The Persistence of Lenient Market Categories

Elizabeth G. Pontikes
University of Chicago
Booth School of Business

William P. Barnett
Graduate School of Business
Stanford University

Word count: 9,779

January 2014

*Thanks to Ron Burt, Jerker Denrell, Amir Goldberg, Andy Rachleff, Huggy Rao, Amanda Sharkey, Jesper Sørensen, and Ezra Zuckerman for useful ideas. This research is funded in part by the Charles E. Merrill Faculty Research Fund at the University of Chicago Booth School of Business. We would like to thank the Graduate School of Business at Stanford and Chicago Booth for their support.
ABSTRACT

Research across disciplines presumes that market categories will have strong boundaries. Categories without well-defined boundaries typically are not useful and do not become institutionalized, so are expected to fade away. In contrast, many contexts contain lenient market categories, or less-constraining market categories, that persist and become important. We argue this fact can be explained by looking at market categories from the producer perspective. Lenient market categories are accepting of many different types of organizations and offer more flexibility. As a result, we expect there to be high rates of entry into lenient categories. At the same time, lenient market categories offer less credibility than categories with strong boundaries, and so organizations will be more likely to exit. When entry rates are higher than exit rates, lenient market categories will endure over time. We also predict that organizations exiting lenient categories will enter other lenient categories, which further fuels their persistence. Finally, this trend is exaggerated when influential external agents favor leniency. We find support for these ideas in a longitudinal analysis of organizational entry into and exit from market categories in the software industry.
Market categories are central to how we understand organizations. Researchers, practitioners, professionals, and the general public use market categories to group organizations for purposes of competitive comparisons, budgetary analysis, anti-trust considerations, and the like. Classically, a market is conceived of as a bounded area that defines a set of substitutes, separated from other markets by a “marked gap” (Robinson 1965). But markets are not an inherent characteristic of an environment. They reflect people’s shared mental representations and form a categorical system (Day and Nedungadi 1994; Sujan 1985) that is socially constructed by market actors (Rosa, Porac, Runser-Spanjol and Saxon 1999). Market categories emerge when producers, consumers, mediators, and other relevant audiences develop agreed-upon boundaries through informal interactions (Hannan, Pólos and Carroll 2007; White 1981; Rosa, Porac, Runser-Spanjol and Saxon 1999). Once established, categories affect how people understand and evaluate producers and products (Hsu, Hannan and Koçak 2009; Mogilner, Rudnick and Iyengar 2008; Leung and Sharkey 2013).

Studies of social categories typically assume that categories of any consequence will have strong boundaries. A number of studies investigate categories with crisp boundaries that are maintained by mediators, critics, or other third parties. These studies show that there are benefits to being typical of accepted categories, and actors and objects that are not easily understood as part of a category are ignored or devalued (Zuckerman 1999; Hsu 2006). It is not as beneficial to be a member of a category that has blurry boundaries (Negro, Hannan and Rao 2010; McKendrick, Jaffee, Carroll and Khessina 2003; Pontikes 2012). An implicit presumption is that categories will either develop strong, socially agreed-upon boundaries, or they will fade.

Yet examples abound of categories with blurry boundaries and indefinite meaning. We call these categories *lenient*. Lenient categories are not necessarily marginal or early stage. Often they are important categories in a domain. For example, “business intelligence” is a market category in the software industry with porous boundaries. It overlaps with a number of others including “online analytical processing,” “predictive modeling,” “decision support,” “knowledge management,” “content management,” and the list goes on. This category has become so encompassing that it prompted Forrester analyst Jim Kobielus
to write a blog titled “What’s not BI?” (Kobielus 2010, emphasis added). Still, “business intelligence” is one of the most covered market categories by industry analysts. The “nanotechnology” category has not developed strong boundaries or specific codes. According to the Nanotechnology Initiative, nanotechnology is any technology of a size between 1 and 100 nanometers. Many different types of scientific research and businesses are considered “nanotechnology,” much to the chagrin of early nanotechnologists who envisioned a more clearly defined discipline (Grodal 2011). But nanotechnology is heavily funded, growing, and well known. Total Quality Management (TQM), a category of business techniques aimed at improving organizational performance, is extremely popular with both researchers and practitioners, even though its definition evolved to be “diffuse and ambiguous” (Zbaracki 1998). Lenient categories do little to convey what people can expect from a member organization. We should expect them to be less effective at facilitating sense making within a domain. Still, lenient categories are common. How do they persist – and even flourish?

We propose that investigating category boundaries from the producer perspective can explain the persistence of lenient categories. Most empirical research on social classification looks at categories that are defined by mediators, such as analysts or critics (Zuckerman 1999; Hsu 2006; Ruef and Patterson 2009). One of the purposes of mediators is to clarify categorical boundaries to help consumers make sense of a domain (Pollock and Williams 2011). Consequently, studying mediator-defined categories may understate the prevalence of lenient categories. Theoretical treatments of social categories conclude that boundaries emerge not from mediators alone, but through informal interactions among multiple audiences, including producers, consumers, and mediators (DiMaggio 1987; Lamont and Molnar 2002; Hannan, Pólos and Carroll 2007; Rosa, Porac, Runser-Spanjol and Saxon 1999). Customers and mediators prefer market categories that have strong boundaries and can be easily distinguished from others (Negro, Hannan and Rao 2010; Pontikes 2012). Researchers have assumed that producers anticipate this preference and also avoid lenient categories.

We propose taking a more nuanced view of how producers see lenient categories. In particular, there is reason to think that lenient categories are viewed more favorably when the producer is not already
a member. Lenient categories permit potential members more flexibility in constructing identity claims. They can include unique organizations that are attractive to people who seek novelty. Precisely because lenient categories lack constraint, a wide range of organizations can credibly claim membership. If we only consider how helpful a category is to consumers, it makes no sense that lenient categories can thrive. But if we also consider a producer’s decision to enter a market category, we can understand how lenient market categories grow and persist.

**LENIENT MARKET CATEGORIES**

Categories help people make sense of a diverse domain. Identifying market categories is necessary in order to study market concentration and product differentiation (Berry and Reiss 2007; Sutton 2007), how customers evaluate different types of products (Day, Shocker and Srivastava 1979; Sujan 1985; Meyers-Levy and Tybout 1989; Ratneshwar and Shocker 1991), and categorical expectations that induce conformity (DiMaggio and Powell 1983; Zuckerman 1999). Historically, scholars have treated market categories as having crisp boundaries. Yet researchers in cognitive science have shown that mental representations of categories are graded, so that categories are fuzzy and include partial members (Rosch 1975; Murphy 2004; Hampton 1998). Studies indicate that whether boundaries are crisp or fuzzy has important implications (Hannan, Pólos and Carroll 2007; Hannan 2010). For example, members of fuzzy categories are not as highly rated by consumers and mediators (Ruef and Patterson 2009; Negro, Hannan and Rao 2010; Pontikes 2012), and it is not as problematic to span categories that have fuzzy boundaries (Kovács and Hannan 2010; Ruef and Patterson 2009). Organizations that innovate are more likely to pioneer a new market when they affiliate with crisp categories (Pontikes 2013).

Previous research investigates category fuzziness in terms of whether boundaries lack definition. In this study, we take a different approach and investigate category leniency. Lenient categories not only have fuzzy boundaries, but also overlap with many different categories.\(^1\) This creates a lack of constraint

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\(^1\) It is important to note that leniency arises when a category *overlaps* with many others, but this does not necessarily imply that the category is superordinate in a hierarchy. A superordinate category is one that contains all members of
in terms of what external audiences expect from organizations that identify with the category. When categories overlap with many others, audiences begin to expect that a wider range of activity is acceptable for category members, changing the interpretation of the category (Negro, Hannan and Rao 2011). For example, in the market for “disk arrays,” organizational members had many alternate identities. As a result, people began to view this market in a variety of ways, and the category did not develop strong, agreed-upon constraints (McKendrick and Carroll 2001).

In the software industry between 1990 and 2002, some of the most important market categories were lenient. These include “customer relationship management,” “business intelligence,” “data mining,” and “e-business applications.” For example, in 1999 Red Herring magazine defined “customer relationship management (CRM)” as software that “lies at the intersection of a business’s back-office ERP functions and its outward-facing front-office applications,” (Zerega 1999). This vague definition encompasses a number of different types of software organizations. CRM became even more lenient; as of 2012, the editors of CRM Magazine state that it is:

*a company-wide business strategy designed to reduce costs and increase profitability by solidifying customer loyalty. True CRM brings together information from all data sources within an organization . . . to give one, holistic view of each customer in real time . . . Once thought of as a type of software, CRM has evolved into a customer-centric philosophy.*

By this definition, CRM no longer constrains an organization to produce software. The leniency of the CRM category did not prevent it from also becoming relevant and prominent, as illustrated in figure 1. The first graph plots the leniency of the “CRM” category over time. CRM is increasing in leniency over this time period, and at the same time the category is increasingly covered in the Wall Street Journal.

Compare this to “entertainment software,” a low-leniency category that developed clear constraints. It refers to organizations that produce video games. This market category has a trade association, the Entertainment Software Association, that represents and helps further the interests of a nested sub-categories. This is not the case for lenient categories in this analysis. For instance, “business intelligence” overlaps with “knowledge management,” but not all “knowledge management” organizations are also “business intelligence.” All categories used in the empirical analysis are at the same hierarchical level.

designated set of “entertainment software” organizations. There is also annual trade fair, the Electronic Entertainment Expo (E3), and the Entertainment Software Rating Board (ESRB), a self-regulating organization that assigns age and content ratings to video games. “Entertainment software” developed a crisp meaning, so organizations that create other types of software directed at entertainment, such as digital audio, could not credibly claim the category. Figure 2 shows the leniency of “entertainment software” over time, as well as mentions in the Wall Street Journal. Though this market category was low-leniency, in the media it is as or less prominent than the high-leniency “customer relationship management” category. As this example illustrates, developing clear boundaries did not necessarily lead to more recognition or relevance in this domain.

More generally, many of the most frequently claimed market categories in the software industry were also some of the most lenient, as shown in figure 3. How can this be? To date, because researchers have focused on the benefits of well-defined boundaries to category members, there has been a presumption that prominent categories will have sharp, constraining boundaries. But lenient categories often persist. The puzzle of persistent, lenient categories can be understood when we take into consideration the role played by producers in creating categorical definitions.

THE ROLE OF PRODUCERS

Recent research on classification investigates formal categories defined by mediators, such as government SIC codes (Zuckerman 1999), critics (Hsu 2006; Negro, Hannan and Rao 2010), analysts (Ruef and Patterson 2009), or on Web sites (Hsu, Hannan and Koçak 2009; Leung and Sharkey 2013; Kovács and Hannan 2010). Analysts create centralized definitions of market categories by issuing reports, lists, and other documents that verbally describe characteristics of vendors in a market category. For example, Pollack and Williams (2011)’s study of Gartner, the prominent information technology analyst organization, quotes an analyst describing the value of Gartner as promoting category labels and definitions: “…we in effect draw a box around something and say: ‘That is the market. There's the
definition of it. These are the elements. These are the players. This is how you evaluate it. This is how you compare.” (p. 204).

Studying mediator-defined categories allows researchers to use an authority to define relevant categories within a domain. At the same time, this approach may overstate the strength of category boundaries. Mediators portray a sharper and more formalized view of categories by excluding marginal actors that may be considered partial category members by other relevant audiences. This is especially problematic because mediators are not all-powerful when it comes to defining categories. For instance, Pollack and Williams (2011) describe how Gartner unsuccessfully declared the death of the “ERP” category they had developed, when producers and customers continued to use the market category. This example underscores Bowker & Star (2000)’s point that formal classification needs to correspond to people’s informal, common-sense groupings. Categories are defined by interactions among multiple audiences; in markets this includes consumers, producers, analysts, critics, media, and investors. Rosa et al (1999) show how producers and industry journalists jointly influence the definition of the “minivan” market category through stories in publications. As they state, “Neither consumers [represented by media publications] nor producers had total control over the category’s final realization, and both sides of the market were instrumental in shaping the category's evolutionary trajectory,” (p. 74).

Producers influence market categories more informally. Simply claiming membership in market categories affects category definitions (Granqvist, Grodal and Woolley 2013; Navis and Glynn 2010). For example, the boundary for the “nanotechnology” category widened when organizations engaged in diverse activities began to claim the label (Grodal 2011). When a number of producers straddle two categories, this leads audiences to reinterpret the meaning of the category (Negro, Hannan and Rao 2011). In general, people infer categorical definitions based on the features of organizations that claim membership (Pontikes and Hannan 2013).

A producer’s decision to affiliate with a market category is based not only on technical characteristics of the organization and its products, but also on more fungible elements such as how its products can be used, its target customers, and of course, which market categories are already established.
This choice is an issue of framing, or providing a “schema of interpretation” for an organization’s products or services (Goffman 1974). Similar to meaning construction in social movements, managers and entrepreneurs use categories as frames intended to make themselves and their products understandable and attractive (Benford and Snow 2000; Navis and Glynn 2010; Déjean et al. 2013). The market category an organization claims not only reflects its internal identity, but also is a guide to how external audiences should evaluate it (Gioia, Schultz and Corley 2000). In many industries – including the software industry – for a given organization there are a number of market categories it could credibly claim, providing a choice of potential frames.

For example, Coremetrics, a company born in the late 1990s that sold a product that tracked and reported on Web-site traffic, initially identified itself as a member of the “e-marketing” category, which implied that it focused on online marketing. This category also included companies that provided email or search marketing, or less technical consulting. It then claimed the “business intelligence” category, an older and more established category that indicated that a company provided in-depth reports on data from across many divisions in an organization. Later, it tried to pioneer a new category for “marketing analytics,” hoping the category would signal its focus on marketing and also emphasize its abilities in technical reporting. This category was not especially distinct from the more established “web analytics” category, which indicated that affiliated organizations produced reports with general metrics for a company’s online site, often sold to information technology departments. The category was a good fit for Coremetrics’ product but included organizations with low-level reporting abilities and did not have the panache of a marketing focus. However, because “marketing analytics” did not catch on, Coremetrics affiliated with the “web analytics” category. As this example indicates, the decision to enter a market category is based on a number of factors, including but not limited to the strength of the category’s boundary.

Organizational Entry
A primary purpose of categorization is to separate objects into different types, reducing cognitive load and helping people make sense of the world around them (Murphy 2004). From this perspective, lenient categories are less useful. Many studies reinforce this point and show that category fuzziness negatively affects members (Negro, Hannan and Rao 2010; 2011; Kovács and Hannan 2010). But there are also benefits to category leniency. In markets, lenient categories provide a number of different ways an organization can satisfy consumer demand. By affiliating with a lenient category, an organization can potentially cultivate an identity that fits into multiple frames. As a result, the organization may be able to appeal to a wide range of perspectives, which can be beneficial, especially under conditions of uncertainty (Padgett and Ansell 1993; Stark 1996). There is also the potential for producers to shape a lenient category around their activities. Leniency allows managers to see what they want to see in a market. Managers of many different types of organizations will be able to comfortably frame their offerings as fitting into a lenient category. This process has been observed among R&D consortia, where general-purpose (lenient) consortia attract more organizations than do consortia with a specific purpose (Barnett, Mischke and Ocasio 2000). Lenient consortia can be framed as consistent with the goals of a larger number of potential members. This is not to say that claiming a lenient category will fully protect organizations from accusations of inauthenticity; a rival might still allege that the organization is not a true member of the market – “Coremetrics is not a real web analytics company.” However, if the category does not impose clear, consensual constraints, this accusation is difficult to verify. The constraints of market categories act as a type of mobility barrier, and leniency lowers that barrier. These considerations imply that lenient categories will attract more organizational entry compared to constraining categories.

One might expect producers to anticipate that lenient categories create ambiguous identities that are harder for customers to interpret. But we suggest that from the vantage point of a producer evaluating whether to enter a category, the potential downsides of leniency will be more difficult to foresee, while the benefits will be more apparent. People have asymmetric beliefs about future as compared to past events, especially when there is ambiguity. For example, people prefer to predict an uncertain outcome before it occurs; they bet more money, are more confident, and are more excited (Brun and Teigen 1990;
Rothbart and Snyder 1970). They also seek ambiguity when the source of ambiguity is related to their own competence (Heath and Tversky 1991), an effect that may account for why so many people enter entrepreneurship despite the known risks (Greico and Hogarth 2004). In general, subjects believe that will is a stronger causal force that will shape future outcomes than it was shaping past events (Helzer and Gilovich 2012). These arguments imply:

H1: Organizations are more likely to enter a more lenient market category.

Organizational Exit

Once an organization is in a lenient category, the situation changes. Producers in a category have first-hand information about whether affiliating with the category is helping them attract customers. Previous research takes this perspective, and concludes that lenient categories are not useful to an observer who is trying to evaluate an organization. Organizations that are considered legitimate members of a well-defined category benefit from the affiliation because the category helps people understand and interpret what the organization does (Hannan, Pólos and Carroll 2007). Lenient market categories do not evoke commonly agreed upon expectations and provide weak signals, and so are less likely to attract interested customers. Studies show that when category boundaries are ambiguous, members do not benefit as much from the category affiliation (Kovács and Hannan 2010; Ruef and Patterson 2009; Negro, Hannan and Rao 2010). For example, a “business intelligence” organization that sells software to build sales reports will be of little use to a customer looking for “business intelligence” that facilitates content management. If producers in a lenient category find that category less useful for attracting customers, we expect they will be more likely to subsequently drop the category.

Lenient categories are more likely to be dropped for a second reason – one linked to the ease with which such categories can be credibly claimed. The less lenient the category, the more likely that organizations claiming the category will conform to its (well-defined) criteria. Very lenient categories are likely to be claimed by a wide variety of organizations. The entry process into lenient categories is inherently more exploratory, allowing for greater variability in the types of the organizations that become
members (March 1991). Some of these entrants will ultimately find themselves well served by having entered, but the permissive entry-selection process will also attract organizations that ultimately will find no benefit from the affiliation. When thresholds for entry are low, we should expect higher rates of subsequent attrition from a category (Barnett, Swanson and Sorenson 2003). Altogether, our arguments imply:

H2: Organizations are more likely to exit a more lenient market category.

MOVEMENT BETWEEN MARKET CATEGORIES

When organizations enter and exit market categories, they engage in a search process surrounding their market identity. This raises the question: what path do identity claims take over time? We might expect that producers will move from lenient to constraining market categories because lenient categories do not provide as much value to their organizational members. An organization taking this path might try to develop a focused identity to send a clear signal to potential customers, using past failures to inform their future choices with respect to category affiliation. However, literature in psychology suggests this is unlikely. Studies show that people are optimistic about future successes even when they have had poor performance in the past (Gilovich 1983) and do not see their past behavior as diagnostic of future outcomes (Helzer and Dunning 2012). Organizations mimic these tendencies, with conservative learning processes that reinforce existing structures even as the organization copes with change (March, Scproull and Tamuz 1991).

Organizations in lenient categories face limited resistance when it comes to taking the organization in new directions, and employees are not accustomed to having to defend whether what they are doing is in line with existing standards or expectations. To move from a lenient to a constraining market category, organizations will have to conform to the new expectations, which will require instituting new structures and routines. Organizations in less lenient categories, by contrast, are already accustomed to conforming to constraints. Moving into constraining categories will not require such organizations to deal with unfamiliar requirements. So we expect:
H3: Organizations that are in lenient market categories are even more likely to enter another lenient category, as compared to organizations in less lenient categories.

EXTERNAL INFLUENCE

External actors also may influence category affiliation. This is especially true if they control important resources. In the software industry, venture capitalists are such an audience (Onorato 1997). Venture capitalists are often on the boards of their portfolio companies, giving them much influence over these organizations (Norton and Tenenbaum 1993). Notably, venture capitalists are known for seeking novelty, since they typically value potential investments that can disrupt the market and result in a large pay-off. Research shows that venture capitalists have the opposite response to consumers when it comes to organizations that bridge category boundaries, and they prefer to invest in organizations that are in lenient market categories (Pontikes 2012). We argue that because venture capitalists value novelty, coupled with their strong influence, they will push recently funded organizations toward entering lenient market categories.

H4: Organizations that have recently received venture capital funding are more likely to enter a lenient market category, as compared to organizations that have not recently received venture capital funding.

EMPIRICAL TEST: THE SOFTWARE INDUSTRY

We study these ideas in the software industry between the years 1990 and 2002. This industry is innovative and complex, so that even experts have difficulty making sense of the variety of producers and products. As a result, a number of analyst organizations have emerged who create market categories to segment the field for their customers (Campbell-Kelly 2003; Pollock and Williams 2011; Wang 2009). The dynamics in this industry mirror how category construction is described in the literature: relevant audiences – producers, analysts, customers and investors – introduce a category that may or may not catch on. Category definitions arise both through formal documents, when an analyst, the media, or even
producers write an article describing a market category, or informally, when a producer with certain characteristics claims membership in a category. There is not one centralized actor who owns category definition, but consensus is reached through informal interactions among multiple actors (Wang 2009).

Software market categories range from constraining to lenient. Some, like the “entertainment software” category described above, evolved to have strong boundaries. This is usually a result of the community organizing to promote a specific definition for the category, a process typical of what is described in studies on social categories. But a number of market categories also evolved to be lenient. A study of market categorization in software describes the leniency of prominent categories “MRP” (manufacturing resource planning), “ERP” (enterprise resource planning), and “CRM” as:

These names refer not to a specific homogeneous product but to a more or less heterogeneous collection of artefacts … Such terminologies proposed a boundary that linked a group of (often quite various) artefacts while differentiating them from others, (Pollock and Williams 2011).

Classification in the software industry contains both constraining and lenient market categories, making it a good context for our study.

DATA AND METHODS

Our data come from press releases issued by software organizations. Within each press release, software organizations frame their offerings by claiming a market category (figure 4 lists examples of category affiliations from press releases). Press releases are not expensive to produce, so they include small and young organizations that are often hard to track. They provide a written record of the market categories organizations claim over time.

---- Insert figure 4 about here ----

Press releases reflect self-claimed membership in market categories. One concern may be whether this is a meaningful classification. Previous research suggests that self-claimed categories are predictive of important outcomes. Categorizing organizations using self-claims from annual reports, as compared to using SIC or NAICS codes, better predicts merger success, profitability, and leverage
(Hoberg and Phillips 2010; 2012). Using self-claimed categories to measure competitive threats is a better predictor of payouts, repurchases, and cash held (Hoberg, Phillips and Prabhala 2013). Self-claimed categories also affect VC funding and revenues (Pontikes 2012), and they reflect producers’ patenting behavior (Pontikes and Hannan 2013). This suggests that self-claimed categories are meaningful, and a better predictor of important outcomes than categories researchers often use (such as SIC codes).

Another concern may be whether other audiences use categories claimed in press releases. To investigate this, categories from press releases were compared to categories covered in reports from a prominent analyst organization, Gartner. Over half of the categories in press releases were covered in Gartner reports. Finally, there is the question of whether anyone reads press releases. It is likely that most press releases are not widely distributed, but information from press releases are covered by the media. A study of public companies found an average of 1.5 media articles per press release issued from 2001 to 2006 (Soltes 2010). We also investigated whether market categories claimed in these data were reflected in other public statements for a random sample of organizations in the data. Organizations claim the same categories in press releases and on their Web sites (from the archived web) 71% of the time, and in their annual reports 81% of the time.

Our initial source of data was all press releases issued through Businesswire, PR Newswire, and Computerwire from 1990 until 2002 that contained at least three mentions of the word “software.” There are 268,963 of these. A combination of custom coded text-matching programs and manual examination of these programs’ output resulted in 4,566 software organizations that issued press releases during this period. An extensive list of market categories was assembled from articles in Software Magazine and Computerworld, from the business sectors listed in Software Magazine’s Software 500, and from manual inspection of the identity statements. Text matching programs searched all identity statements for these categories. This provided the organizations’ claims to market categories for each year between 1990 and 2002. The final data contain 456 market categories and 4,566 organizations.

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3 We include press releases from 1989 to construct variables to estimate outcomes in the year 1990.
For analysis, we create organization-category dyads to investigate whether the organization from the dyad enters or exits the category from the dyad. A dyadic analysis allows us to use both organization and category covariates in our models. For our entry analysis, data include dyads of organizations paired with categories they are not already in, for the years in which the organization is issuing press releases.\footnote{For organizations that “skip” years in terms of claiming categories in press releases, we attribute the previous year’s category claims to the skipped year.} We only include a dyad if the organization has never previously affiliated with the category. Our data contain 1,893,569 potential organization-category pairs, 23,629 market category entries, and 6,485,521 organization-category-years. For our exit analysis, data include dyads for each organization and the categories it claims in the current year. Our data include 21,589 organization-market-category pairs and 13,880 category exits over 39,359 organization-category-years.

**Leniency**

Lenient categories have high overlap with other categories in a domain. Mathematically, we build the measure of leniency using the fuzziness of a category’s boundaries, an established construct in the literature on cognition and categorization. Fuzziness refers to categories that do not have clear boundaries separating members from non-members (Rosch and Mervis 1975; McCloskey and Glucksberg 1978; Hampton 1998). A category is fuzzy if it has a high degree of overlap with at least one other category. Lenient categories are not only fuzzy, but also overlap broadly with other categories in a domain. Leniency is calculated by multiplying fuzziness of a market category by the number of distinct other categories with which they identify — thereby emphasizing a lack of constraint. By conceiving of market categories as fuzzy sets, organizations can have partial membership. We assume that the more frequently an organization claims a category, the stronger its affiliation. Therefore, we calculate organization $i$’s grade of membership in category $A$, or $\mu_i(A)$, by dividing (the number of times organization $i$ claims category $A$ in its press releases) by (the number of times it claims any category) in a given year:

$$\mu_i(A) = \frac{\text{claims}_i(A)}{\text{claims}_i((A,B,...))}$$ (1)
The contrast of category A can be calculated as the average grade of membership of member organizations (Hannan, Pólos and Carroll 2007):

\[
\text{contrast}_A = \frac{\sum_{i: \mu_i(A) > 0} \mu_i(A)}{N_A}
\]

(2)

Here, \( N_A \) is the number of organizations with non-zero grade of membership in A. Leniency multiplies the inverse of contrast by the (natural log of the) number of distinct other categories with which members identify. Leniency is measured for every year.

\[
\text{leniency}_A = (1 - \text{contrast}_A) \times \ln(N_{ocat})
\]

(3)

**Dependent Variables**

We use market category entry as the dependent variable to test hypotheses 1, 3, and 4. This is a binary variable that equals 1 if the organization claims the category from the dyad in the current year, and 0 if the organization does not claim the category. We code market entry as 1 only if the organization has never previously claimed to be a member of that category.

We use market category exit as the dependent variable to test hypothesis 2. This is a binary variable that equals 1 if the organization drops the category from the dyad in the current year, and 0 if the organization does not drop the category. We code exit as 1 in the last year that the organization from the dyad claims membership in the market category from the dyad. Our data include the years 1990 through 2002, so we cannot define market exit for the year 2002. As a result, we run our exit analysis for the years 1990 through 2001.

**Independent Variables**

We test hypotheses 1 and 2 using the leniency of the category from the dyad. We test hypothesis 3 by interacting the leniency of the organization’s categories with the leniency of the category from the dyad (the target category): (leniency of organization’s categories \( \times \) leniency of the target category). The leniency of an organization’s categories is computed as a weighted average of the leniency of the
categories the organization is in, weighted by its grade of membership in each category. We test hypothesis 4 by interacting the leniency of the target category with a dummy variable that indicates whether the organization received venture capital funding in the previous year: (leniency of the target category) x (organization received venture capital funding).

Control Variables

We include a number of category-level and organizational-level variables in our model as controls. For category characteristics, we include the number of organizations in the category (weighted by grade of membership), to control for category size, accounting for the possibility that populated categories might attract more entries.5 We also include the number of organizations that entered and exited the category (also weighted by grade of membership) to account for whether the category is growing or declining in popularity. Finally, we included the age of the market category measured since 1990 (the inception of our data).

Organizational-level controls include the number of categories the organization is in to control for generalism. We include whether the organization was in Software Magazine’s Software 500, an annual ranking of software organizations by revenue, to account for heterogeneity in size and quality. Organizations may be more likely to enter new categories after receiving new investments, so we also include whether the organization has received venture capital funding. We include the time since an organization has last entered any category, and the age of the organization, measured since 1990 (the inception of our data). All independent and control variables are measured as of the beginning of each time period. Table 1 provides descriptive statistics for the dependent, independent, and control variables for all organization-category dyads in our entry data. These data contain all “potential” pairings of organizations with market categories. Table 2 provides descriptive statistics for the dependent, independent, and control variables for the organization-category dyads in our exit data, which contain all actual pairings of organizations and market categories.

5 This is also called the fuzzy density of the category.
--- Insert tables 1 and 2 about here ---

**Model**

To test our hypotheses we estimate the instantaneous hazard rate of an organization’s **entry into** and **exit from** the market category of the organization-category dyad, in separate models. This is the instantaneous likelihood that the organization enters or exits a particular market category during time period \( t \) in the limit where \( t \to 0 \), and can be operationalized in terms of two random variables: \( Y(t) \), which indicates whether an organization enters or exits a market category at time \( t \), and \( t_n \), the time of its entry or exit:

\[
r(t) = \lim_{t \to 0} \frac{\Pr(Y(t - t_n + t) | Y(t - t_n) = 0)}{t}
\]

This rate is estimated as a function of the independent and control variables listed above:

\[
r(t, t_n) = r_0(t - t_n) \times \exp(\text{ind} \times x_{\text{ind}} + \text{control} \times x_{\text{control}})
\]

We use piecewise continuous hazard rate models employing the stpiece routine in Stata written by Jesper Sørensen. Robust standard errors are used, clustered by category.

**RESULTS**

*Entry into and Exit from Lenient Categories*

Table 3 contains tests of hypotheses 1 and 2. Models 1-2 are entry models that test hypothesis 1.

----- Insert table 3 about here -----  

Model 1 includes controls only. Model 2 includes the leniency of the market category from the organization-category dyad. Results show that the more lenient the category, the more likely an organization will enter it, significant at \( p<0.001 \). Model 2 is also an improvement in fit over model 1 at \( p<0.001 \), providing support for hypothesis 1. An organization is more than twice as likely to enter a market category with mean leniency and six times more likely to enter a category one standard deviation
above mean leniency, as compared to a category one standard deviation below mean leniency.\(^6\) Figure 5 plots these effects.

----- Insert figure 5 about here -----

Models 3 and 4 are exit models that test hypothesis 2. Model 3 contains controls only, and model 4 includes the leniency of the category from the dyad. Results show that organizations are more likely to exit lenient categories, significant at p<0.001. Model 4 is an improvement over model 5 at p<0.001, providing support for hypothesis 2. Organizations are 14\% more likely to exit a category of mean leniency, and 20\% more likely to exit categories one standard deviation above mean leniency, as compared to a category one standard deviation below mean leniency.\(^7\) Figure 6 illustrates these effects.

----- Insert figure 6 about here -----

Organizations are more likely to both enter and exit lenient market categories. The rate of entry is much higher than the rate of exit, helping to explain the prominence of lenient market categories in this domain.

----- Insert table 4 about here ---

**Movement Between Market Categories**

Table 4 contains tests of hypotheses 3 and 4. Model 5 tests hypothesis 3. It is an entry model that contains the interaction between the leniency of an organization’s categories and the leniency of the target category. We include the leniency of the organization’s categories as a control. Results show that the interaction is positive and significant at p<0.001, and that model 5 is an improvement in fit over model 2 for two degrees of freedom, providing support for hypothesis 3. Organizations that are in lenient categories are even more likely to enter a lenient category than organizations in constraining categories. When the interaction is included, the main effect of the leniency of the categories the organization is already in is negative and significant. The effect of leniency of the target category remains positive and

\(^6\) From table 1, the mean level of category leniency is 1.4, and one standard deviation above the mean is 2.4 in the entry data.

\(^7\) From table 2, the mean level of category leniency is 2.1, and one standard deviation above the mean is 3.0, for the exit data.
significant at \( p < 0.001 \). Together, these results show that once an organization is in a high-lenience market category, not only is it especially likely to claim another lenient category; but it is also less likely to claim a constraining category.

To explore this further, in model 6 we investigate whether the relative difference in leniency between the target market category and the organization’s categories affects entry rates. We include the ratio between the leniency of the target category and the leniency of the organization’s categories. Results show that this effect is negative and significant at \( p < 0.01 \). The leniency of the target category remains positive and significant at \( p < 0.001 \). This model indicates that organizations move into lenient categories in increments. Although they are more likely to both enter and exit lenient categories, they are unlikely to jump from highly constraining to highly lenient ones. Together, models 5 and 6 indicate that an organization’s path from constraining to lenient market categories is a slow spiral. Once an organization is in lenient categories, it is more likely to move to another lenient market category, in support of hypothesis 3.

**External Influence**

Model 7 tests hypothesis 4, that organizations recently receiving venture capital funding are more likely to enter lenient categories. Results show the interaction between an organization receiving venture capital funding and category leniency is positive and significant at \( p < 0.01 \), and model 7 is an improvement in fit over model 2. An organization that recently received venture capital funding is 9% more likely to claim a lenient category, compared to an organization that did not receive venture capital funding. Also note that when the interaction is included the positive main effect of an organization having received venture capital funding loses its significance due to a reduction in the coefficient. This indicates that organizations that receive venture capital funding are not simply more likely to claim a new market category; rather they are more likely to claim *lenient* categories. For comparison purposes, model 8 includes the interaction in exit models. The effect is insignificant due to a small coefficient. Organizations that receive venture capital funding are more likely to *enter* lenient categories, but not *exit* them. Together, this
supports the idea that venture capitalists prefer lenient categories, and indicates that this preference can further fuel their growth.

Control Variables

The control variables also affect entry into and exit from market categories. Category size affects entry. Market categories that are large and that have a lot of recent entries are more likely to attract more entries, while categories with recent exits are less likely to have entries. This indicates that organizations look to the choices of others when entering markets. Older market categories are also more likely to attract entrants, although the effect is not robust to the inclusion of leniency. Organizations that are in the Software 500 are more likely to claim a new category, suggesting that resources may affect an organizations ability (or perceived ability) to expand or change. As we would expect, an organization that has recently entered a new category is less likely to do so again. Older organizations are less likely to enter categories.

Results show that organizations are less likely to exit large market categories. It is informative to compare the effect of size to the effect of leniency. The effect of category size is symmetric – it both increases entry and decreases exit. Large categories are more attractive to potential entrants as well as to existing members. This may be because the size of a category indicates that there is stable customer demand or other resources. Recent entries do not affect exit in the base model, although the effect becomes negative and significant when leniency is included. Recent exits have a positive effect. This indicates that organizations may also follow their peers when it comes to category exit. The age of a market category does not show a significant effect. Organizations that are in software magazine and older organizations are more likely to exit categories. Together with the entry effect, this may indicate that organizations rich in resources are more willing or able to change their identities. Those that receive venture capital funding are also more likely to exit, indicating that venture capital investors influence the identity claims of their portfolio firms. Organizations that have recently exited a category are more likely
to subsequently exit another. This may be picking up on troubled organizations that are refocusing their market identities.

DISCUSSION
Existing research implicitly assumes that only well-defined market categories become relevant. But we note many instances where lenient categories are some of the most important in a domain. The software industry provides examples of this; however the phenomenon is by no means restricted to software. From “nanotechnology” in science to “social entrepreneurship” in business to “leadership” curricula offered at many schools of business, lenient categories abound. But why? If the purpose of a market categories is to define what an organization does, how can lenient categories flourish?

Attention to the producer perspective can explain the persistence of lenient market categories. Previous research has studied categories defined by mediators to represent the consumer perspective. A mediator’s job is to maintain clear boundaries to facilitate sense making by consumers. As an authority, they can exclude marginal actors to present crisp categories. But restricting our attention to such mediators overstates the extent to which social categories have strong boundaries. Mediators do not have the ultimate say in category definition. Boundaries are formed through informal interactions among multiple audiences. Producers can influence categorical definitions by claiming to be part of a category and by promoting their own categorical definitions. In any individual instance, a mediator or producer’s definition of a category may or may not be accepted by the broader population. But in aggregate, these interactions produce an informal consensus about what a category means and its boundaries.

How producers view lenient categories differs from mediators and consumers in important ways. Previous research has implicitly assumed that producers anticipate the perspective of consumers and avoid lenient categories. However, there are also benefits to lenient categories that have been overlooked. Lenient categories allow a wide range of organizations to credibly claim membership. They provide managers flexibility to interpret what they think a category “really is,” and perhaps even hope to define the category’s boundaries and position their organization as central in the new competitive sphere. In this
way, lenient market categories provide a lower threshold for entry in terms of product-market fit. We suggest that from the vantage point of a producer that is not in a category, thinking about joining the category in the future, the uncertainty surrounding lenient categories will be attractive and exciting, and so lenient categories will invite high rates of entry. In support of these ideas, results show organizations are much more likely to enter lenient categories.

Once in a category, producers have concrete information about how well their identity is received. Experiences where time spent courting potential customers who are looking for functionality the producer does not provide will be noted. Sales numbers, media coverage, and recruiting indicate how the organization fares with respect to its competitors. Managers may realize they are unable to shape the category in the ways they had hoped. If lenient categories do not provide as much value as do constraining ones, we should expect a higher rate of exit. Indeed, findings also support this idea.

These results indicate that lenient market categories are not necessarily temporary or a passing fad. There is more flow through lenient categories, with organizations both entering and exiting at higher rates. If lenient market categories have higher rates of entry than exit, they can persist and become important in a domain. In the software industry, results show that entry into lenient categories is much higher than exit, which is consistent with the observation that some of the largest categories in the software industry during this time period were lenient. Lenient categories may realize a high entry to exit ratio in domains where pressures for organizations to find a satisfactory product-market fit outweigh the challenges that arise when a market is not well defined. In industries where products are unique and where there is a strong focus on innovation, we may find that the flexibility lenient categories afford outweighs benefits associated with constructing a clear and commonly accepted definition for a market.

Results also show that once organizations are in a lenient category, they tend to move to other lenient categories, rather than to constraining ones. This may seem paradoxical; if leniency is part of the problem with a market category that leads organizations to exit, why would they not move to a more constraining one? Organizations that claim lenient categories are more likely to be searchers that do not clearly fit into a constraining category. To move from a lenient to a constraining category, an organization
must implement significant changes in terms of its structures, routines, and even its outlook, which will make such a move more hazardous. Further, organizations learn in ways that tend to reinforce their experiences, and managers may not interpret problems they are encountering as attributable to leniency. A different lenient category will be more familiar in terms of how employees have learned to view and interpret market categories, and so will seem more promising to managers.

Findings showing that organizations are less likely to enter categories that are much more lenient than their current category are also consistent with this interpretation. Organizations incrementally move to categories that are slightly more lenient. Once they land in a highly lenient category, they are unlikely to move back into a constraining one. These results have implications for how industries evolve to be like the software industry, with many important lenient categories. This outcome may be path-dependent, where a few lenient categories happen to initially appear. Once these grow, dynamics of the market set in, and organizations in lenient categories fuel the proliferation of other lenient categories.

Results indicate that when influential actors seek novelty, this can further fuel the growth of lenient market categories. In this context, venture capitalists are an important resource for software organizations. They look for novelty, which means seeking out organizations that do not conform to clear categories. Findings here show that recently funded organizations are more likely to join lenient categories, consistent with the notion that venture capitalists influence entry decisions and prefer leniency in their quest for novelty. These investors indirectly contribute to the persistence of lenient categories.

Findings imply that there may be much to gain from modeling category entry as a selection process. The growth of market categories can result from either high entry or low exit, but often it is assumed that when there is explosive growth, both will operate symmetrically. On the contrary, here we show that at times the same process that leads to high rates of entry can also lead to high rates of exit (Barnett, Swanson and Sorenson 2003). For example, leniency makes market categories more attractive from the perspective of product-market fit, and less attractive from the perspective of the benefits an organization will receive from affiliating with the category. By modeling entry and exit as separate processes, we can gain a clearer understanding of market evolution.
Finally, results support the idea that there is a trade-off to identifying with a lenient as opposed to a constraining category. Contrary to assumptions in previous literatures, we show that lenient market categories can persist over time, and that this is because lenient market categories are an attractive point of entry for organizations. The assumption in previous research that lenient categories are less useful than constraining ones and so will eventually fade away relies too heavily on the presumption that there will be an alternative category that is constraining, which is be a viable choice for an organization. Instead, the realities of the market push managers to face trade-offs. For organizations that do not easily fit into well-defined markets, joining a lenient market category may be its best option. Once an organization affiliates with a lenient category, it is more likely to subsequently join other lenient categories. This means that we should not expect lenient categories to be fleeting. Rather, they can become an established and important part of market classification.
REFERENCES


# Tables

**Table 1.** Descriptive statistics for entry analysis.\(^1\)

<table>
<thead>
<tr>
<th>Organization enters category</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Leniency of &quot;target&quot; category) / (leniency of organization's categories)</td>
<td>0.0036</td>
<td>0.0603</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>(Leniency of &quot;target&quot; category) x (leniency of organization's categories)</td>
<td>0.6229</td>
<td>1.4315</td>
<td>0</td>
<td>67.05</td>
</tr>
<tr>
<td>Leniency of organization's categories (weighted average)</td>
<td>2.480</td>
<td>2.779</td>
<td>0</td>
<td>15.75</td>
</tr>
<tr>
<td>Organization received VC funding x category leniency</td>
<td>1.657</td>
<td>1.155</td>
<td>0</td>
<td>4.01</td>
</tr>
<tr>
<td>Leniency of category</td>
<td>0.1243</td>
<td>0.5070</td>
<td>0</td>
<td>4.063</td>
</tr>
<tr>
<td>Number of organizations in the category (weighted by GoM)</td>
<td>1.403</td>
<td>0.9920</td>
<td>0</td>
<td>4.063</td>
</tr>
<tr>
<td>Entries into category last year</td>
<td>4.688</td>
<td>10.33</td>
<td>0</td>
<td>163.8</td>
</tr>
<tr>
<td>Exits from category last year</td>
<td>0.3527</td>
<td>0.4778</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>2.309</td>
<td>5.479</td>
<td>0</td>
<td>86.70</td>
</tr>
<tr>
<td>Number of categories organization is in</td>
<td>2.079</td>
<td>5.226</td>
<td>0</td>
<td>102.7</td>
</tr>
<tr>
<td>Organization was in software magazine last year</td>
<td>5.787</td>
<td>3.669</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Organization received VC funding x category leniency</td>
<td>1.914</td>
<td>2.231</td>
<td>0</td>
<td>41</td>
</tr>
<tr>
<td>Number of organizations in the category (weighted by GoM)</td>
<td>0.1362</td>
<td>0.3430</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Entries into category last year</td>
<td>0.0809</td>
<td>0.2727</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Exits from category last year</td>
<td>1.077</td>
<td>1.501</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>2.814</td>
<td>2.852</td>
<td>0</td>
<td>41</td>
</tr>
<tr>
<td>Number of categories organization is in</td>
<td>1998.6</td>
<td>2.600</td>
<td>1990</td>
<td>2002</td>
</tr>
</tbody>
</table>

\(^1\)These data contain 1,893,569 potential organization-market category pairs for the years 1990 through 2002. There are 23,629 market category entries over 6,485,521 organization-category-years.

**Table 2.** Descriptive statistics for exit analysis.\(^1\)

<table>
<thead>
<tr>
<th>Organization exits category</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leniency of category</td>
<td>0.3527</td>
<td>0.4778</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Organization received VC funding x category leniency</td>
<td>2.103</td>
<td>0.8985</td>
<td>0</td>
<td>4.046</td>
</tr>
<tr>
<td>Number of organizations in the category (weighted by GoM)</td>
<td>0.2040</td>
<td>0.7036</td>
<td>0</td>
<td>4.046</td>
</tr>
<tr>
<td>Entries into category last year</td>
<td>23.06</td>
<td>32.94</td>
<td>0</td>
<td>163.8</td>
</tr>
<tr>
<td>Exits from category last year</td>
<td>12.05</td>
<td>18.14</td>
<td>0</td>
<td>86.70</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>9.296</td>
<td>15.15</td>
<td>0</td>
<td>80.21</td>
</tr>
<tr>
<td>Number of categories organization is in</td>
<td>6.885</td>
<td>3.236</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Organization was in software magazine last year</td>
<td>2.888</td>
<td>3.791</td>
<td>0</td>
<td>41</td>
</tr>
<tr>
<td>Organization received VC funding x category leniency</td>
<td>0.2194</td>
<td>0.4139</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Time since organization last exited a category</td>
<td>0.0885</td>
<td>0.2841</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Organization受到了 VC funding last year</td>
<td>1.182</td>
<td>1.792</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Organization age (since 1990)</td>
<td>3.098</td>
<td>2.984</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Year</td>
<td>1997.9</td>
<td>2.745</td>
<td>1990</td>
<td>2001</td>
</tr>
</tbody>
</table>

\(^1\)These data contain 21,589 organization-market category pairs for the years 1990 through 2001. There are 13,880 market category exits over 39,359 organization-category-years.
Table 3. Piecewise continuous hazard rate models on the rate of organizational entry into and exit from a market category.

<table>
<thead>
<tr>
<th>Category covariates</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leniency of category</td>
<td>0.774***</td>
<td>0.0600***</td>
<td>(0.0436)</td>
<td>(0.0171)</td>
</tr>
<tr>
<td>Number of organizations in the category</td>
<td>0.0226**</td>
<td>0.0288***</td>
<td>-0.00806*</td>
<td>-0.00756*</td>
</tr>
<tr>
<td>Entries into category last year</td>
<td>0.0468***</td>
<td>0.0225**</td>
<td>-0.00498</td>
<td>-0.00763*</td>
</tr>
<tr>
<td>Exits from category last year</td>
<td>-0.0372***</td>
<td>-0.0366***</td>
<td>0.0229***</td>
<td>0.0238***</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>0.0659***</td>
<td>0.0101</td>
<td>-0.00172</td>
<td>-0.00519</td>
</tr>
<tr>
<td>Organization covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of categories organization is in</td>
<td>0.0854***</td>
<td>0.0926***</td>
<td>0.0127***</td>
<td>0.0127***</td>
</tr>
<tr>
<td>Organization was in <em>Software Magazine</em></td>
<td>0.505***</td>
<td>0.542***</td>
<td>0.151***</td>
<td>0.142***</td>
</tr>
<tr>
<td>rankings last year</td>
<td>(0.00209)</td>
<td>(0.00193)</td>
<td>(0.00230)</td>
<td>(0.00232)</td>
</tr>
<tr>
<td>Organization received VC funding last year</td>
<td>0.218***</td>
<td>0.280***</td>
<td>0.158***</td>
<td>0.154***</td>
</tr>
<tr>
<td>Time since organization last exited a category</td>
<td>-0.0552***</td>
<td>-0.0289***</td>
<td>0.0246***</td>
<td>0.0255***</td>
</tr>
<tr>
<td>Time since organization last entered a category</td>
<td>-0.0380***</td>
<td>-0.0152*</td>
<td>0.0314***</td>
<td>0.0313***</td>
</tr>
<tr>
<td>Time piece: 0-1 year</td>
<td>-6.080***</td>
<td>-7.257***</td>
<td>-1.583***</td>
<td>-1.632***</td>
</tr>
<tr>
<td>Time piece: 1-2 years</td>
<td>-6.749***</td>
<td>-8.111***</td>
<td>-1.884***</td>
<td>-1.936***</td>
</tr>
<tr>
<td>Time piece: 2-4 years</td>
<td>-6.736***</td>
<td>-8.137***</td>
<td>-2.150***</td>
<td>-2.200***</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Log pseudo-likelihood</td>
<td>-132768.2</td>
<td>-128802.8</td>
<td>-24797.3</td>
<td>-24786.1</td>
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<tr>
<td>Degrees of freedom</td>
<td>24</td>
<td>25</td>
<td>24</td>
<td>25</td>
</tr>
</tbody>
</table>

+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001; Standard errors are clustered by category. All independent variables are measured at the start of each time period.

1 Models are run on 1,893,569 potential organization-market category pairs for the years 1990 through 2002. There are 23,629 market category entries over 6,485,521 organization-category-years.

2 Models are run on 21,589 organization-market category pairs for the years 1990 through 2001. There are 13,880 market category exits over 39,359 organization-category-years.
Table 4. Piecewise continuous hazard rate models on the rate of organizational entry into and exit from a market category.

<table>
<thead>
<tr>
<th>Interactions</th>
<th>Model 5¹</th>
<th>Model 6¹</th>
<th>Model 7¹</th>
<th>Model 8²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Leniency of &quot;target&quot; category) / (leniency of organization's categories)</td>
<td>-0.0262** (0.00885)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Leniency of &quot;target&quot; category) x (leniency of organization's categories)</td>
<td>0.0722*** (0.0112)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organization received VC funding x category leniency</td>
<td></td>
<td>0.0899** (0.0344)</td>
<td></td>
<td>0.00496 (0.0298)</td>
</tr>
<tr>
<td>Category covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leniency of category</td>
<td>0.673*** (0.0538)</td>
<td>0.783*** (0.0433)</td>
<td>0.766*** (0.0438)</td>
<td>0.0595*** (0.0174)</td>
</tr>
<tr>
<td>Number of organizations in the category (weighted by GoM)</td>
<td>0.0302*** (0.00449)</td>
<td>0.0289*** (0.00440)</td>
<td>0.0289*** (0.00439)</td>
<td>-0.00755* (0.00302)</td>
</tr>
<tr>
<td>Entries into category last year</td>
<td>0.0214** (0.00826)</td>
<td>0.0224** (0.00821)</td>
<td>0.0223** (0.00819)</td>
<td>-0.00765* (0.00330)</td>
</tr>
<tr>
<td>Exits from category last year</td>
<td>-0.0386*** (0.00842)</td>
<td>-0.0367*** (0.00816)</td>
<td>-0.0368*** (0.00818)</td>
<td>0.0238*** (0.00404)</td>
</tr>
<tr>
<td>Age of category (since 1990)</td>
<td>0.0111 (0.0120)</td>
<td>0.0100 (0.0122)</td>
<td>0.0101 (0.0121)</td>
<td>-0.00520 (0.00547)</td>
</tr>
<tr>
<td>Organization covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leniency of organization's categories (weighted average)</td>
<td>-0.132*** (0.0325)</td>
<td>0.0150 (0.0203)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of categories organization is in</td>
<td>0.0923*** (0.00192)</td>
<td>0.0917*** (0.00192)</td>
<td>0.0925*** (0.00193)</td>
<td>0.0122*** (0.00232)</td>
</tr>
<tr>
<td>Organization was in Software Magazine rankings last year</td>
<td>0.545*** (0.0354)</td>
<td>0.536*** (0.0354)</td>
<td>0.544*** (0.0364)</td>
<td>0.142*** (0.0260)</td>
</tr>
<tr>
<td>Organization received VC funding last year</td>
<td>0.269*** (0.0350)</td>
<td>0.275*** (0.0348)</td>
<td>0.0733 (0.0789)</td>
<td>0.142+ (0.0780)</td>
</tr>
<tr>
<td>Time since organization last exited a category</td>
<td></td>
<td></td>
<td></td>
<td>0.0255*** (0.00448)</td>
</tr>
<tr>
<td>Time since organization last entered a category</td>
<td>-0.0259*** (0.00732)</td>
<td>-0.0268*** (0.00737)</td>
<td>-0.0288*** (0.00744)</td>
<td></td>
</tr>
<tr>
<td>Organization age (since 1990)</td>
<td>-0.0131+ (0.00711)</td>
<td>-0.0156* (0.00713)</td>
<td>-0.0149* (0.00710)</td>
<td>0.0313*** (0.00391)</td>
</tr>
<tr>
<td>Time piece: 0-1 year</td>
<td>-7.074*** (0.155)</td>
<td>-7.292*** (0.146)</td>
<td>-7.241*** (0.139)</td>
<td>-1.632*** (0.106)</td>
</tr>
<tr>
<td>Time piece: 1-2 years</td>
<td>-7.990*** (0.180)</td>
<td>-8.142*** (0.181)</td>
<td>-8.096*** (0.147)</td>
<td>-1.935*** (0.108)</td>
</tr>
<tr>
<td>Time piece: 2-4 years</td>
<td>-8.023*** (0.187)</td>
<td>-8.167*** (0.188)</td>
<td>-8.122*** (0.155)</td>
<td>-2.200*** (0.119)</td>
</tr>
<tr>
<td>Time piece: 4+ years</td>
<td>-8.005*** (0.199)</td>
<td>-8.129*** (0.202)</td>
<td>-8.086*** (0.172)</td>
<td>-2.439*** (0.123)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Log pseudo-likelihood</td>
<td>-128722.5 (27)</td>
<td>-128787.5 (27)</td>
<td>-128796.2 (26)</td>
<td>-24786.1</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>27</td>
<td>27</td>
<td>27</td>
<td>26</td>
</tr>
</tbody>
</table>

+ p<0.10  * p<0.05  ** p<0.01  ***p<0.001; Standard errors are clustered by category. All independent variables are measured at the start of each time period.

¹ Models are run on 1,893,569 potential organization-market category pairs for the years 1990 through 2002. There are 23,629 market category entries over 6,485,521 organization-category-years.

² Models are run on 21,589 organization-market category pairs for the years 1990 through 2001. There are 13,880 market category exits over 39,359 organization-category-years.
Figures

Figure 1. Leniency of the “customer relationship management” category, and number of mentions of the category in the *Wall Street Journal*, over time.
Figure 2. Leniency of the “entertainment software” category, and number of mentions of the category in the Wall Street Journal, over time.
Figure 3. Relationship between category leniency and its number of members.

![Relationship between category leniency and its number of members.](image)

Figure 4. Sample Press release and statements of category affiliations.

<table>
<thead>
<tr>
<th>Organization</th>
<th>Date</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Watson General</td>
<td>May 1994</td>
<td>Watson General currently provides remote software monitoring systems.</td>
</tr>
<tr>
<td>American Software</td>
<td>May 1994</td>
<td>American Software develops, markets and supports the industry’s most comprehensive offering of integrated supply chain management systems.</td>
</tr>
<tr>
<td>MicroStrategy</td>
<td>January 1996</td>
<td>MicroStrategy is the leading provider of relational OLAP (ROLAP) products and services for developing and accessing enterprise data warehouses.</td>
</tr>
<tr>
<td>VCON</td>
<td>October 1996</td>
<td>VCON is one of the leading manufacturers and marketers of desktop videoconferencing hardware and software products in the industry.</td>
</tr>
<tr>
<td>TSSI</td>
<td>May 1999</td>
<td>TSSI is a leading provider of test automation software technology and solutions.</td>
</tr>
<tr>
<td>Accrue Software</td>
<td>October 1999</td>
<td>Accrue Software, a leading provider of e-business analysis software and services.</td>
</tr>
<tr>
<td>Citrix Systems</td>
<td>February 2000</td>
<td>Citrix Systems, Inc. is a global leader in application server software and services.</td>
</tr>
<tr>
<td>Acxiom</td>
<td>April 2000</td>
<td>Acxiom Corporation is a global leader in real-time customer data integration and customer relationship management.</td>
</tr>
<tr>
<td>Plasmon</td>
<td>August 2000</td>
<td>Plasmon, a leading manufacturer of automated data storage solutions, today announced its Diamond storage management software.</td>
</tr>
<tr>
<td>Veridicom</td>
<td>November 2001</td>
<td>Veridicom, Inc. is a leader in fingerprint-based biometrics solutions.</td>
</tr>
</tbody>
</table>
Figure 5. Predicted effects of organizational entry into market categories, by leniency.\(^1\)

![Graph](image1.png)

\(^1\) Plot is based on results from model 2.

Figure 6. Predicted effects of organizational exit from market categories, by leniency.

![Graph](image2.png)

\(^1\) Plot is based on results from model 4.