to organizations in less ambiguous categories.

H1b: Organizations that *span many categories* will be *less appealing* to consumers, as compared to organizations that span fewer categories.

Audiences with Voice: Venture Capitalists

Audiences with voice will take a substantially different perspective on organizations. Previous studies on categorization indicate that audiences of enthusiasts, who are invested in a domain, are less negatively influenced by unclear categorization. For example, active users of an online review site did not devalue organizations in ambiguous categories as strongly (Kovács and Hannan, 2009). For people familiar with a domain, increasing the number of categories that group a set of objects does not affect satisfaction with their choice (Mogilner, Rudnick, and Iyengar, 2008). In addition, studies also show how enthusiasts create new markets and redefine existing domains, indicating that such an audience is not put off by organizations that defy the existing category structure. For example, institutional entrepreneurs worked to shape the way art museums functioned to define a new organizational form (DiMaggio, 1991). Activists drew on existing cultural materials to construct a new form for nonprofit Consumer Watchdog Organizations (Rao, 1998). Enthusiast audiences are embedded in the same categorical structures as more passive audiences, but are motivated to question these categories in the quest for novelty.

These studies suggest that audiences that have influence over organizations, who are looking to establish the next "new thing," are less likely to devalue those that are not clearly categorized. In fact, they may find such organizations more appealing. An identity that is *unclear* is also *flexible.* Previous research in the network tradition suggests that individuals and organizations can benefit from having flexible identities. Multivocality, or cultivating an identity that can be interpreted differently from multiple perspectives, can facilitate an individual's rise to power (Padgett and Ansell, 1993). Actors that broker otherwise unconnected groups can realize benefits from access to diverse information (Burt, 1992). Organizations that are members of ambiguous categories or that span multiple categories retain the flexibility to be interpreted in multiple ways. They can more easily initiate change or adapt to changes in an industry, and they have more leeway to modify how they position their offerings without appearing to be chameleon. There is also potential to shape the definition of an ambiguous category or to construct a new category at the intersection of existing categories. Therefore organizations with flexible identities are more likely to be seen as having the potential to establish unique market niche, which will appeal to audiences with voice that seek novelty.

Venture capitalists are an example of such an audience in the software industry. First, they have a great deal of influence over investment companies. Venture capitalists invest in risky, early stage companies that have little performance history. Some ways they manage risk are by staging investments so that future funding is tied to performance goals, and by participating on the company's board (Norton and Tenenbaum, 1993). In this way, venture capitalists are also involved in managing the direction of their companies. Many see their investments more as business partnerships than as a stock portfolio; the average holding period for a venture capital investment is five years (Sahlman, 1990), and once a venture capitalist invests in a company, she is more likely to re-invest even if expected returns are declining (Guler, 2007). Venture capitalists do not simply pull out of investments when changes within an industry make them less financially attractive; rather, they work with managers to help the organization succeed. Therefore it is important for venture capitalists to consider at the outset how easily an organization can reframe its products or services responding to potential changes in an industry. Organizations with flexible identities will be better able to respond to such changes without as much disruption, and venture capitalists can actively direct how the company reacts. An audience with influence has the power to shape an organization. As a result, organizations with flexible identities, that can be easily shaped, will appeal to this audience.

Second, venture capitalists look to invest in organizations that have produced something novel and that have the potential to make a large impact in their industry. Most investments result in losses, but a few generate such large returns such that a handful of companies in a venture capitalist's portfolio result in over half of the investor's profits (Sahlman, 1990).

Previous research which surveys venture capitalists indicates that they prefer organizations that are "market makers," (MacMillan, Zemann, and Subbanarasimha, 1987), or one with a "unique product, which create[s] a new niche for itself," (Hisrich and Jankowicz, 1990). Venture capitalists do not just invest in an organization, but also in the "future of a particular technology or market," (Tyebjee and Bruno, 1984). Unlike consumers, venture capitalists do not use existing industry categories to find an organization that can best meet a specific goal. Rather, they attempt to invest in a company that can redefine the category structure. As a result, venture capitalists are motivated to deeply understand and think beyond the limitations presented by existing categories within an industry. This type of audience, which seeks novelty, will not devalue organizations that are members ambiguous categories and that span categories. First, because this audience scouts for an organization that is innovative, this type of organization will not be ignored. Second, because they are willing to put cognitive energy into understanding an organization, it will not be devalued simply because of its categorical affiliations.

Finally, organizations with unclear identities are more likely to make it through the selection process of an audience looking for young innovative organizations. Industry lists that group organizations by category are not a fruitful place to look for the next "new thing." Venture capitalists tend to find out about promising investments through contacts. In order to attract financing, organizations must first get "on the radar" of an interested venture capitalist. Those that span categories and that are in ambiguous categories are in positions of brokerage in the category structure. By occupying "structural holes," brokers have access to a wide range of diverse contacts (Burt, 1992; Fernandez and Gould, 1994). In biotechnology, organizations with many different connections had the most power in shaping their field (Powell et al., 2005). Further, positions of brokerage are especially advantageous when networks serve as conduits of resources (Podolny and Baron, 1997), which is the case for venture capital financing. Positions of brokerage make organizations in ambiguous categories or that span multiple categories more likely to have contact with a larger number of potential investors. In addition, after an organization is in the consideration set, it must gain approval by all or a subset of the general partners of a fund (Guler, 2007), and many investments are made through syndication, or co-investment among multiple venture capital funds, increasing the number of perspectives that evaluate (and must come to consensus on) a prospective venture. Organizations with flexible identities are more likely to appeal to this variety of outlooks.

Together, these arguments suggest that audiences with influence that prize novelty, such as venture capitalists, will not be put off by organizations that are categorically hard to understand. Rather, organizations with flexible identities will be seen as potential market makers. In addition, these organizations will be more likely to attract interest from this type of audience. As a result, I hypothesize:

> H2a: Organizations that are members of *more ambiguous categories* will be *more appealing* to venture capitalists, as compared to organizations in less ambiguous categories.
>
> H2b: Organizations that *span multiple categories* will be *more appealing* to venture capitalists, as compared to organizations that span fewer categories.

The above hypotheses propose that two distinct audiences, consumers and venture capitalists, have opposing reactions to organizations that are not clearly categorized. This may seem ironic, since venture capitalists aim to invest in companies that will at some point be appealing to consumers. However, it is important to remember that venture capitalists invest in early stage companies, which do not yet have broad consumer appeal. The reactions to categorization from these two audiences may form a complementary two-stage process. Venture capitalists first sort through organizations that are difficult to understand and choose the most promising. In the second stage, consumers choose from among survivors which organizations to patronize. Organizations that are able to define or co-opt a niche may thrive at both stages, whereas those that remain in an ambiguous categorical state may not be as successful.

Categorization in the Software Industry

I test these ideas in the empirical context of the software industry during the period from 1990 through 2002. Software has been around since computers were commercialized in the 1950's, although initially it was not considered a separate industry. Early software programs were hard coded in machine language that was specific to a computer. The first higher-level programming language, FORTRAN, was created in 1957. It allowed programmers to code software that would run on many different machines, which set the stage for software to be viewed as an independent product. In 1968, under fear of anti-trust regulation, IBM announced that it was unbundling its hardware and software, facilitating the entry of many independent software vendors into the industry (Steinmueller, 1995; Campbell-Kelly, 2003).

The software industry emerged under the public radar. From 1966 until 1980, *Businessweek* did not publish any articles that focused on the software industry, and thereafter its next article on the industry was published in 1984 (Campbell-Kelly, 2003). Perhaps because of the lack of attention from the mainstream press, specialized publications such as *Computerworld* and *Software Magazine,* and publications from industry analysts such as Forrester Research, IDC, and Gartner were important sources of information about the industry. Rankings such as *Software Magazine's* Software 500 also helped to publically define the industry.

Initial classifications for software companies began to emerge in the 1970s. At that time, the main division was between "system" and "application" software, which was subdivided into industry classifications. After the invention of the personal computer in the 1980's, the software industry grew and its category structure became more complex. In 1982 the label "productivity application" appeared, which included spreadsheets, word processing, and personal databases. Later in the decade growing hardware markets for printers, modems, and hard disks gave rise to the category of "utility software," (Steinmueller, 1995). In the 1990's a number of new categories emerged including "network management tools", "ERP", "security software", "object management software", "middleware", "financial applications", "human resource management", "CAD", and "integrated voice response systems," (Frye and Melewski, 1995). Data from firm press releases gathered for this study indicate that from 1990 to 2002, software organizations used over 400 categories to assert their identities within the industry.

The categories that emerged in the software industry ranged from extremely well defined to very ambiguous. Categories that were well defined had distinct boundaries and a strong consensus around what types of offerings, services, or activities were expected from organizational members. Often, boundaries were created and maintained by software organizations and other activists lobbying the press to promote a specific definition for the category. For instance, when the category for "relational database" emerged in the early 1980s, a wide range of organizations began adopting the label without providing comprehensive relational software. In response Edgar Codd, the pioneer of relational technology, published an article in

Computerworld called "Is your DBMS Really Relational?" where he outlined 12 rules as a test to determine whether a company could call themselves a "relational database" provider.

Other categories grew to become relatively ambiguous. For these categories, there was not strong consensus on what types of offerings members should provide, nor on which organizations could credibly claim an affiliation. For example, a decade after the category "knowledge management software" first appeared, it was described by Forrester Research as "an unhelpful term that describes a broad range of software products and enterprise services," (Walker and Schadler, 2002). Another ambiguous category, "e-business applications", was one of the most widely adopted labels during this time period, as it could apply to any company that provides products and services that were at all related to business on the internet. Despite the "unhelpfulness" of ambiguous categories, they proliferated. Why would organizations claim membership in ambiguous categories? There is a trade-off to being affiliated with a well defined as opposed to an ambiguous category. Membership in a well-defined category makes an organization easy to identify and understand. However, the strong expectations associated with these categories are constraining. Ambiguous categories do not provide as strong a signal, but they are more lenient. Organizations in these categories can engage in a wide range of activities and still be considered credible members. At any point in time, active software categories ranged from very unambiguous to very ambiguous.

Venture capital financing was critical to the development of the software industry. The annual amount of venture capital investment in the United States tripled from 1991 to 1996, and information technology companies received between 50% and 60% of these investments. In addition, the software industry was the largest or second largest recipient of venture capital investments for each year in the 1990's (Onorato, 1997). Typically, companies would seek venture capital funding to grow; rarely did a software company make it "big" without venture financing. So venture capital investment fueled the growth of this industry, and this audience was as important as potential customers.

In sum, categorization was important to organizations in the software industry, and categories ranged from well defined to very ambiguous. In addition, both customers and venture capitalists were important audiences for software organizations. This makes the software industry a good context to investigate the ideas in this study.

Data and Methods

This study uses data on categories, consumer evaluations, and venture capitalist evaluations of software companies from 1990 to 2002. Data on categorization come from press releases issued by the organizations themselves, which include identity statements where companies self-categorize. Data on consumer evaluations come from an annual ranking of software companies from *Software Magazine*. Data on venture capital evaluations, measured by whether an organization received venture capital funding, come from the VentureXpert database maintained by Thomson Financial.

<u>Categorization</u>: Data for software organizations and categories were collected using press releases issued by software companies from 1990 to 2002. Software companies actively used press releases to distribute news and create a public face for media analysts, potential venture capitalists, and consumers. Because press releases are not especially costly to produce, they provide a good source of data that include small and young organizations that are otherwise difficult to track. Within press releases companies would claim an affiliation with a category. For example, in a press release from February 2000, Citrix systems states, "Citrix Systems, Inc. is a

global leader in application server software and services," (figure 1 lists other examples of identity statements from press releases in these data). Press releases map software organizations to categories over time, and they capture category labels organizations may have tried out but that did not gain traction. Therefore the data include prominent categories, early stage categories, and potential categories that did not catch on.

---Insert figure 1 about here ---

This study uses a data set of software companies and categories created from the 268,963 press releases issued between 1990 and 2002 that contain at least three mentions of the word "software." From these press releases, company names and the categories in which they claim membership were extracted. The final data contain 4,835 companies and 467 categories. Figure 2 shows the category map of the software industry for selected years. These are network plots where the number of overlapping members links categories. The size of each node depicts category leniency. Leniency, defined in detail below, is one measure of category ambiguity. It takes into account both the percentage of members that overlap with another category, and the number of other categories in the industry with which the category has overlap. These plots show that high-leniency categories are more central, as expected. Some low-leniency categories also cluster together, but are less centrally located. These plots show the extensive the category structure of the software industry, and how rapidly it changes over time.

---Insert figure 2 about here ---

<u>Consumer Evaluation</u>: Data measuring consumer evaluations were collected from *Software Magazine*'s annual ranking of software organizations. This report ranks software companies in terms of their software revenues taking into account revenue from software licenses, maintenance and support, training, software-related services, and consulting. This list includes

both public and private companies.[2] *Software Magazine* is a well-respected specialized industry publication that began ranking software companies in 1982. Initially, it ranked the top 50 companies. The list expanded as the industry expanded, first to the top 100, and in 1996, to the top 500, where it remained steady. Thus the report is dubbed "The Software 500." During the time period of this study, the Software 500 rankings were highly regarded. Making it onto the list, or rising in rank, was a source of status that was publicized by organizations in press releases. Because rank in the Software 500 is based on software revenues, it is an indicator of how appealing a software company is to the audience of consumers. Although venture capital funding could keep a company alive, revenues measure whether consumers were actually purchasing their offerings.

<u>Venture Capitalist Evaluation</u>: I measure venture capitalist evaluations of companies in terms of whether they received venture capital funding in a given year. Data come from the VentureXpert database from Thomson Financial.

Measures

<u>Dependent and Independent Variables</u>: To investigate the hypotheses, I estimate the effects of <u>category ambiguity</u> and <u>category spanning</u> on <u>consumer evaluations</u> and <u>venture capitalist evaluations</u>.

Consumer evaluation: I use rank in *Software Magazine*'s Software 500 as a measure of consumer evaluation. I use <u>inverse rank</u>, which is the number of companies ranked minus the rank of the organization, so that a higher inverse rank is associated with more positive consumer evaluation.

[2] The Software 500 includes software specialists, hardware vendors that also produced software, and consulting companies that created some custom software. Rankings are based on software revenue. For the purposes of this study, consulting companies were not included.

Thus, high inverse rank means an organization is more highly ranked. Note that I separately test results for 1996 – 2002, to check if expanding the number of companies ranked affects results.

Venture capitalist evaluation: I use received venture capital funding in the current year as the dependent variable to measure venture capitalist evaluation. This is a binary variable where 0 indicates the organization did not receive venture capital funding in the focal year, and 1 indicates that it did receive funding.

Category Spanning: I use the number of categories in which the organization claims to be a member in the given year to measure its degree of category spanning, to test H1b and H2b.

Category Ambiguity: I use two measures of category ambiguity: fuzziness and leniency to test H1a and H2a. Fuzziness indicates whether a category overlaps with other categories and leniency measures how constraining a fuzzy category is. Both indicate category ambiguity; a category that is not differentiated from other categories and that does not constrain its members does not have a consensually agreed upon definition.

To measure the fuzziness of an organization's categories and leniency of an organization's categories, I first create measures for fuzziness and leniency at the category level. Previous research shows that when members of a label have unfocused identities, such as if they are de alio firms that primarily identify with another category, the label is less likely to gain legitimacy and develop a social meaning (McKendrick and Carroll, 2001; McKendrick et al., 2003). Building on this, I use fuzziness, the proportion of category members that also identify with other categories (Hannan, Pólos, and Carroll, 2007), as one measure of ambiguity. When a fuzziness is high, it means a large number of members also identify with at least one other category.

Some categories not only have a high percentage of members that identify with one or two other categories, but their members also identify with almost *any other* category. For example, organizations that affiliated with the category "Portal" also were members of 160 other categories. These categories are in the center of the category maps shown in figure 2. Categories with such broad overlap do not impose strong constraints on members. To distinguish between categories that overlap with a handful of others in a cluster, and categories that overlap with almost every other category in the industry, I also use a metric for leniency, which measures the lack of constraint imposed by a category. Leniency is computed as fuzziness times the number of distinct other identities a category's members take on. When leniency is high, it indicates that a large portion of members not only identify with other categories, but also that they identify with *many* other categories. Leniency is a nuanced measure of ambiguity that considers not only *whether* a category's members affiliate with other categories, but also *where else* they identify.

Mathematically, to create these measures I first determine which categories an organization affiliates with in each year using press release data. Following Hannan, Pólos and Carroll (2007), I conceive of categories as fuzzy sets, so that an organization can be a partial member of a category. Research in cognitive psychology indicates that this is the way people think of categories (Rosch and Mervis, 1975). Thus, an organization can be "sort of" a "database" company, but primarily in "security software." An organization's grade of membership in a category indicates the extent to which it identifies with the category, and is calculated based on the number of times it mentions the category in press releases, divided by the number of times it mentions any category, for each year. Grade of membership takes values between 0 and 1. I then compute the fuzzy density (N_C) for a category as a sum of the grades of membership of organizations that claim membership in it. The "support" for a category, (N), is defined as the number of organizations who have non-zero membership in the category and can be thought of as the category's potential membership. A category's contrast, or its fuzzy density divided by its support ($\frac{N_C}{N}$), measures the extent to which a category's members have focused identities. The opposite of contrast is fuzziness:

$$fuzz_C = 1 - contrast_C \tag{1}$$

Fuzziness measures the extent to which a category's members identify elsewhere (Hannan, Pólos, and Carroll, 2007). To compute leniency, I multiply the category's fuzziness by the (natural log of the) number of distinct other categories with which members identify:

$$leniency_C = fuzz_C x \ln(N_{ocat}) \tag{2}$$

The distribution of fuzziness in these data is shown in figure 3, the distribution of leniency in figure 4, and the relationship between leniency and fuzziness in figure 5. Categories that have low fuzziness also have low leniency. However, categories with high fuzziness can either be high-leniency or low-leniency.

--- Insert figure 3, figure 4, and figure 5 about here ---

To measure the fuzziness and leniency of an organization's categories, I compute a weighted average that sums the product of the organization's grade of membership in a category with the category's fuzziness and leniency:

$$Average\ fuzziness = \sum_{i \in C} gom_i x fuzz_i \tag{3}$$

$$Average\ leniency = \sum_{i \in C} gom_i x leniency_i \tag{4}$$

Control Variables: I include a number of control variables to account for other factors that may influence the dependent variables. I include the number of times the organization has received venture capital funding over its history, whether it has previously appeared in the *Software*

Magazine rankings, its inverse rank (based on revenue), whether the organization is public, and whether the organization is the only member of its category to account for differences in quality and size among organizations. I use the fuzzy density of an organization's categories (sum of the number of members weighted by grade of membership) to control for whether audiences prefer organizations in popular categories. I include a tenure variable that measures the time since the organization is tracked in the data as a proxy for age, and time since organization last received venture capital funding as a clock in the venture capital funding estimation. All independent variables are measured at the start of each time period.

Statistical Methodology

To test hypotheses 1a and 1b, I estimate the effects of category ambiguity and category spanning on an organization's *Software Magazine* inverse rank. The range of values for inverse rank is between 1 and 500, and so is left and right censored. I use Tobit estimation, which is appropriate for modeling a variable that covers a limited range of values. The Tobit model combines a probit estimate of the probability that a case will have a limit value with an OLS estimate of the effects of the independent and control variables on inverse rank. An organization may be ranked in multiple years, which departs from standard assumptions of statistical independence. Therefore I cluster the standard errors by organization. I estimate this model using Stata 11.

To test hypotheses 2a and 2b, I investigate the time it takes for an organization to receive venture capital funding. To estimate this, I use a piecewise continuous hazard rate model. This model estimates the instantaneous likelihood of an event, here the probability that the organization receives venture capital funding during time period Δt in the limit where $t \rightarrow 0$.

This instantaneous hazard rate of receiving funding can be operationalized as:

$$r(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \tag{5}$$

Where T is a random variable representing the time to receiving funding, and t is time (years) since the organization has last received funding. The piecewise exponential specification allows the base rate of receiving funding to vary in time "pieces" according to the number of years in which the organization has been "waiting" for funding. Therefore this specification does not require a strong assumption about the form of time dependence. I estimate this rate as a function of the independent and control variables listed above:

$$r(t) = \exp(\tau + \beta \cdot \mathrm{x} + \gamma \cdot \mathrm{z}) + \varepsilon \tag{6}$$

where x is a vector of covariates to test the hypotheses, z is a vector of control variables, and τ is the set of duration-specific effects. I cluster standard errors by organization to correct for departures from statistical independence of the observations. I estimate this in Stata 11 using the stpiece procedure written by Jesper Sørensen.

Results

Consumer Evaluations

Descriptive statistics for the variables used in the consumer evaluation estimations are presented in table 1, and correlations are presented in table 2. Leniency and fuzziness are highly correlated, and they also are highly correlated with some of the control variables. This could raise concerns about multicollinearity. Therefore I ran separate estimations that do not include correlated variables, which are reported in the Appendix.

Results testing hypotheses H1a and H1b are reported in table 3. Models 1-6 are Tobit models with inverse rank as the dependent variable. Model 1 contains controls only. Fuzzy density is non significant in this model, although it becomes positive and significant when category ambiguity is included. This indicates that holding ambiguity fixed, consumers prefer organizations that are in popular categories. An organization that is the only member of its category is less likely to rank highly. This indicates that being in a recognized category may increase an organization's exposure, leading to higher revenue. As expected, having a longer tenure, being public, and having a higher inverse rank in the previous year are also associated with high inverse rank. These variables indicate whether an organization has been successful previously, and the organization's size in terms of revenues.

Models 2-3 test hypothesis H1a, which asserts that the more ambiguous an organization's categories, the lower the appeal to an audience of consumers. Category ambiguity is represented by category leniency in model 1 and fuzziness in model 2. Results show strong support for this hypothesis using both measures. Leniency has a negative effect of -23.42 (3.41), significant at $p<0.001$ in model 2, and fuzziness has a negative effect of -92.61 (14.26), significant at $p<0.001$ in model 3. Both model 2 and model 3 are improvements in fit over model 1, significant at $p<0.001$. This pattern of results holds when leniency and fuzziness are included in models without highly correlated controls, illustrated in models A1-A2 in the Appendix. These results show that organizations in ambiguous categories are less appealing to customers, in support of hypothesis 1a. For an organization at the mean value of all control variables, decreasing category ambiguity by one standard deviation can result in an increase in inverse rank of over twenty points.[3]

Model 4 tests H1b, and results do not support this hypothesis. The number of categories in which an organization is a member has a *positive* effect on inverse rank, significant at

[3] This estimate is based on results from models 2 and 3, using the means and standard deviations for leniency (2.448/1.156) and fuzziness (0.562/0.225) in these data.

$p<0.001$. This effect holds in model 5, which includes all variables: category ambiguity, leniency and fuzziness. Note that even though leniency and fuzziness are highly correlated, when they are included together in model 5 the negative effects of both hold, significant at $p<0.05$ for leniency, and $p<0.10$ for fuzziness. This shows that the two measures of category ambiguity have compounding effects on reducing consumer appeal. Organizations in fuzzy categories, that have a high degree of overlap with one or more other categories, suffer in terms of consumer evaluations. If these categories are lenient and overlap with a large swath of the category map, the organizations are devalued even more. These findings lend strong support for hypothesis 1a. Consumer audiences find organizations in ambiguous categories less appealing.

These results do not show support for hypothesis 1b, regarding category spanning. In fact, category spanning has a positive and significant effect on inverse rank. This is surprising, since previous research shows that organizations in multiple categories suffer in terms of audience appeal in many different contexts. Ruef and Patterson (2009) show that category spanning is not problematic when classification systems are in flux, because there is no boundary violation if there is no boundary. Similarly, Kovács and Hannan (2009) show that category spanning is problematic only for categories with low fuzziness. Building on these results, in model 6 I test whether spanning ambiguous categories has a different impact on consumer appeal, as opposed to spanning unambiguous categories.

Results show that the positive effect is driven by organizations in ambiguous categories. Perhaps once an organization identifies with an ambiguous category the harm that arises from having an unfocused identity is already done and expanding into other ambiguous categories simply expands the organization's reach. Category spanning for organizations in unambiguous categories is non-significant, indicating that there is not a measurable benefit to spanning these categories. But this model still does not yield the expected negative effect. This may be because this study uses total software revenues to measure consumer appeal. There is a trade-off to being highly appealing to a narrow range of potential consumers, or moderately appealing to a broad base. Even if a generalist organization is not likely to attract customers of a particular category, the sum of its revenues across all categories might make up for its lack of appeal in any one. This explanation is consistent with Hsu (2006)'s findings that although movies that spanned genres had lower ratings, genre spanning did not have a significant effect on box office gross. When outcome variables are based on measures that are summed across categories (such as total revenues), category ambiguity may be a better measure for how unfocused identities affect evaluations.

Consumer Evaluations: Supplementary Analyses

Table 4 contains results of supplementary analyses and tests against alternative hypotheses for the consumer analysis.

Are these findings influenced by changes to the Software 500 methodology? One question is whether the findings presented here are robust to changes in the methodology of the Software 500 rankings. Initially, *Software Magazine* ranked independent software vendors only. In 1996[4], *Software Magazine* expanded its rankings to include non-independent companies, and ranked 500 (as opposed to 100) organizations. To test whether these findings are robust to these changes, models 7 and 8 are run on data for the years between 1996 and 2002. Results show that both leniency and fuzziness have negative effects on ranking, significant at $p<0.001$, providing additional support for hypothesis 1a.

[4] Note the 1997 issue of *Software Magazine* provides data for 1996.

Does category ambiguity negatively affect public and private organizations? One question that may arise is whether category ambiguity has detrimental affects on consumer evaluations for both public and private organizations. Public organizations are accountable to shareholders and are required to broadcast statements about their companies, providing an opportunity to explain their categorical affiliations. So it is possible that membership in an ambiguous category has a different effect on consumer evaluations for private as opposed to public organizations. Models 9 – 12 test effects of leniency and fuzziness on private as opposed to public organizations. Results show that there are strong negative effects from both measures of category ambiguity on private and public organizations, all significant at $p<0.01$. However, the magnitude of the leniency effect is twice as large for private as opposed to public organizations. These results show that category ambiguity results in lower consumer evaluations for all organizations and that private organizations, which do not disclose as much company information, may be more strongly affected.

Venture Capitalist Evaluations

Descriptive statistics for the variables used in the venture capitalist evaluation estimations are presented in table 5, and correlations are presented in table 6. The risk set for this analysis is private organizations. Leniency and fuzziness are highly correlated, and they also present high correlations with some of the control variables. This could raise concerns about multicollinearity. Therefore I ran separate estimations that do not include correlated variables, which are reported in the Appendix.

Results testing hypotheses H2a and H2b are reported in table 7. Model 13 contains controls only. The fuzzy density of an organization's categories has a positive and significant effect, indicating that venture capitalists prefer organizations in popular categories. Being the only member of a category has a positive and significant effect on being funded in some models, although this effect is not robust across all specifications. This may indicate that venture capitalists prefer organizations that pioneer a new category. An organization's tenure is negative and significant at $p<0.05$, which shows that the longer that an organization has not received funding, the less likely that it is to do so. As expected, the number of times an organization has previously received funding is positive and highly significant ($p<0.001$). This is consistent with Guler (2007)'s findings that venture capitalists are more likely to sequentially invest in companies even when expected returns decline. Having appeared in the *Software Magazine* ranking has a negative effect, significant at $p<0.001$ on receiving funding. *Software Magazine* ranks organizations based on revenue, and organizations with higher revenues are less likely to seek additional funding.

Models 14-15 test hypothesis 2a, which proposes that organizations in more ambiguous categories are more appealing to venture capitalists. They show strong support for this hypothesis. When included independently in these models, category leniency has a positive effect on the likelihood of receiving venture capital funding, significant at $p<0.001$ in model 14, and category fuzziness has a positive effect, significant at $p<0.001$ in model 15. This pattern of results holds when leniency and fuzziness are included in models without highly correlated controls, illustrated in models A1-A2 in the Appendix. Models 13 and 14 show an organization that is in a category one standard deviation above the mean for leniency or fuzziness is over 1.5 times more likely to receive venture capital funding, compared to an organization in a category at the mean values of leniency or fuzziness.[5] The same category ambiguity that makes

[5] This estimate is based on results from models 14 and 15, using the means and standard deviations for leniency (1.91/1.39) and fuzziness (0.45/0.29) in these data.

organizations *less appealing* to consumers makes them *more appealing* to venture capitalists. These effects are illustrated in figure 6. This figure shows the relationship between category ambiguity and both consumer and venture capitalist evaluations.

--- Figure 6 about here ---

The thin lines show the relationship between category fuzziness and leniency to rank in the Software 500, which measures consumer evaluations, and the thick lines show the relationship between these variables and venture capital funding. As category ambiguity increases, organizations are less appealing to consumers but more appealing to venture capitalists.

Model 16 tests hypothesis 2b, which predicts that organizations that span categories will be more appealing to venture capitalists. Results do not show support for this hypothesis. The effect of category spanning is negative and significant at $p<0.05$. The effect remains negative when category ambiguity measures are included in model 17, but it is not robust across all specifications. To investigate this effect further, in model 18, I test whether the effect of category spanning is consistent for organizations in ambiguous and unambiguous categories. As in the consumer analysis, the surprising effect of category spanning is driven by organizations in ambiguous categories. For unambiguous categories, the effect is no longer significant. Therefore, results do not support the hypothesis that venture capitalists prefer category spanners. Further, they indicate that although venture capitalists prefer organizations with flexible identities, it may be detrimental to have multiple flexible identities.

Model 17 also shows that venture capitalist preferences for organizations in ambiguous categories are driven by category fuzziness. When fuzziness and leniency are included in the model together, the effect of leniency becomes negative and significant at $p<0.01$. This indicates that venture capitalist preference for ambiguity is motivated by categories that have high overlap with a limited number of other categories, as opposed to very lenient categories that overlap with almost any other category in the industry. However, it is important to remember that fuzziness and leniency are highly correlated, and this result does not indicate that venture capitalists are averse to organizations in highly lenient categories. Rather, *for a given level of fuzziness* the rate of venture capital funding decreases with leniency. The effects of fuzziness and leniency on venture capital funding rates for the range of observable data are plotted in figure 7.

--- Insert Figure 7 about here ---

This plot shows that the multiplier of the rate of receiving venture capital funding is above one for all combinations of fuzziness and leniency in these data, indicating that venture capitalists prefer organizations in ambiguous categories. Overall, the funding rate increases as category leniency increases, so that organizations in high leniency categories are generally preferred to those in low leniency categories. But for a given level of category fuzziness, the more lenient the category, the less likely the organization will receive venture capital funding. This may be because during this time period in the software industry, some of the categories that have the highest leniency also happen to be very prominent, such as “enterprise,” “e-business,” and “CRM.” It also may indicate that there is a limit to the amount of ambiguity venture capitalists seek. On the whole venture capitalists prefer ambiguous categories, but the preference does not increase with rising ambiguity. This contrasts with the results from model 5 in the consumer analysis, where fuzziness and leniency retain their negative effects on Software 500 rank even when included together. Consumers are put off by ambiguity, and the more ambiguous the category, the more extreme the effect. Venture capitalists are attracted to ambiguity, but the effect is tempered as ambiguity increases.

In sum, these models provide support for hypothesis 2a: organizations in ambiguous categories are more likely to receive venture capital funding. Together with the consumer analysis, these results indicate that the audience of venture capitalists is quite different than the audience of consumers in terms of how they respond to organizations with unclear identities.

Venture Capitalist Evaluations: Supplementary Analysis

Are these effects driven by category novelty? One objection to the results presented on venture capitalist evaluations may be that ambiguous categories tend to be younger, and that venture capitalists are interested in organizations that pioneer a new category. For this explanation, it is the newness of the category that is driving the venture capitalist preference. To test against this alternative, models 19 and 20 include a covariate that measures the tenure of an organization's categories, and the positive effects of leniency and fuzziness, significant at $p<0.001$, are robust to this inclusion.[6] This provides additional support for hypothesis 2a.

Discussion

Despite evidence that organizations with unclear identities are less appealing – and less successful – than their focused counterparts, organizations continue to expand their footprints across multiple categories, and highly ambiguous categories abound. Why? This paper suggests that whether organizations with unfocused identities are appealing or unappealing depends on the audience that is evaluating the organization. Categorical ambiguity makes an organization unclear to an audience without influence that uses categories to find a specific product, but this same ambiguity makes an organization flexible to an audience with influence that prizes novelty.

[6] The inclusion of category tenure in a model that includes both leniency and fuzziness yields the same effects as reported in model 17.

Results here provide support for this perspective. Consistent with previous research on categories (Zuckerman, 1999; Hsu, 2006), this study shows that organizations that do not have clear categorical affiliations suffer in evaluations from an audience of consumers. However, affiliating with ambiguous categories makes organizations *more* attractive to venture capitalists. This is consistent with the notion that organizations with flexible identities benefit from multivocality (Padgett and Ansell, 1993) and positions of brokerage (Burt, 1992) for an audience with voice that seeks novelty.

Ironically, the same categorical affiliation that is unappealing to one audience is more appealing to another. This could present a conundrum to a fledgling software company, since both the venture capital and consumer audiences are critical to success. However, these results may reflect a two-stage process, where venture capitalists take the role of helping to define the category structure when investing in formative companies. Consumers then use this category structure to evaluate organizations. Software ventures may attempt to develop sharper identities as they grow, in an attempt to increase consumer appeal. However, if this is the goal, the investor may have reason to be wary. Theories of organizational inertia suggest that it may be difficult for an organization to change its identity as it ages (Hannan and Freeman, 1984). It will be interesting in future research to address how categorical affiliations of ventures evolve.

This study also indicates that in an environment with highly ambiguous categories, spanning does not have the same meaning as in an environment with well-defined categories. Results here show that for both consumer and venture capital evaluations, effects of category spanning depend on whether the categories are ambiguous or unambiguous. Further, for both audiences, the effect of spanning ambiguous categories is in the opposite direction as predicted. In terms of the consumer analysis, this pattern is consistent with Ruef and Patterson (2009), which finds that boundary spanning is not problematic when category definitions are in flux, and with Kovács and Hannan (2009), which shows that penalties associated with category spanning decrease with category fuzziness. Findings here provide further evidence that spanning categories is perceived differently when categories do not have a well-defined, consensual meaning. Category-level measures of ambiguity may be more precise indicators of whether an organization has an unclear (or flexible) identity in environments where categories are ambiguous. Therefore, this study also illustrates the importance of considering category-level variables like fuzziness and leniency when characterizing an organization's identity.

These findings also provide insight into how classification structures evolve differently across industries. In the software industry, there is an important audience that has influence over organizations and that prizes novelty: venture capitalists. Receiving financing was crucial for the industry's development and for the survival of most firms. Given the results presented above, it is not surprising that the resulting category map evolved to the picture illustrated in figure 2, as an overlapping network of ambiguous categories. Industries are consumer driven might evolve to have very well defined categories. In other industries, there may be important audiences such as large business-to-business clients who have more influence over organizations than do a typical software consumer, and who may be less averse to ambiguous identities. Taking into account the structure of important audiences is critical to understanding the evolving category structure in an industry. As with many things, it seems the effects of a clear or diluted identity depend on who is watching.

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Zuckerman, E., T. Kim, K. Ukanwa, and J. von Rittman

2003 "Robust Identities or Nonentities? Typecasting in the Feature-Film Labor Market." American Journal of Sociology, 108: 1018-1074.

Figures

Figure 1. Sample Press Release and Statements of Category Affiliations.

Business Wire

Accrue **Announces BuyPath Offering Unmatched Merchandising Analysis of the Visitor Path From Entry to Purchase**

1,098 words
4 October 1999
13:21 GMT
Business Wire
English
(c) 1999 Business Wire

FREMONT, Calif.--(BUSINESS WIRE)--Oct. 4, 1999--

New Feature of Accrue Insight(TM) eBusiness Analysis

Application Provides Powerful Analysis of Web Site Navigation

by Customer Segment

Accrue Software, Inc. (NASDAQ: ACRU), a leading provider of eBusiness analysis software and services, today announced BuyPath(TM), a new feature of Accrue Insight(TM) that enables eBusiness marketers to analyze and compare site navigation for customer segments and to gain insights into visits that involve transactions or that touch high-value content.

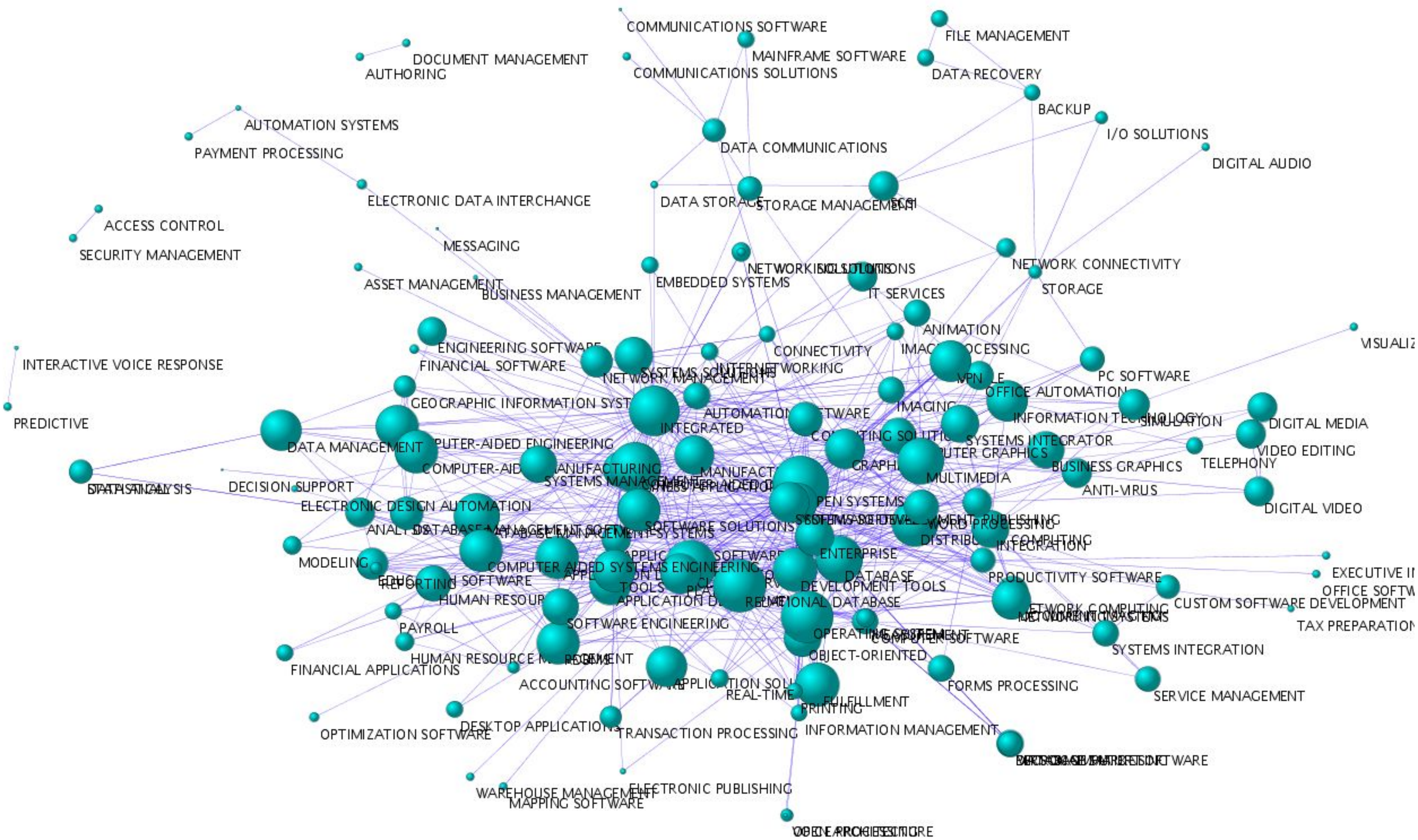
Using BuyPath, the marketer can determine which visitor segments are the most valuable and which referrers and content are most effective in accomplishing eBusiness goals. A key goal of ecommerce is converting visitors into customers. BuyPath enables the comparison of the navigation patterns of precisely-defined customer segments.

For example, comparing new visitors from Yahoo! against returning visitors from Excite, eCommerce

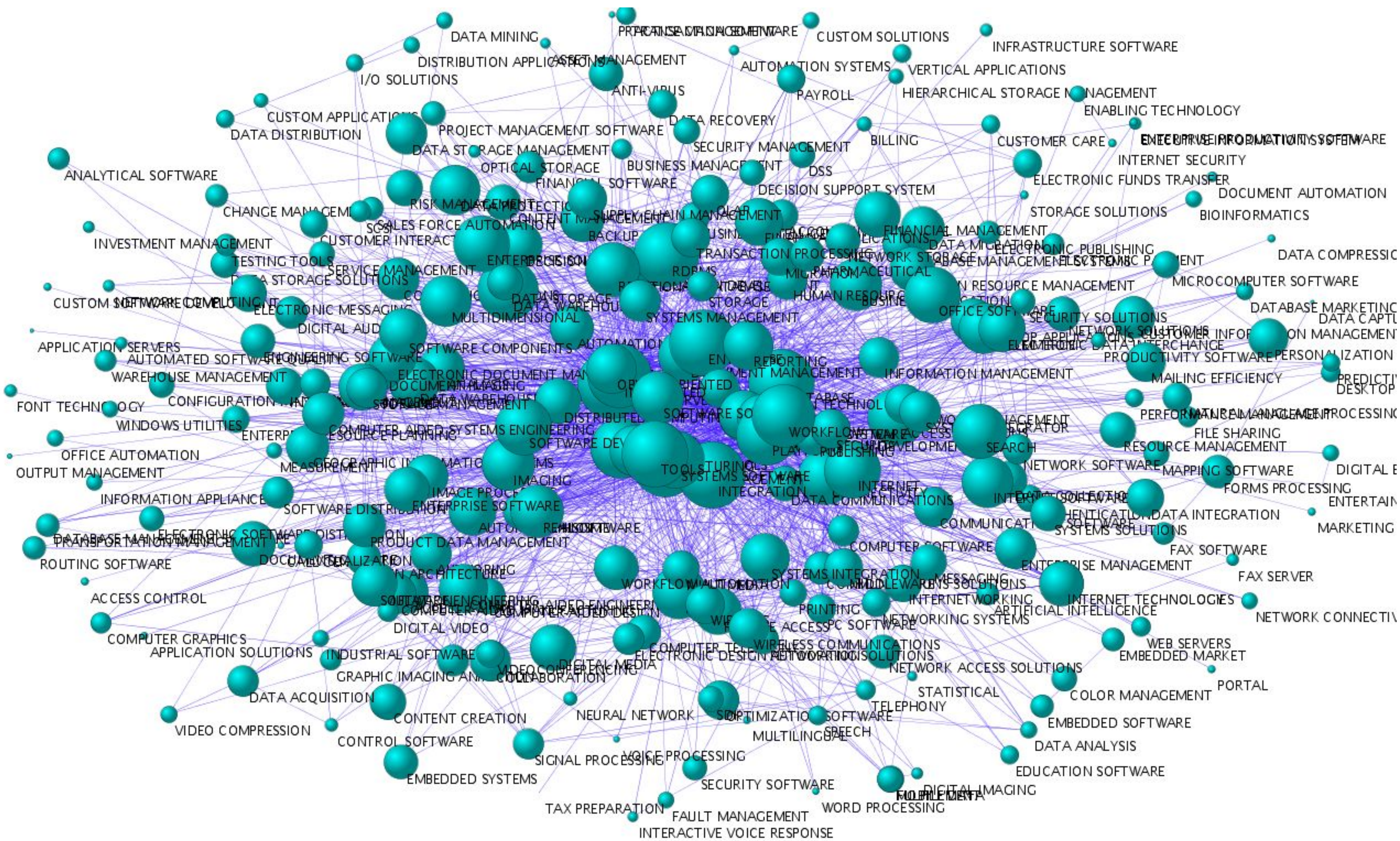
Company	Date	Description
Citrix Systems	February 2000	Citrix Systems, Inc. is a global leader in application server software and services
Plasmon	August 2000	Plasmon, a leading manufacturer of automated data storage solutions, today announced its Diamond® storage management software.
Watson General	May 1994	Watson General currently provides remote software monitoring systems.
Comergent Technologies	Sept 2002	Comergent Technologies® Inc., the leading provider of sell-side e-business software solutions
Accrue Software	October 1999	Accrue Software, a leading provider of e-business analysis software and services
ACP	July 2001	ACP provides enterprise web publishing and e-business solution
Alliance	March 2001	Alliance offers the technical and business advantages of the Sybase Enterprise Portal with a wide range of e-business solutions, including content, e-commerce, and business process automation and analysis

Figure 2. Category Maps of the Software Industry Over Time.

1991



1995


DATA MINING
CUSTOM SOLUTIONS
INFRASTRUCTURE SOFTWARE
DISTRIBUTION APPLICATIONS
AUTOMATION SYSTEMS
VERTICAL APPLICATIONS
I/O SOLUTIONS
ANTI-VIRUS
PAYROLL
HIERARCHICAL STORAGE MANAGEMENT
ENABLING TECHNOLOGY
CUSTOM APPLICATIONS
DATA RECOVERY
DATA DISTRIBUTION
PROJECT MANAGEMENT SOFTWARE
SECURITY MANAGEMENT
BILLING
CUSTOMER CARE
INTERNET SECURITY
ANALYTICAL SOFTWARE
OPTICAL STORAGE
DSS
ELECTRONIC FUNDS TRANSFER
DOCUMENT AUTOMATION
FINANCIAL SOFTWARE
DECISION SUPPORT SYSTEM
BIOINFORMATICS
STORAGE SOLUTIONS
SALES FORCE AUTOMATION
INVESTMENT MANAGEMENT
TESTING TOOLS
DATA COMPRESSIC
SERVICE MANAGEMENT
TRANSACTION PROCESSING
ELECTRONIC PUBLISHING
MICROCOMPUTER SOFTWARE
HUMAN RESOURCE MANAGEMENT
DATABASE MARKETING
MULTIDIMENSIONAL
SYSTEMS MANAGEMENT
SECURITY SOLUTIONS
APPLICATION SERVERS
AUTOMATED SOFTWARE QUALITY
SOFTWARE COMPONENTS
PRODUCTIVITY SOFTWARE
PERSONALIZATION
WAREHOUSE MANAGEMENT
INFORMATION MANAGEMENT
MAILING EFFICIENCY
FONT TECHNOLOGY
WINDOWS UTILITIES
FILE SHARING
RESOURCE MANAGEMENT
OFFICE AUTOMATION
OUTPUT MANAGEMENT
NETWORK SOFTWARE
MAPPING SOFTWARE
INFORMATION APPLIANCE
FORMS PROCESSING
DATA COMMUNICATIONS
DATA INTEGRATION
MARKETING
ENTERPRISE SOFTWARE
PRODUCT DATA MANAGEMENT
COMPUTER SOFTWARE
FAX SOFTWARE
ROUTING SOFTWARE
ENTERPRISE MANAGEMENT
FAX SERVER
ACCESS CONTROL
SYSTEMS INTEGRATION
INTERNET TECHNOLOGIES
NETWORK CONNECTIV
PRINTING
ARTIFICIAL INTELLIGENCE
DIGITAL VIDEO
NETWORKING SYSTEMS
COMPUTER GRAPHICS
WEB SERVERS
APPLICATION SOLUTIONS
INDUSTRIAL SOFTWARE
WIRELESS COMMUNICATIONS
EMBEDDED MARKET
NETWORK ACCESS SOLUTIONS
PORTAL
DATA ACQUISITION
STATISTICAL
COLOR MANAGEMENT
TELEPHONY
CONTENT CREATION
NEURAL NETWORK
OPTIMIZATION SOFTWARE
EMBEDDED SOFTWARE
VIDEO COMPRESSION
MULTILINGUAL
SPEECH
CONTROL SOFTWARE
DATA ANALYSIS
SIGNAL PROCESSING
VOICE PROCESSING
EDUCATION SOFTWARE
EMBEDDED SYSTEMS
SECURITY SOFTWARE
DIGITAL IMAGING
TAX PREPARATION
FAULT MANAGEMENT
WORD PROCESSING
INTERACTIVE VOICE RESPONSE

1999

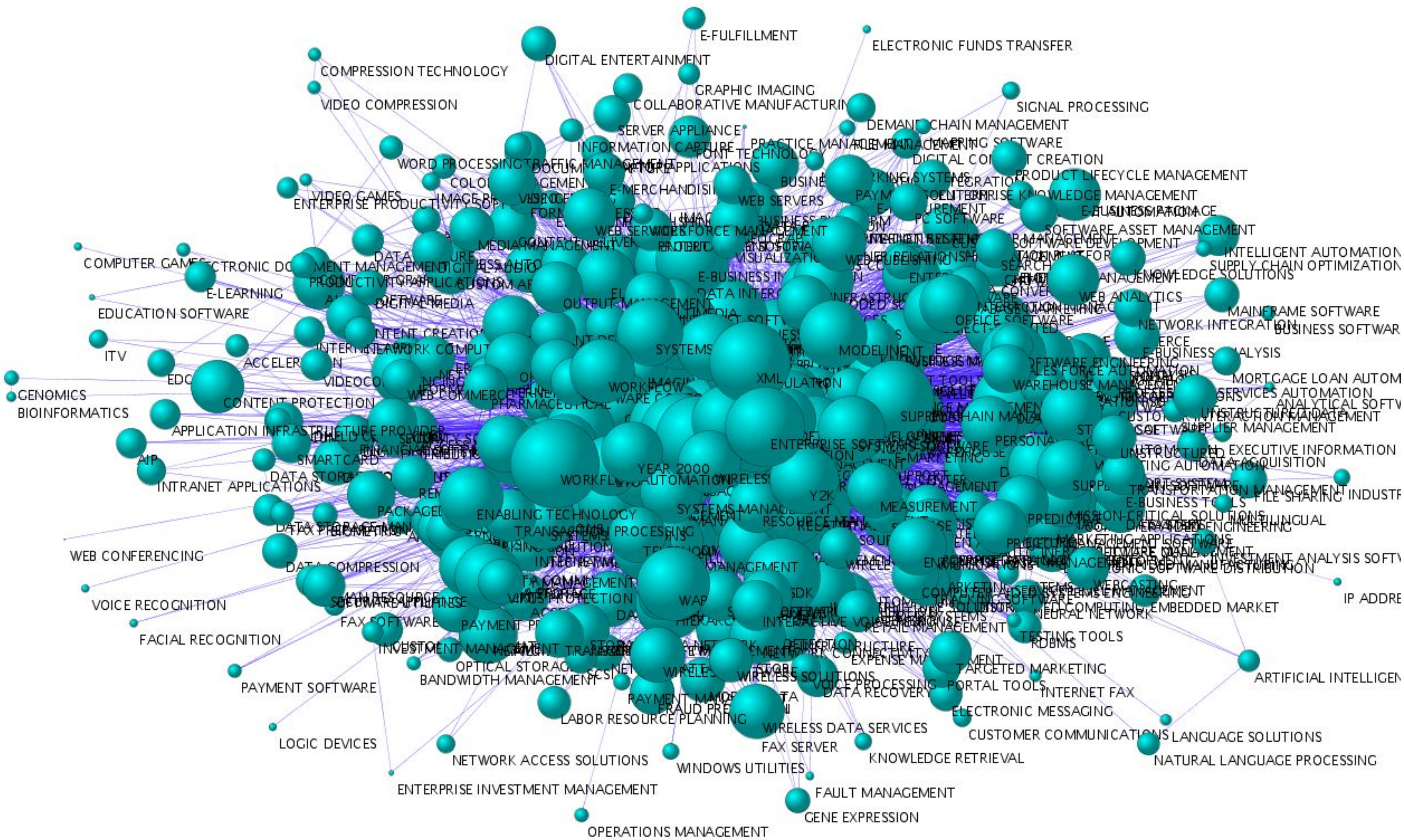

E-FULFILLMENT
ELECTRONIC FUNDS TRANSFER
DIGITAL ENTERTAINMENT
COMPRESSION TECHNOLOGY
VIDEO COMPRESSION
GRAPHIC IMAGING
COLLABORATIVE MANUFACTURING
SIGNAL PROCESSING
DEMAND CHAIN MANAGEMENT
SERVER APPLIANCE
INFORMATION CAPTURE
DIGITAL CONTENT CREATION
PRODUCT LIFECYCLE MANAGEMENT
ENTERPRISE KNOWLEDGE MANAGEMENT
WEB SERVERS
PC SOFTWARE
SOFTWARE ASSET MANAGEMENT
INTELLIGENT AUTOMATION
SUPPLY CHAIN OPTIMIZATION
COMPUTER GAMES
E-LEARNING
EDUCATION SOFTWARE
DIGITAL MEDIA
WEB ANALYTICS
NETWORK INTEGRATION
MAINFRAME SOFTWARE
BUSINESS SOFTWARE
ITV
GENOMICS
BIOINFORMATICS
CONTENT PROTECTION
APPLICATION INFRASTRUCTURE PROVIDER
SMARTCARD
MORTGAGE LOAN AUTOM
ANALYTICAL SOFTW
SUPPLIER MANAGEMENT
EXECUTIVE INFORMATION
DATA ACQUISITION
INTRANET APPLICATIONS
AIP
YEAR 2000
XML
SYSTEMS
MODELING
Y2K
MEASUREMENT
ENABLING TECHNOLOGY
TRANSACTION PROCESSING
FILE SHARING
INDUSTR
WEB CONFERENCING
DATA COMPRESSION
ANALYSIS SOFTW
IP ADDRE
VOICE RECOGNITION
FACIAL RECOGNITION
FAX SOFTWARE
EMBEDDED MARKET
NEURAL NETWORK
TESTING TOOLS
RDBMS
OPTICAL STORAGE
BANDWIDTH MANAGEMENT
TARGETED MARKETING
INTERNET FAX
PORTAL TOOLS
ARTIFICIAL INTELLIGEN
PAYMENT SOFTWARE
WIRELESS SOLUTIONS
VOICE PROCESSING
DATA RECOVERY
ELECTRONIC MESSAGING
LABOR RESOURCE PLANNING
WIRELESS DATA SERVICES
CUSTOMER COMMUNICATIONS
LANGUAGE SOLUTIONS
LOGIC DEVICES
NETWORK ACCESS SOLUTIONS
FAX SERVER
KNOWLEDGE RETRIEVAL
NATURAL LANGUAGE PROCESSING
WINDOWS UTILITIES
ENTERPRISE INVESTMENT MANAGEMENT
FAULT MANAGEMENT
GENE EXPRESSION
OPERATIONS MANAGEMENT

Figure 3. Distribution of Category Fuzziness

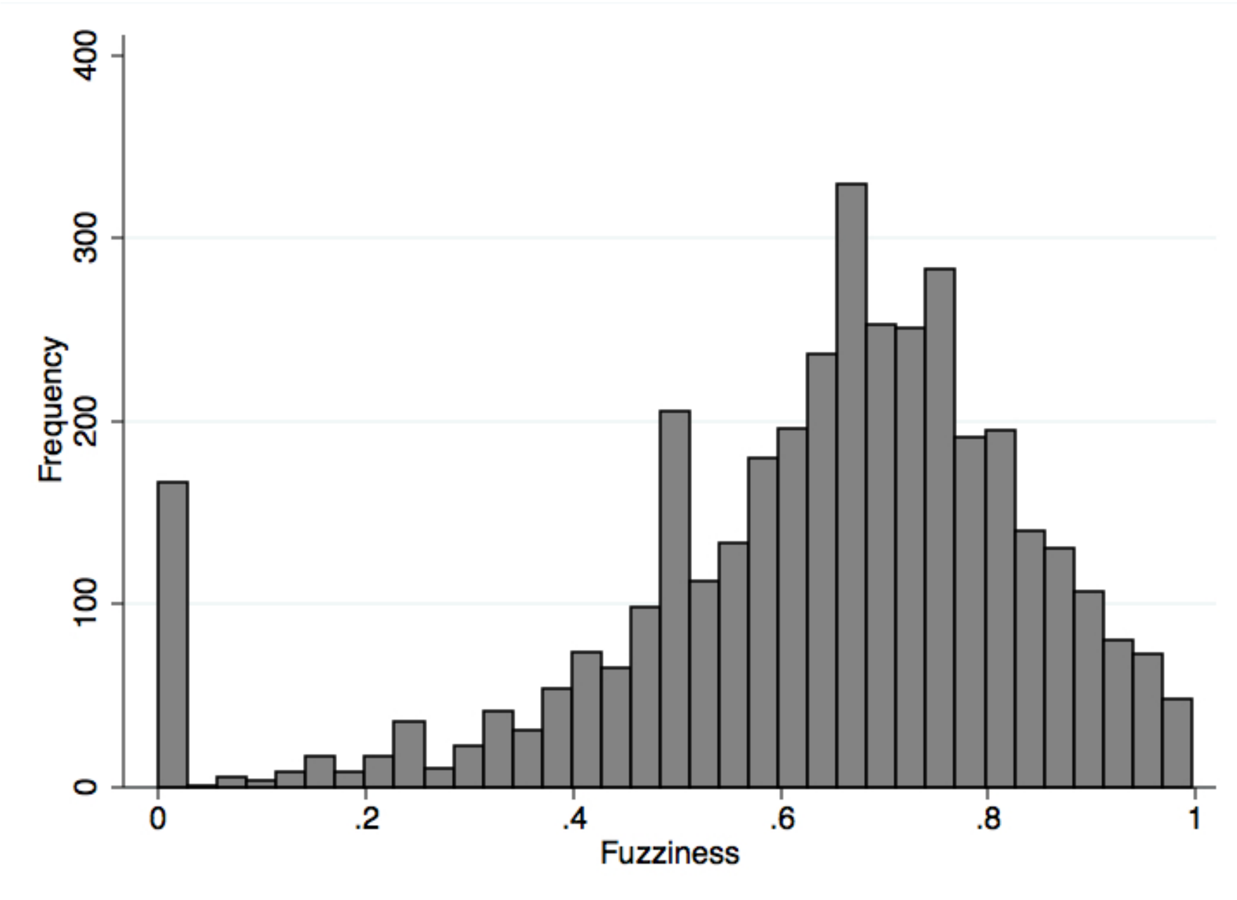


Figure 4. Distribution of Category Leniency

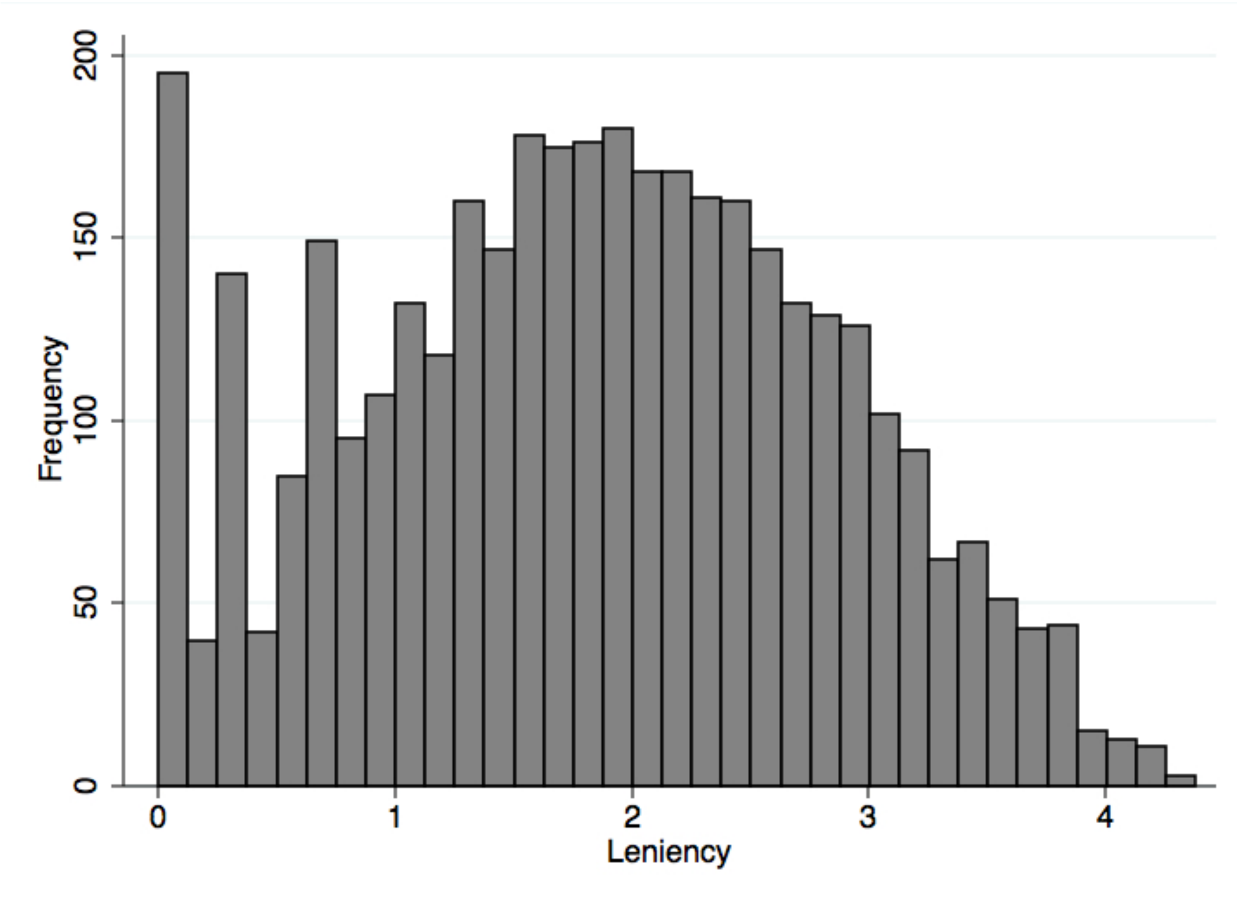


Figure 5. Relationship between Category Leniency and Fuzziness.

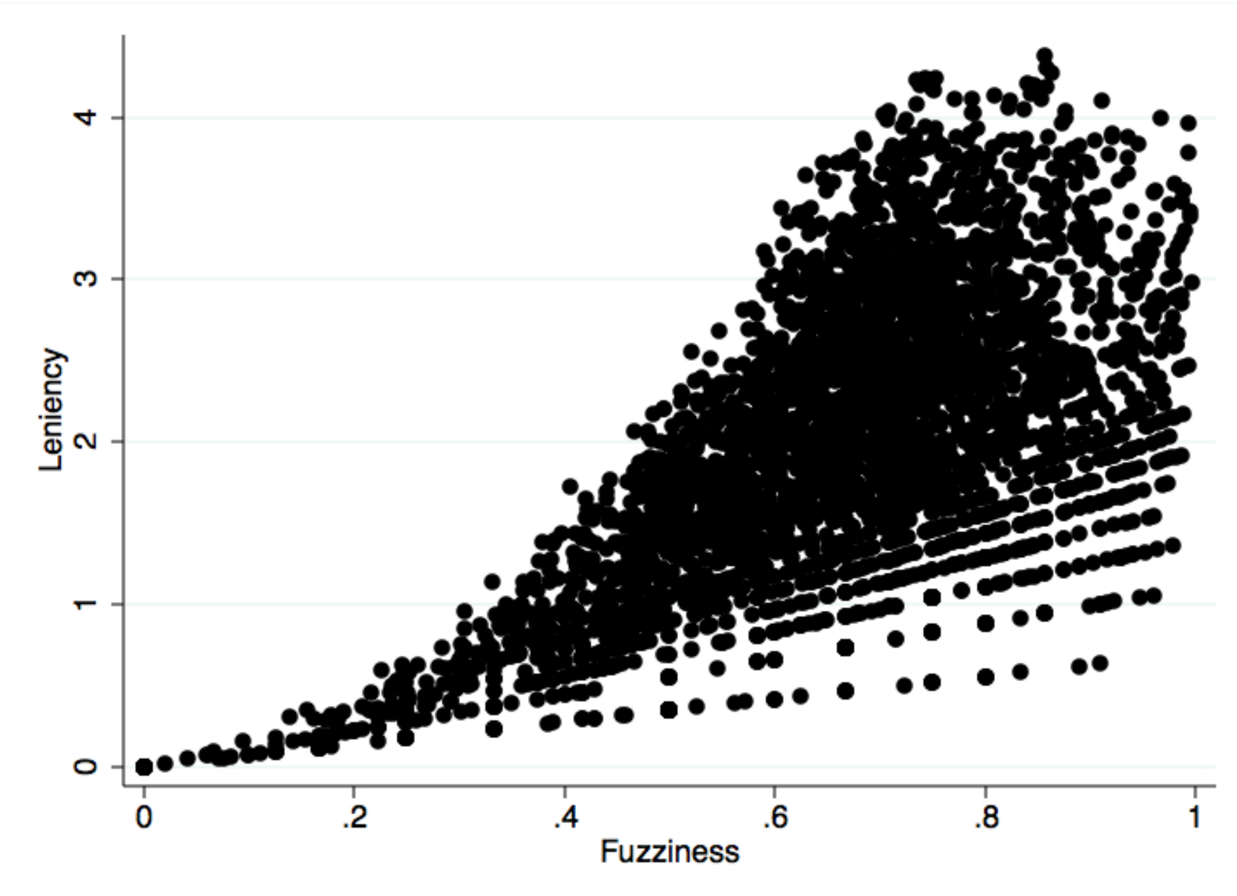
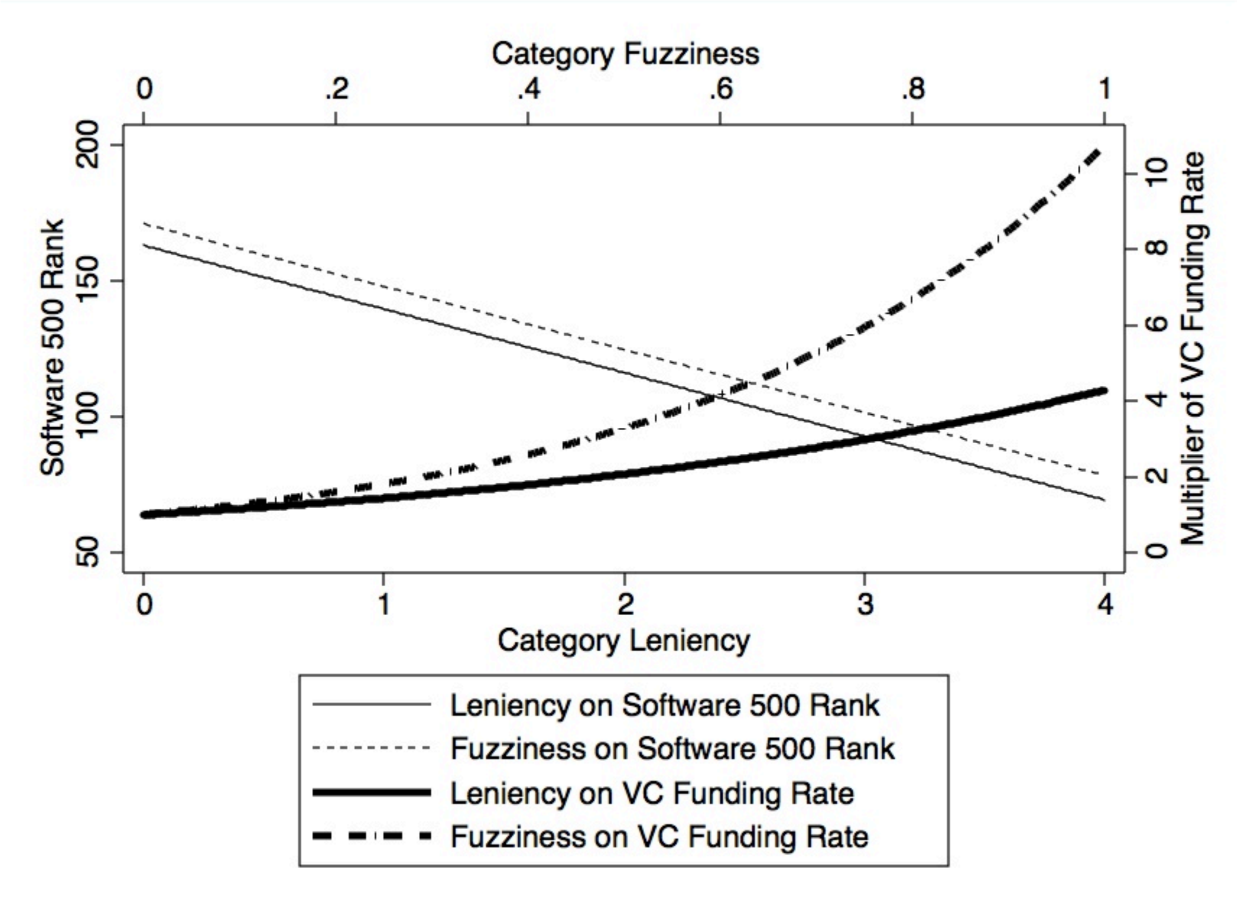
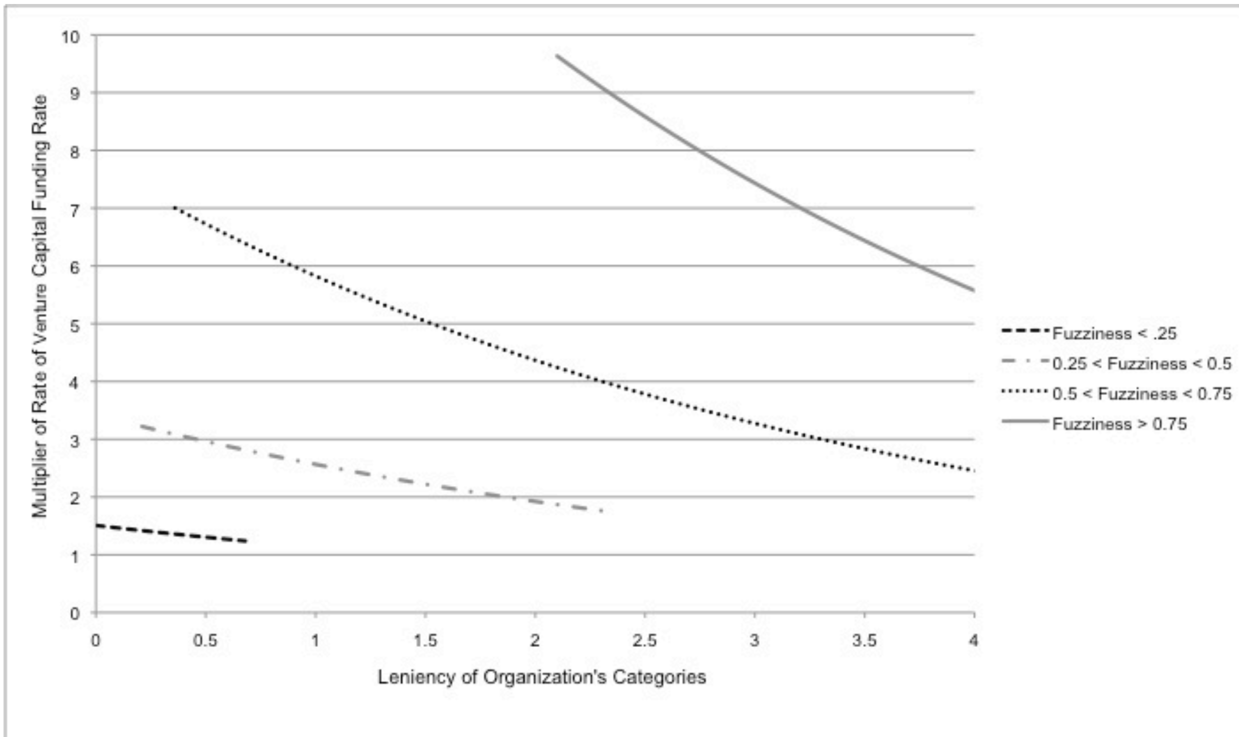


Figure 6. Consumer and Venture Capital Evaluations by Category Ambiguity. [1]



[1]This plot is based on results from models 2 and 3 for Software 500 Rank evaluated at mean levels for all control variables. It is based on models 14 and 15 for venture capital funding.

Figure 7. Combined Effects of Fuzziness and Leniency on Venture Capital Fundings. [1]



[1]This plot is based on results from model 17. The multiplier rate is evaluated for fuzziness values at the midpoint of each range.

Tables

Table 1. Descriptive Statistics for the Consumer Analysis.

	Mean	Standard Deviation	Minimum	Maximum
Inverse Rank (dependent variable)	246	149	1	500
Category Leniency	2.448	1.156	0	4.242
Category Fuzziness	0.5620	0.2246	0	0.8229
Number of Categories Organization is "in"	4.104	4.554	0	47
Number of Categories Organization is "in" - high leniency	3.990	4.621	0	47
Number of Categories Organization is "in" - low leniency	0.1144	0.5400	0	8
Fuzzy Density of Categories Organization is "in" (logged)	3.929	1.954	0	7.355
Organization is the Only Member of its Category	0.0040	0.0631	0	1
Organization is Public	0.3828	0.4861	0	1
Tenure	4.012	3.162	0	13
Inverse Rank (previous year)	166	173	0	500
Year	1998	2.885	1990	2002

N=3,007

Table 2. Correlations for the Consumer Analysis.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Inverse Rank (dependent variable)	(1)											
Category Leniency	(2)	0.27										
Category Fuzziness	(3)	0.31	0.92									
Number of Categories Organization is "in"	(4)	0.35	0.42	0.41								
Number of Categories Organization is "in" - high leniency	(5)	0.36	0.44	0.42	0.99							
Number of Categories Organization is "in" - low leniency	(6)	-0.13	-0.25	-0.11	-0.07	-0.18						
Density of Categories Organization is "in" (logged)	(7)	0.38	0.86	0.81	0.63	0.64	-0.15					
Organization is the Only Member of its Category	(8)	-0.05	-0.13	-0.16	-0.04	-0.05	0.10	-0.10				
Organization is Public	(9)	0.23	0.20	0.21	0.23	0.22	0.03	0.27	-0.01			
Tenure	(10)	0.49	0.50	0.49	0.46	0.47	-0.07	0.54	-0.04	0.27		
Inverse Rank (previous year)	(11)	0.65	0.47	0.42	0.45	0.45	-0.11	0.50	-0.03	0.27	0.56	
Year	(12)	0.38	0.49	0.30	0.23	0.25	-0.28	0.40	-0.07	0.01	0.33	0.38

Table 3. Tobit Models on Software Magazine Inverse Rank. Effects of Category Ambiguity (Leniency and Fuzziness), and Number of Categories. [1]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Category Leniency		-23.42 ***			-11.75 *	-11.94 *
		(3.41)			(5.659)	(5.999)
Category Fuzziness			-92.61 ***		-40.42 +	-39.78
			(14.26)		(23.50)	(24.77)
Number of Categories Organization is "in"				2.912 ***	1.806 ***	
				(0.4920)	(0.4467)	
Number of Categories Organization is "in" - ambiguous						1.801 ***
						(0.4432)
Number of Categories Organization is "in" - unambiguous						1.441
						(2.590)
Fuzzy Density of Categories Organization is "in" (logged)	-0.7016	10.13 ***	7.571 ***	-4.215 ***	6.165 **	6.198 **
	(1.360)	(2.016)	(1.831)	(1.518)	(2.279)	(2.273)
Organization is the Only Member of its Category	-37.11 **	-54.22 ***	-62.54 ***	-39.86 ***	-58.50 ***	-58.24 ***
	(13.18)	(14.22)	(13.94)	(13.32)	(14.55)	(14.65)
Organization is Public	20.23 ***	18.73 ***	19.08 ***	19.94 ***	18.80 **	18.81 ***
	(4.855)	(4.731)	(4.753)	(4.736)	(4.672)	(4.680)
Tenure	7.072 ***	7.247 ***	7.634 ***	6.637 ***	7.135 ***	7.137 ***
	(1.128)	(1.097)	(1.106)	(1.125)	(1.109)	(1.109)
Inverse Rank (previous year)	0.4669 ***	0.4683 ***	0.4679 ***	0.4542 ***	0.4601 ***	0.4601 ***
	(0.0193)	(0.0192)	(0.0193)	(0.0188)	(0.0189)	(0.0189)
Constant	1.449	9.771 *	26.43	1.210	16.38 **	16.66 *
	(4.557)	(4.385)	(5.829)	(4.596)	(6.529)	(6.553)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-17748.35	-17718.31	-17722.24	-17730.85	-17710.89	-17710.88
Degrees of freedom	17	18	18	18	20	21
Number of observations	3007	3007	3007	3007	3007	3007

[1] All Independent variables are measured at the beginning of each time period.
***p<0.001 **p<0.01 * p<0.05. Two-tailed tests. Standard errors are clustered by organization.

Table 4. Tobit Models on Software Magazine Rank. Effects of Category Ambiguity (Leniency and Fuzziness), and Number of Categories for 1996 – 2002 and for Private vs. Public Organizations. [1]

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Risk Set:	*Years: 1996 – 2002 All Organizations*[2]		*Private Organizations*	*Public Organizations*	*Private Organizations*	*Public Organizations*
Category Leniency	-20.97 ***		-22.16 ***	-12.92 **		
	(3.907)		(4.739)	(4.969)		
Category Fuzziness		-86.62 ***			-85.25 ***	-79.50 ***
		(17.60)			(18.84)	(22.89)
Number of Categories Organization is "in"	1.805 ***	2.170 ***	2.048 **	1.935 ***	2.605 **	2.130 ***
	(0.4683)	(0.4998)	(0.7131)	(0.4776)	(0.7475)	(0.5094)
Fuzzy Density of Categories Organization is "in" (logged)	7.054 **	4.471 +	5.574 +	5.235 +	2.428	4.576 +
	(2.541)	(2.354)	(3.238)	(2.862)	(2.892)	(2.702)
Organization is the Only Member of its Category	-77.64 ***	-83.49 ***	-34.77 *	-79.74 ***	-42.80 ***	-97.08 ***
	(21.14)	(21.48)	(14.60)	(20.61)	(14.40)	(21.99)
Organization is Public	21.84 ***	22.26 ***				
	(5.487)	(5.502)				
Tenure	7.164 ***	7.440 ***	8.110 ***	4.866 **	8.488 ***	4.966 **
	(1.145)	(1.151)	(1.454)	(1.601)	(1.473)	(1.605)
Inverse Rank (previous year)	0.4539 ***	0.4529 ***	0.4830 ***	0.4263 ***	0.4799 ***	0.4270 ***
	(0.0194)	(0.0195)	(0.0240)	(0.0322)	(0.0239)	(0.0324)
Constant	143.42 ***	142.01 ***	19.45 ***	12.28 +	35.07 ***	30.93 ***
	(8.964)	(9.086)	(4.119)	(7.069)	(6.261)	(9.532)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-15350.95	-15351.93	-11090.29	-6537.08	-11090.87	-6534.53
Degrees of freedom	13	13	18	18	18	18
Number of observations	2571	2571	1856	1151	1856	1151

[1] All Independent variables are measured at the beginning of each time period.
[2] These model contains fewer year dummies, thus the reduced degrees of freedom.
***p<0.001 **p<0.01 * p<0.05. Two-tailed tests. Standard errors are clustered by organization.

Table 5. Descriptive Statistics for Venture Capitalist Evaluation Analysis.[1]

	Mean	Standard Deviation	Minimum	Maximum
Organization Receives Venture Capital Funding	0.0681	0.2519	0	1
Category Leniency	1.912	1.391	0	4.242
Category Fuzziness	0.4460	0.2893	0	0.8620
Number of Categories Organization is "in"	2.005	2.342	0	35
Number of Categories Organization is "in" - high leniency	1.869	2.395	0	35
Number of Categories Organization is "in" - low leniency	0.1360	0.5092	0	14
Age of Categories Organization is "in"	4.981	3.856	0	12
Fuzzy Density of Categories Organization is "in" (logged)	2.846	2.097	0	7.174
Organization is the Only Member of its Category	0.0070	0.0836	0	1
Tenure	2.492	2.669	0	13
Number of Times Organization Has Received VC Funding	0.1688	0.5873	0	7
Organization is in *Software Magazine* rankings	0.0840	0.2773	0	1

N=17,031

Table 6. Correlations for Venture Capitalist Evaluation Analysis.[1]

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Organization Receives Venture Capital Funding	(1)											
Category Leniency	(2)	-0.05										
Category Fuzziness	(3)	-0.05	0.95									
Number of Categories Organization is "in"	(4)	-0.02	0.55	0.58								
Number of Categories Organization is "in" - high leniency	(5)	-0.02	0.58	0.57	0.98							
Number of Categories Organization is "in" - low leniency	(6)	-0.02	-0.18	-0.04	0.00	-0.21						
Fuzzy Density of Categories Organization is "in" (logged)	(7)	-0.04	0.91	0.87	0.71	0.71	-0.08					
Organization is the Only Member of its Category	(8)	-0.01	-0.12	-0.13	-0.04	-0.07	0.14	-0.09				
Tenure	(9)	-0.08	0.50	0.54	0.40	0.39	0.02	0.50	0.00			
Number of Times Organization Has Received VC Funding	(10)	0.26	0.19	0.19	0.17	0.17	0.00	0.19	-0.01	0.20		
Organization is in *Software Magazine* rankings	(11)	-0.03	0.20	0.21	0.28	0.28	-0.02	0.22	-0.01	0.20	0.03	
Tenure of Categories Organization is "in"	(12)	-0.08	0.86	0.82	0.46	0.47	-0.11	0.80	-0.06	0.57	0.14	0.16

[1] Private Companies Only.

Table 7. Piecewise Continuous Hazard Rate Models on Likelihood to Receive Venture Capital Funding. Effects of Category Ambiguity (Leniency and Fuzziness) and Number of Categories. [1]

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Category Leniency		0.3644 ***			-0.2880 **	-0.2901 **	0.3879 ***	
		(0.0630)			(0.1017)	(0.1062)	(0.0771)	
Category Fuzziness			2.377 ***		3.273 ***	3.280 ***		2.536 ***
			(0.2296)		(0.3856)	(0.3950)		(0.2482)
Number of Categories Organization is "in"				-0.0377 *	-0.0455 *		0.0013	-0.0311
				(0.0186)	(0.0221)		(0.0196)	(0.0202)
Number of Categories Organization is "in" - ambiguous						-0.0456 *		
						(0.0220)		
Number of Categories Organization is "in" - unambiguous						-0.0491		
						(0.0739)		
Tenure of Categories Organization is "in"							-0.0134	-0.0358 +
							(0.0216)	(0.0187)
Fuzzy Density of Categories Organization is "in" (logged)	0.2643 ***	0.0735 +	0.0277	0.2954 ***	0.1243 **	0.1247 **	0.0746	0.0748 *
	(0.0201)	(0.0383)	(0.0280)	(0.0258)	(0.0451)	(0.0454)	(0.0497)	(0.0368)
Organization is the Only Member of its Category	0.5388	0.7661 +	1.113 **	0.563	1.177 **	1.179 **	0.777 +	1.165 **
	(0.4040)	(0.4094)	(0.4161)	(0.4044)	(0.4172)	(0.4117)	(0.4106)	(0.4188)
Tenure	-0.0576 *	-0.0627 *	-0.0735 **	-0.0552 *	-0.0726 **	-0.0726 **	-0.0604 *	-0.0656 *
	(0.0271)	(0.0258)	(0.0258)	(0.0269)	(0.0262)	(0.0262)	(0.0261)	(0.0261)
Number of Times Organization Has Received VC Funding	0.4320 ***	0.3954 ***	0.3094 ***	0.4315 ***	0.2953 ***	0.2953 ***	0.3944 ***	0.3068
	(0.0471)	(0.0477)	(0.0499)	(0.0470)	(0.0507)	(0.0508)	(0.0479)	(0.0503)
Organization is in *Software Magazine* rankings	-0.4439 ***	-0.4199 **	-0.4437 ***	-0.4208 **	-0.4335 ***	-0.4336 ***	-0.4251 **	-0.4395 **
	(0.1394)	(0.1375)	(0.1344)	(0.1408)	(0.1354)	(0.1353)	(0.1394)	(0.1370)
Log Pseudolikelihood	-3438.24	-3422.17	-3398.31	-3436.57	-3394.41	-3394.41	-3421.97	-3396.45
Degrees of Freedom	22	23	23	23	25	26	25	25

[1] There are 1,160 events for 4,623 private organizations over 17,031 organization-years. All independent variables are measured at the beginning of each time period.

***p<0.001 **p<0.01 * p<0.05 +p<0.10. Two-tailed tests. Standard errors are clustered by organization

Table 7 (cont'd). Piecewise Continuous Hazard Rate Models on Likelihood to Receive Venture Capital Funding. Effects of Time Pieces. [1]

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Time Since Last Funding: 0-1 Year	-1.754 ***	-1.733 ***	-1.877 ***	-1.747 ***	-1.940 ***	-1.939 ***	-1.925 ***	-1.977 ***
	(0.1803)	(0.1813)	(0.1851)	(0.1806)	(0.1900)	(0.1946)	(0.1887)	(0.1927)
Time Since Last Funding: 1-2 Years	-3.462 ***	-3.585 ***	-3.972 ***	-3.484 ***	-4.090 ***	-4.088 ***	-4.021 ***	-4.118 ***
	(0.2129)	(0.2180)	(0.2272)	(0.2143)	(0.2347)	(0.2411)	(0.2287)	(0.2356)
Time Since Last Funding: 2-5 Years	-4.174 ***	-4.270 ***	-4.646 ***	-4.192 ***	-4.768 ***	-4.767 ***	-4.689 ***	-4.792 ***
	(0.2332)	(0.2368)	(0.2493)	(0.2336)	(0.2579)	(0.2637)	(0.2514)	(0.2595)
Time Since Last Funding: 5-10 Years	-4.208 ***	-4.294 ***	-4.644 ***	-4.226 ***	-4.761 ***	-4.760 ***	-4.688 ***	-4.786 ***
	(0.3120)	(0.3108)	(0.3184)	(0.3101)	(0.3233)	(0.3279)	(0.3185)	(0.3243)
Time Since Last Funding: 10+ Years	-3.988 ***	-4.081 ***	-4.363 ***	-3.992 ***	-4.444 ***	-4.443 ***	-4.409 ***	-4.477 ***
	(0.5738)	(0.5731)	(0.5768)	(0.5730)	(0.5802)	(0.5830)	(0.5781)	(0.5810)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[1] There are 1,160 events for 4,623 private organizations over 17,031 organization-years. All independent variables are measured at the beginning of each time period.

***p<0.001 **p<0.01 * p<0.05 +p<0.10. Two-tailed tests. Standard errors are clustered by organization

Appendix

Table A. Tobit Models on Software 500 Rank and Piecewise continuous hazard rate models on likelihood to receive venture capital. Highly Correlated Controls Excluded.[1]

	Model A1	Model A2	Model A3	Model A4
Model:	*Consumer: Tobit*		*VC: Piecewise Continuous*	
Category Leniency	-4.467 +		0.4576 ***	
	(2.344)		(0.0321)	
Category Fuzziness		-18.83 +		2.486 ***
		(10.93)		(0.1521)
Organization is the Only Member of its Category	-46.24 ***	-47.33 ***	0.793 +	1.120 **
	(14.86)	(15.09)	(0.4067)	(0.4109)
Organization is Public	26.16 ***	26.04 ***		
	(4.80)	(4.79)		
Inverse Rank (previous year)	0.5428 ***	0.5417 ***		
	(0.0162)	(0.0162)		
Number of Times Organization Has Received VC Funding			0.3245 ***	0.2212 ***
			(0.0332)	(0.0361)
Organization is in *Software Magazine* rankings			-0.4184 **	-0.4599 ***
			(0.1349)	(0.1313)
Time Since Last Funding: 0-1 Year			-1.725 ***	-1.879 ***
			(0.1815)	(0.1845)
Time Since Last Funding: 1-2 Years			-3.611 ***	-4.016 ***
			(0.2155)	(0.2229)
Time Since Last Funding: 2-5 Years			-4.393 ***	-4.811 ***
			(0.2225)	(0.2331)
Time Since Last Funding: 5-10 Years			-4.646 ***	-5.073 ***
			(0.2566)	(0.2652)
Time Since Last Funding: 10+ Years			-4.683 ***	-5.078 ***
			(0.5412)	(0.5412)
Constant	6.863	9.828 +		
	(4.740)	(5.972)		
Year Dummies	Yes	Yes	Yes	Yes
Log pseudolikelihood	-17798.67	-17799.25	-3426.70	-3402.53
Degrees of freedom	16	16	21	21
Number of Observations	3007	3007	17031	17031

[1] All independent variables are measured at the beginning of each time period.

***p<0.001 **p<0.01 * p<0.05 +p<0.10. Two-tailed tests. Standard errors are clustered by organization