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Article · August 2007

Source: RePEc

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Research Paper No. 1968 (R)

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July 2007

Research Paper Series

STANFORD
GRADUATE SCHOOL OF BUSINESS

Research paper 1968

A Formal Theory of Multiple Category Memberships and Two Empirical Tests*

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February 28, 2007
Revised July 5, 2007

Abstract

This paper integrates two perspectives on why producers who span categories suffer social and/or economic disadvantage. According to the *audience-side* perspective, audience members refer to established categories to make sense of producers; they perceive producers who incorporate features from multiple categories to be poor fits with category expectations and less appealing relative to category specialists. The *producer-side* view holds that producers who span categories have lower ability to target effectively each category's audience, which decreases their appeal to audience members. This paper integrates these two perspectives by developing a formal account of how penalties arise as a consequence of audience-side and producer-side processes. Rather than treating these as rival explanations, we propose that both types of processes contribute to the penalties seen for category spanning. Analysis of data on the consequences of spanning categories in two dissimilar contexts, eBay auctions and U.S. feature film projects, provides support for the formal theory.

*This research was supported by the Stanford Graduate School of Business. We received valuable comments from Glenn Carroll, Susan Olzak, Gábor Péli, László Pólos, and Huggy Rao.

Introduction

In markets, as in all social domains, actors rely on systems of categories to interpret experiences. Category systems appear as social facts—they set rules about market boundaries and tell what appropriately lies within those boundaries. These shared understandings stabilize a market by channeling perceptions and actions in predictable ways. At the same time, they shape and constrain market dynamics by determining how market actors understand and negotiate their social worlds.

Given this premise, it should come as no surprise that sociologists have become interested in what happens when actors challenge neat partitions among categories by taking actions that attach them to multiple categories. A central insight of research on this topic is that generalists—those that establish associations with multiple categories—suffer social and/or economic disadvantage. The negative consequence of spanning categories has been shown empirically in diverse contexts: category spanners receive less attention and legitimacy and have lower chances of survival (Zuckerman 1999; Dobrev, Kim, and Hannan 2001; Zuckerman, Kim, Ukanwa, and von Rittman 2003). However, different research traditions provide divergent rationales for why such penalties arise. Two basic perspectives have emerged.

The first view, dominant in work within new institutionalism and the sociology of markets, proposes that audiences pressure agents to conform to categorical expectations with implicit, or even explicit, threats of social and economic sanctions (Meyer and Rowan 1977; White 1981; DiMaggio and Powell 1983; Podolny 1993; Scott 2001). Audience members rely on category boundaries to identify and make sense of producers (those agents who put goods and services on offer in the market), and producers that span diverse categories are likely to be ignored (Zuckerman 1999; 2000) or explicitly devalued (Pólos, Hannan, and Carroll 2002; Rao, Monin, and Durand 2005; Hsu 2006). When categories are oppositional (Carroll and Swaminathan 2000; Zuckerman and Kim 2003) or involve moral imperatives (Durkheim 1912; Douglas 1966), category spanning violates cultural codes and, therefore, meets with sharp punishment. Even for less sharply opposed categories, however, this perspective stresses that the threat of audience-imposed punishment presents a significant barrier to participation in multiple categories (and the associated roles).

These arguments generally build on the notion that an actor's position in a social structure and its underlying attributes can be decoupled. Because attributes such as quality and skill are difficult to assess directly in many contexts, audience members often rely on observable signals such as past experience (Zuckerman et al. 2003), status (Podolny 1993; Gould 2002), and social ties (Faulkner 1983; Stuart, Huang, and Hybels 1999) to make inferences about quality. However, such observables do not necessarily map closely the underlying attributes they are meant to capture. As a result, reliance on observables often biases perceptions of actor's attributes.

Such decoupling is a main reason offered for the negative consequences of bridging categories. For example, when audiences infer a producer's ability from its experience and assume that different categories entail unique combinations of abilities, category spanning is seen as indicating a lack of expertise in each category, even if this is not actually the case (Zuckerman et al. 2003).

A second perspective considers how category spanning affects directly the attributes and capabilities of producers that generate appeal to an audience ("quality"). It posits that category bridgers fail to develop the capabilities to excel in any of them (Hannan and Freeman 1977, 1989). Spanning categories requires dispersing focus and efforts across activities. Because tastes and preferences vary over categories, the activities needed to appeal to the audience as an instance of one category differ from those of other categories. As a result, category spanning reduces a producer's appeal to audiences within each targeted category (Hannan, Carroll, and Pólos 2003). In volatile contexts, generalism might actually benefit producers, as it entails spreading risk across diverse, uncertain categories (Hannan and Freeman 1977, 1989). However, the basic dynamic remains: producers, across all types of contexts, suffer some reduction in performance when they choose to span categories.

To be sure, these perspectives are not antithetical. Yet research generally tends to adopt one perspective or the other. This tendency might be viewed as part of the larger challenge of reconciling audience-side and producer-side accounts of actor's outcomes. As Zuckerman et al. (2003: 1022–3) observe,

> ...the difficulty of adjudicating between typecasting and processes based on underlying skill differences represents in microcosm the larger challenge faced by structural sociology: to demonstrate that structural position can have causal force although occupancy of a particular position is, at least in part, endogenously determined by endowments and preferences.

In this paper, we tackle this challenge in two ways. First, we develop a formal account of mechanisms behind the penalties for spanning market categories using both audience-side and producer-side considerations. Applying formal logic to this issue seems particularly apt because a general relationship has been documented (the costs incurred for spanning multiple categories), but the interplay of the specific mechanisms driving such penalties remains elusive. Our goal is to integrate important aspects of the two kinds of processes. Therefore, we do not treat them as rival explanations.

We present empirical tests of a set of theorems from the formal theory using data on category spanning in two dissimilar contexts: eBay auctions and U.S. feature film projects. In the case of eBay, we compare sellers who auction goods in multiple categories with those who focus exclusively on one category. For films, we examine how the diversity of genres that audiences associate with a film affects its appeal to critics and filmgoers as well as its success at the box office. Together, these tests provide support for the central implications of a theory that integrates aspects of audience-side and producer-side perspectives.

Theory

We begin our formal treatment of the theory by reprising parts of Hannan, Pólos, and Carroll's (2007) theories of categories and niches. Following several major lines of work in cognitive psychology and cognitive science (see Rosch 1975; Rosch and Mervis 1975; Hampton 1998), this theory treats categories as fuzzy sets—situations in which membership can be partial, a matter of degree (Zadeh 1965). This fuzziness reflects the fact that some producers and/or their offerings seem to fit categories more neatly and cleanly relative to others. For example, films such as *Stagecoach* (1939), *My Darling Clementine* (1946), and *High Noon* (1952) are clear and commonly-cited examples of the genre "western." By contrast, films that blend this genre with elements from other genres, such as musical westerns, e.g., *Annie get Your Gun* (1950), *Calamity Jane* (1953), and *Oklahoma!* (1955), comedic westerns, e.g., *Cat Ballou* (1965), *Blazing Saddles* (1974), and *City Slickers* (1991), or science fiction/western hybrids, e.g., *Wild Wild West* (1999) and *Serenity* (2005), are incomplete matches to the western genre.

Consistent with the classical sociological notion that social identity is granted by external agents, this theory holds that members of key audiences make assessments of category membership. Audience members assess memberships in categories with reference to the schemata they hold for relevant category labels. The various fields in cognitive science use the term schema in several ways. Murphy (2002: 47) provides a nice summary of the common core notion:

> A schema is a structured representation that divides up the properties of an item into dimensions (usually called *slots*) and values on those dimensions (*fillers* of the slots)... The slots have restrictions on them that say what kinds of fillers than can have... Furthermore, the slot may place constraints on the specific value allowed for that type... The fillers of the slots are understood to be competitors... Finally, the slots themselves may be connected by relations that restrict their values.

Perhaps it might be useful to consider a simple example. In one of our empirical studies, we treat film genres as instances of schemata. Dancyger and Rush (2002: 74) summarize the conventions of one genre, "western", with the following list of feature values:

> "The hero, a man alone, functions with a world view that is both moral and decent.
>
> The hero has a distinct skill with guns and horses.
>
> The antagonist has mercantile goals—the accumulation of money, land, and cattle—and will recognize no person or ethic that stands in his way.
>
> The land plays a pastoral, but critical role. It not only represents freedom, but also primitivism.

Civilization is represented by those forces that represent an organizing influence on life—the town, the army, married life, and children.

The struggle between the forces of primitivism (such as the land and the Indians) and those of civilization (such as the army and the town) form a particular dilemma for the Western hero. In which world will he reside? His heart sides with the forces of primitivism, but his head sides with the forces of civilization. This is the classic conflict for the Western hero.

The drama plays itself out in a ritualized form—gunfights, cattle drives—and individual conflicts are acted out rather than negotiated."

A film that matches these feature values exactly would be considered as a full-fledged instance of the "western" genre. Films that mix this genre with others fit only some parts of the schema for the "western" and would be considered less typical of the genre. (Of course, most films do not fit this genre at all.) In this sense, a schema for a label such as "western film" is a model that explains what objects are full-fledged members of the category, what objects do not belong to the category, and what objects lie at various positions between these extremes.

In the foregoing example, the category schema applies to attributes of the product. In other cases, category schemata apply to attributes of producers or both to features of products and features of producers. For example, features of microbrewers, such as organizational size and methods of production, determine audience members' evaluations of fit with the category (Carroll and Swaminathan 2000).

In the formal theory presented below, we consider producers and audience members within categories in a market at a time point. We quantify the causal stories as holding for all instances of these types. We use the following informal sorting of the variables of quantification: l refers to a category, m to a market, x to a producer, y to an audience member, and t to a time point. (This convention allows us to avoid telling in each formula that one entity is a category in a particular market, another is an audience member, and so forth.) We use the term "producer" broadly to refer to agents who present an audience with offerings in the hopes of securing their approval and resources. This encompasses enduring organizations as well as single-project organizations as in the film case or, as in the eBay case, sellers who post auction offerings.

A key concept is the notion of *grade of membership in a category* (or degree of typicality as a member of a category). In formal terms, the function $\mu_{i(l)}(x, y, t)$, gives the grade of membership (GoM) of the producer x in the "meaning" (or intension) of the label l from y's perspective at time point t. If the audience member y perceives that the producer x is a full-fledged member of a category (its feature values fit exactly y's schema for the category), then y assigns GoM of 1 to that producer. Conversely, a GoM of 0 signifies that y regards the producer as not belonging to the category. GoMs between 0 and 1 reflect the extent to which the audience member perceives a fit between the producer and the category schema. To return to the example of the "western" film, most audience members assign full membership to *High Noon* but some lesser grade of membership to the hybrids mentioned above.

A parallel notion applies to the audience side of the market interface: audience members vary in the degree to which they share the predominant meaning associated with the category label. Therefore, it makes sense to use a fuzzy-set construction on *both* sides of the role relation. An audience member's GoM in the intensional consensus about a label reflects the degree to which his/her meaning agrees with those of the others. The function $\nu_{i(l)}(y,t)$ gives the GoM of the audience member y in the consensus in an audience about the meaning (intension) of the label l at time t. A member of the audience for films would be typical (have a high value of ν), for instance, if they assigned a very high GoM in that category to *Stagecoach* and *High Noon* and a lower value to the hybrids. An atypical member of this audience might also regard, say, *Cat Ballou* and *Blazing Saddles* as full members of the genre.

A category is a label about whose meaning an audience develops a high degree of consensus. Such "intensional" consensus means agreement about the patterns of feature values that are consistent with full membership in the label. This means that audience members associate very similar schemata with the label. Let $\textsc{cat}(l,m,t)$ be a predicate that reads as "the audience in the market m has reached a high level of consensus about the meaning of the category with the label l at time t." In other words, this predicate tells that l is a category to that audience at that time point.

The framework developed by Hannan, Pólos, and Carroll (2007: Chs. 2–5) considered a single category. We expand it to apply to the full set of categories associated with a market. For instance, one of our empirical analyses considers the super-category of films and the categories to be analyzed are film genres.[1] We denote the set of categories (within some unspecified super-category) in the market m at time t as $\mathbf{l}(m,t)$:[2]

We restrict our arguments to apply to the typical members of the audience for the superset of categories—the set of categories to be analyzed. The typical members of the audience for a superset of categories have a high GoM in the intensional consensus supporting each of the categories. This restriction allows us to exclude audience members holding idiosyncratic category beliefs, whose preferences are difficult to predict. Let the predicate $\textsc{Ty}(\mathbf{l},y,t)$ read that "the agent y is a typical member of the audience for the superset of categories $\mathbf{l}$ at time t."

[1] As in this example, the superset is also a category in its own right. But this need not be the case.

[2] We avoid dealing with the complications of entailed in nestings among the categories in a super-category. Some categories are embedded within others, e.g., the "spaghetti western" genre is nested within "western." Membership in a set of nested categories has a different meaning than membership in non-nested ones. We accordingly focus on a set of categories in which none is a subtype of another for the audience in question.

Engagement, Intrinsic Appeal, and Actual Appeal

Success in a market requires gaining the attention of relevant audiences and demonstrating to them that their offerings have appeal. Whether and how much an offer actually appeals to an audience member, however, depends on two factors. The first is the intrinsic appeal of the offering to an audience member—the degree to which the offering fits the audience member's tastes. Members of an audience prefer offerings that meet their understandings of the categories, so long as the category has a positive valence (see below). The intrinsic appeal of an offering in a category to an audience member, in notation $\widetilde{\alpha}(l, x, y, t)$ is a function that maps four-tuples consisting of a category (l), a producer/offering (x), an audience member (y), and a time point (t) to the $[0, 1]$ interval. A value of 0 means that the offering has no intrinsic appeal, a value of 1 means that it has full intrinsic appeal, and so forth.

We restrict attention to positively-valued categories, those for which greater fit with an audience member's schema for a category yields greater fit with tastes for offerings from that category.[3] We define this notion, using a nonmonotonic logic,[4] as follows:

Definition 1 (Positively-valued category)**.** *A positively-valued category is one for which the typical members of the audience find intrinsically more appealing the offerings of more clear-cut members of the category, those with higher GoM in the meaning of the category,* $\mu_{i(l)}$.

$$\begin{aligned}\textsc{pcat}(l, m, t) \leftrightarrow \textsc{cat}(l, m, t) \wedge \mathfrak{N}\, t, x, x', y\, [\, \textsc{Ty}(\mathbf{l}, y, t) \\ \wedge (\mu_{i(l)}(x, y, t) > \mu_{i(l)}(x', y', t)) \rightarrow \mathrm{E}(\widetilde{\alpha}(l, x, y, t)) > \mathrm{E}(\widetilde{\alpha}(l, x', y, t))].\end{aligned}$$

[Read: l is a positively-valued category in the market m at time t if and only if l is a category in the market m at time t and it is normally the case, for all time points, pairs of producers, and audience members, that if the audience member is typical of the audience for the market at that time point and the audience member assigns a higher GoM in the category to one producer than another, then the expected actual appeal to that audience member is higher for producer with the higher GoM.]

[3]In contrast, negatively-valued categories, such as "sweat shop" or "loan shark," membership in the category results in negative valuations.

[4]Specifically, here and elsewhere we use a nonmonotonic logic developed by Pólos and Hannan (2002, 2005). (In logic, nomonotonicity means that adding premises to an argument might kill implications of the unaugmented argument.) This logic is designed for testing the validity of inferences from arguments that build on *rules-with-exceptions.* The logic uses a quantifier, denoted by $\mathfrak{N}$, that parallels the standard universal quantifier of first-order logic ($\forall$). It tells what is normally the case. Because more specific information can override the implications of a set of rules-with-exceptions, the implications (lemmas and theorems) have a different status than the premises. This difference is marked syntactically in the logic by the fact that it uses a different quantifier, $\mathfrak{P}$, to tell what follows as presumedly the case at the present stage of a theory. Finally, the logic marks syntactically the difference between substantive premises, quantified by $\mathfrak{N}$, and auxiliary assumptions by using the quantifier $\mathfrak{A}$ for the latter.

Henceforth we concentrate on positively-valued categories in a market; and we denote this set by $\mathbf{l}_p(m,t)$.

Note that intrinsic appeal refers to an audience-side process. Intrinsic appeal arises from judgments by audience members about what fits and does not fit a category. Thus intrinsic appeal is not directly under the control of the producers.[5]

The actual appeal of an offering to an audience member also depends on the producer's engagement: activities it undertakes to tailor the offer and its mode of presentation, and its organizational identity to the local subaudience. Offerings that would fit an audience member's taste lack actual appeal if they are unknown or unavailable to the audience member or are presented in a manner that clashes with her aesthetics. In many cases, key engagement activities include developing and displaying credible signals of *authenticity* (Carroll and Swaminathan 2000; Baron 2004; Hsu and Hannan 2005). Clearly, engagement refers to the producer side of the process discussed at the outset.

Definition 2 (Category engagement)**.**

A. *The level of category-engagement function,* $en(l,x,t)$*, maps four-tuples of categories, producers, and time points to the nonnegative real line. This function gives the level of the engagement of producer* x *in category* l *at time* t*.*

B. *The grade-of-membership function for engagement in categories,* $\epsilon(l,x,t)$*, is the share of producer* x*'s engagement in category* l *at time* t*.*

$$\epsilon(l,x,t) = \frac{en(l,x,t)}{En(x,t)}, \quad \text{where } En(x,t) = \textstyle\sum_{l \in \mathbf{l}_p}(m,t)en(l,x,t).$$

An offering's intrinsic appeal and the producer's engagement in the pertinent category might be correlated because a producer who devotes more energy to learning about an audience's schemata and tailoring the features of its offerings to them may be more likely to produce more appealing offerings. However, an offering might have intrinsic appeal in a category while its producer does not engage in the category. Situations like this become apparent when a product becomes a "surprise" success in some market other than that initially targeted by the producer, as has happened with various "high-end" branded clothing, e.g., Tommy Hilfiger and Northface, that became unexpected successes with low-income urban youth. Conversely, a producer's offering could lack intrinsic appeal as an instance of a category despite considerable engagement. Carroll and Swaminathan (2000) recount repeated fruitless attempts by major American brewers such as Anheuser Busch and Miller to present themselves as producers of microbrews.

Hannan, Pólos, and Carroll's (2007: Chs. 8–10) reformulation of niche theory can be seen as an effort to integrate aspects of the audience-side and producer-side processes, because they posit that the *actual* appeal of an offering depends on intrinsic appeal (and, therefore, on attributions of degrees of membership in

[5] Producers have some indirect control, because they might be able to choose the feature values on which the audience members make assessments of fit.

categories) and engagement. In formal terms, the actual appeal to the audience member y of the offering x in the category l at time t, in notation $\alpha(l, x, y, t)$, is a function that maps four-tuples of classes/categories, producers, audience members, and time points to $[0, 1]$.

The production function for actual appeal requires nonzero "inputs" of both factors to generate positive actual appeal. Suppose that we know that one producer's offering has greater intrinsic appeal in a category than another's; and *all* that we know about engagement is that each producer engages the audience as a putative member of the category. The new niche theory builds on the view that a sensible inference in such a case is that the offering with the greater intrinsic appeal will also have the greater actual appeal;[6] and they treat these two inputs symmetrically, as follows.

Postulate 1 (For positively-valued categories, expected actual appeal increases with intrinsic appeal and engagement)**.**

A. *The expected actual appeal of an offering in a category to an audience member normally equals zero if its intrinsic appeal is zero:* $\widetilde{\alpha}(l, x, y, t) = 0$ *or the producer's engagement in the category is zero:* $\epsilon(l, x, t) = 0$.

B. *The expected actual appeal of an offer in a positively-valued category to an audience member normally increases with its intrinsic appeal (as long as engagement is nonzero).*

C. *The expected actual appeal of an offer in a positively-valued category normally increases with the producer's engagement in a category (as long as its intrinsic appeal exceeds zero).*

Principles of Allocation

Niche theories assume a tradeoff between niche width and strength of appeal at positions within the niche (Hannan and Freeman 1977; Péli 1997; Hsu 2006). In particular, they impose a "constant-sum" constraint on appeal—lacking more specific information about producers, the default expectation is that producers have a fixed amount of adaptive capacity to appeal to audiences in their targeted categories. We adapt this idea to the multicategory context by arguing that an increased span over categories comes at the expense of lowered appeal in some categories.

In reformulating niche theory, Hannan, Pólos, and Carroll (2007: Ch. 8) propose allocation principles for both engagement and intrinsic appeal to an audience distributed over a sociodemographic space. We adapt their formulation to the multicategory case by positing that the sum of GoMs for each producer as well as the amount of resources producers devote to presenting themselves and their offerings as instances of different categories are unlikely to exceed a fixed amount. This is represented with the default assumption that both a

[6]This construction reflects the absence of knowledge of any function that converts the two inputs into actual appeal. If this function were known, then we would provide an exact analytical definition.

producer's total engagement and its total level of category membership over categories (normally) are the same for all producers in a population at a given time.[7]

Postulate 2 (Principles of allocation)**.**

A. *The expected sum of total category memberships to a typical audience member is the same for all producers in a market.*

$$\mathfrak{N}\, m, t, x, y\, [\, \mathrm{TY}(\mathbf{l}_p, y, t) \rightarrow (\mathrm{E}(M(x, y, t)) = \mathcal{M}_m)],$$

where $M(x, y, t) = \sum_{l \in \mathbf{l}_p(m,t)} \mu_{i(l)}(x, y, t)$*.*

B. *The expected level of total category engagement is the same for all producers in a market.*

$$\mathfrak{N}\, m, t, x\, [\, \mathrm{E}(En(x, t)) = \mathcal{E}_m\,].$$

[Read for part A: it is normally the case for all markets, time points, producer, and audience members that if the audience member is typical then the expectation of the sum of the GoMs in the market categories that it assigns to the producer equals a population-specific constant, denoted by $\mathcal{M}_m$.]

We impose an auxiliary assumption on the distribution of GoMs across categories.[8]

Auxiliary assumption 1. *The maximal sum of a producer's GoMs in the categories in market's superset of categories equals 1.*

$$\mathfrak{A}\, m\, [\mathcal{M}_m \leq 1].$$

[Read: as an auxiliary assumption, the constant $\mathcal{M}_m$ cannot exceed unity for any market.]

This assumption simplifies formal development of the trade-offs between GoMs and intrinsic appeal by stipulating that a category generalist cannot have a greater level of total category membership than a category specialist. Of course, the maximal sum of GoMs across categories might differ across empirical settings. For example, the maximal sum might exceed one when the schemata for different categories contain complementary elements. In invoking this auxiliary assumption, we focus on a simple case in order to develop our main predictions.

[7] The nonmonotonic logic plays an important role here. In the absence of any more specific information, the default expectation is that pairs of producers do not differ in terms of expected total membership and total engagement.

[8] Auxiliary assumptions are premises that theorists introduce into arguments to link causal stories and desired theorems. They often take the form of some simplifying assumptions, descriptions of constraints that make mathematical modeling possible. Such assumptions are not persistent in an evolving theory, because they are made for special purposes but are not claimed to be causal insights. Auxiliary assumptions, which are marked syntactically with the quantifier $\mathfrak{A}$, play the same role in inference as the causal stories quantified by $\mathfrak{N}$ so long as they are not withdrawn.

Multiple Category Memberships

We next turn to the main contribution of our formalization effort: broadening the theory to apply to a set of category memberships. We do so by integrating elements of niche theory with the theory of categories.

Targeting a diverse array of categories can be thought of as a kind of generalism. In terms of GoMs, a generalist distributes its sums of GoMs across categories fairly evenly. In contrast, a specialist focuses its efforts on fitting one or a few categories and, therefore, has an unequal distribution of GoMs across categories.[9]

Definition 3 (Niches in categories)**.**

A. *A producer's category-membership niche to an audience member is a fuzzy set whose GoM function is its GoM in each category from perspective of the agent.*

$$\boldsymbol{\mu}(x, y, t) = \{l, \mu_{i(l)}(x, y, t)\}, \quad l \in \mathbf{l}_p(m, t).$$

B. *A producer's category-engagement niche is a fuzzy set whose GoM function in a category is the proportion of its engagement that it devotes to the category.*

$$\boldsymbol{\epsilon}(x, t) = \{l, \epsilon(l, x, t)\}, \quad l \in \mathbf{l}_p(m, t).$$

Distinctions between specialist and generalist forms pertain to niche width. What does niche width mean in the current context?

Hannan and Freeman (1989: 104), following MacArthur (1972), defined niche width as the variance in resource utilization over positions (for the case in which the positions are points on the real line). Other work builds on related ideas. McPherson (1983) defined the (realized) niche of a population of voluntary associations (or of a particular association) by the variance of the socio-demographic characteristics of the members of the associations. He defined the niche as a hypercube with each side given by a segment of length 1.5 times the standard deviation of the membership's values on the dimension; subsequent research in this tradition has used a variety of multipliers of the standard deviation. Péli and Nooteboom (1999) developed a model with niche width defined as the radius of a hypersphere in a resource dimension.

We now develop a parallel approach to niches defined in a category space. However, in the general case under consideration, the categories are unordered. We build on Hannan, Pólos, and Carrolls (2007) general (nonmetric) niche theory and use an index of diversity, Simpson's (1949) index, to represent this idea. This index is a standard measure of the diversity of a distribution over a set of discrete categories. We first convert the GoMs in categories into relative frequencies by dividing each producer/product's category GoM by the sum over categories of its GoMs. Then the Simpson index is defined as one minus the sum over the social positions of the square of the probability mass for a category. (The engagement function is already a relative frequency and does not need adjustment.)

[9]Received niche theory considers multiple social positions within an audience for a category.

Definition 4 (Niche width)**.**

A. *Width of a category-membership niche:*

$$wd(\boldsymbol{\mu}(x,y,t)) = 1 - \textstyle\sum_{l \in \mathbf{l}_p(m,t)} \widetilde{\mu}^2_{i(l)}(x,y,t),$$

where $\widetilde{\mu}_{i(l)}(x,y,t) = \mu_{i(l)}(x,y,t)/\mathcal{M}_m$.

B. *Width of a category-engagement niche:*

$$wd(\boldsymbol{\epsilon}(x,t)) = 1 - \textstyle\sum_{l \in \mathbf{l}_p(m,t)} \epsilon^2(l,x,t).$$

These two measures index the degree of generalism on the two key dimensions of the niche. One producer is more generalist in membership (engagement) than another if it has a broader membership (engagement) niche.

Membership in multiple (non-nested) categories likely confuses the audience. Producers that try to fit multiple categories naturally exhibit feature values that are atypical in some or all of the categories. And the more a producer fits one category, the less likely are its feature values to be typical of another category. This, we propose, is a driving force behind the trade-off proposed in niche theory between the diversity in categories targeted by a producer and its peak performance across categories.

In support of this notion, Hsu (2006) finds that audiences express greater dissensus about the category memberships of films that target multiple categories (genres) as compared to those that target a single genre. Apparently, a producer's perceived fit with any of the schemata that the agents apply to categories weakens as the producer or product stretches to incorporate features from a greater diversity of categories. Audience members cannot, as a result, come to agreement about categorization. An implication is the principle of allocation in fit to schemata that parallels the original principle used to describe trade-offs in niche theory.

The intuition motivating a principle of allocation in category memberships holds that a producer's maximal GoM generally decreases with the evenness of its profile of GoMs across types, i.e., the wider its category-membership niche. More specifically, if a category-membership profile broadens, then at least one category membership must decline due to the principle of allocation. It is difficult to anticipate which category memberships within a producer's profile will decline with an increase in niche width.

We expect a corresponding constraint on a producer's engagement profile. Engaging multiple categories limits a producer's ability to devote attention, time, and other resources to learning about the preferences of the typical audience for that category, tailoring its features to those tastes, and develop authenticity. The principle of allocation in engagement implies that a producer's engagement within at least one category must decline as its engagement profile broadens.

Given the complexity just noted, the implications of our theory can be seen most clearly when we compare a pure category-specialist, a producer with a

GoM in a category equal to one, with a category-generalist.[10]

Theorem 1.

Let l be a positively-valued category in the market m at time t: $l \in \mathbf{l}_p(m,t)$.

A. *A category-membership specialist has a higher average GoM in its focal category than any category-generalist.*

$$\mathfrak{P}\, l, m, t, x, x', y\, [\, (\mu_{i(l)}(x,t) = 1) \\ \wedge (wd(\boldsymbol{\mu}(x,y,t)) < wd(\boldsymbol{\mu}(x',y,t))) \rightarrow (\mu_{i(l)}(x,y,t) > \mu_{i(l)}(x',y,t))].$$

B. *A category-engagement specialist has a higher level of engagement in its focal category than any engagement-generalist.*

$$\mathfrak{P}\, l, m, t, x, x'\, [\, (\epsilon(l,x,t) = 1) \wedge (wd(\boldsymbol{\epsilon}(x,t)) < wd(\boldsymbol{\epsilon}(x',t))) \\ \rightarrow (\epsilon(l,x,t) > \epsilon(l,x',t))].$$

(The proofs of this and the following theorems are presented in the Appendix.)

The consequence of this line of argument is that a generalist's offering in a category likely gets judged as inferior to the offering of a category specialist.

Theorem 2 (Specialist appeal advantage)**.**

Let l be a positively-valued category in the market m at time t and y be a typical member of the audience.

A. *The expected actual appeal of the offering of a category-membership specialist in its focal category exceeds that any generalist (for typical members of the audience), as long as the specialist engages its focal category.*

$$\mathfrak{P}\, l, m, t, x, x', y\, [\, (\mu_{i(l)}(x,y,t) = 1) \wedge (\epsilon(l,x,t) > 0) \\ \wedge (wd(\boldsymbol{\mu}(x,t)) < wd(\boldsymbol{\mu}(x',t))) \rightarrow \mathrm{E}(\alpha(l,x,y,t)) > \mathrm{E}(\alpha(l,x',y,t))];$$

B. *The expected actual appeal of the offering of a category-engagement specialist in its focal category exceeds that any generalist (for typical members of the audience), as long as the offering has nonzero intrinsic appeal in the category in which the specialist focuses its engagement.*

$$\mathfrak{P}\, l, m, t, x, x', y\, [\, (\epsilon(l,x,t) = 1) \wedge (\mu_{i(l)}(x,y,t) > 0) \\ \wedge (wd(\boldsymbol{\epsilon}(x,t)) < wd(\boldsymbol{\epsilon}(x',t))) \rightarrow (\mathrm{E}(\alpha(l,x,y,t)) > \mathrm{E}(\alpha(l,x',y,t)))].$$

[10] The comparison is interesting only if the category-membership niches have positive overlap, because the following theorem is trivially true if they do not.

On the one hand, the offering of a membership-specialist has higher expected actual appeal in its focal category than the offering of any membership-generalist. On the other hand, the offering of an engagement-specialist has higher expected actual appeal than any engagement-generalist's offering within its focal engagement category. What can we conclude when a producer is, say, a category-specialist and an engagement-generalist? Reasoning about category-membership might lead to one conclusion, while reasoning about engagement might lead to the opposite conclusion.[11] As noted earlier, we currently lack knowledge as to any exact function that converts intrinsic appeal and engagement into actual appeal. We have no basis for expecting either input to be dominant over the other. Because neither argument is more specific than the other, no clear expectation can be drawn.

To this point we have compared pairs of producers who differ in specialism. These arguments apply in situations of pairwise competition for the support of typical members of the audience. Generally we want to know how specialist and generalist producers fare in broader competitive arenas, markets in which they face a range of competitors. We address this issue by specializing the argument to what we call diverse markets.

Definition 5 (Diverse market)**.** *A market is diverse if it is normally the case, for each (positively valued) category and each typical audience member, that at least one producer with maximal grade of membership in the category who also fully engages the category.*

$$\begin{aligned}\textsc{Div}(m,t) \leftrightarrow \forall\, l, y\, [\, (l \in \mathbf{l}_p(m,t)) \wedge \textsc{Ty}(\mathbf{l}_p, y, t) \\ \rightarrow \exists\, x\, [\, (\mu_{i(l)}(x,y,t) = 1) \wedge (\epsilon(l,x,t) = 1)]].\end{aligned}$$

In the case of a diverse market, it follows immediately that generalists' offerings are always inferior in expected appeal to the offering of at least one other producer, no matter which categories they pursue.

Theorem 3 (Generalists lack high appeal in diverse markets)**.**

Let l be a positively-valued category in the market m at time t and y be a typical member of the audience.

A. *In a diverse market, generalists in category membership have lower expected actual appeal than at least one producer in every category (to typical audience members and positively-valued categories).*

$$\begin{aligned}\mathfrak{P}\, l, m, t, x, y\, [\, \textsc{Div}(m,t) \wedge (wd(\boldsymbol{\mu}(x,y,t)) > 0) \\ \rightarrow \exists\, x'\, [\mathrm{E}(\alpha(l,x,y,t)) < \mathrm{E}(\alpha(l,x',y,t))]].\end{aligned}$$

[11] Logicians call such a case a Nixon Diamond, which dates the period in which logics designed to deal with these issues were first developed. The story behind the name goes as follows. President Richard Nixon was both a Quaker and a Republican. Reasoning about Nixon as a Quaker leads to the conclusion that he would be a "dove" (antiwar); reasoning about him as a Republican leads to the conclusion that he is a "hawk" (pro-war). However, neither argument is more specific (specifically the first elements in the two rule chains "is a Quaker" and "is a Republican" do not have a clear specificity difference) and, therefore, there is no basis for drawing a conclusion.

B. *In a diverse market, generalists in category engagement have lower expected actual appeal than at least one producer in every category (to typical audience members and positively-valued categories).*

$$\mathfrak{P}\, l, m, t, x, y\, [\, \textsc{Div}(m,t) \wedge (wd(\boldsymbol{\epsilon}(x,t)) > 0) \\ \rightarrow \exists\, x'\, [\mathrm{E}(\alpha(l,x,y,t)) < \mathrm{E}(\alpha(l,x',y,t))]].$$

Theorems 2 and 3 concern the relative appeal of producers' offerings to audience members. However, for many applications, including one of our empirical examples (eBay auctions), appeal is not directly observable, but the relative success of producers in the market can be observed. Therefore, it is useful to extend the formalization to apply to relative success, often called fitness. Fitness refers generally to a producer's ability to thrive within its environment—to obtain necessary resources, to persist, and to grow.

All of the relevant arguments propose a direct link between the fitness of a producer and the appeal of its offerings. Audience members more readily award social and material resources to producers whose offerings they find more appealing. Therefore, the greater the appeal of a producer's offerings within a category relative to those of other producers, the greater its viability in the category.

Definition 6 (Fitness in a category)**.** *A producer's relative fitness in a category is its share of the total appeal of its offerings to the typical members of the audience as contrasted with the appeals of all of the offerings in the category.*

$$\phi(l,x,t) = \frac{Ap(l,x,t)}{\sum_{x'} Ap(l,x',t)},$$

where $Ap(l,x,t)$ denotes x's total appeal in category l at time t to the typical members of the audience, i.e.,

$$Ap(l,x,t) = \textstyle\sum_{y|\mathrm{TY}}(l,y,t)ap(l,x,y,t).$$

In normal markets, fitness increases monotonically with total actual appeal.

Postulate 3. *A producer's expected fitness in a positively-valued category normally increases monotonically with the total appeal of its offerings in that category.*

$$\mathfrak{N}\, l, t, x, x'\, [\, (l \in \mathbf{l}_p(m,t) \wedge (Ap(l,x,t) > Ap(l,x',t)) \rightarrow (\mathrm{E}(\phi(l,x,t)) > \mathrm{E}(\phi(l,x',t)))\,].$$

Finally, we have a theorem that parallels Theorem 3:[12]

[12] As noted earlier, claims quantified by $\mathfrak{N}$ state what we think is normally the case, and such generic sentences can be overridden by more specific (or incomparably specific) information that points in the opposite direction. Suppose for instance that producers that suffer from internal disorganization or political strife normally have lower fitness than producers that do not face these obstacles. Suppose further that we consider two producers, A and B, and A has higher total appeal in the focal category than B but A abounds with internal political conflict and B does not. Then the combination of the coexistence of the two causal stories, their incomparable specificity, and these facts will block any conclusion about A and B that depends on the postulate stated above.

Theorem 4 (Generalist fitness in diverse markets)**.**

Let l be a positively-valued category in the market m at time t and y be a typical member of the audience.

A. *In a diverse market, generalists in category membership have lower expected fitness in all positively-valued categories than at least one producer (to typical audience members).*

$$\mathfrak{P}\, l, m, t, x\, [\, \textsc{Div}(m,t) \wedge (wd(\boldsymbol{\mu}(x,y,t)) > 0) \rightarrow \exists\, x'\, [\mathrm{E}(\phi(l,x,t)) < \mathrm{E}(\phi(l,x',t))]].$$

B. *In a diverse market, generalists in category engagement have lower expected fitness in all positively-valued categories than at least one producer (to typical audience members).*

$$\mathfrak{P}\, l, m, t, x\, [\, \textsc{Div}(m,t) \wedge (wd(\boldsymbol{\epsilon}(x,t)) > 0) \rightarrow \exists\, x'\, [\mathrm{E}(\phi(l,x,t)) < \mathrm{E}(\phi(l,x',t))]].$$

In summary, this theory implies that a generalist will suffer in terms of decreased appeal and fitness relative to a specialist within the specialist's focal category. This prediction parallels the trade-offs identified in niche theory, which proposes that specialists out-compete generalists in arenas that they both target (Freeman and Hannan 1983; Hannan and Freeman 1989). And, when our arguments are extended to diverse competitive arenas in which specialists exist in each category, the theory implies that generalists can expect lower overall appeal for their offerings relative to at least some of their specialist counterparts. Our account runs parallel to existing theory, but it specifies in greater depth the distinct mechanisms that contribute to the expected disadvantages of generalism in terms of audience appeal. Principles of allocation in both category-membership and engagement profiles lead to an expectation of poorer performance for generalists relative to specialists.

While our theorems pertain to the difference in expected performance for specialists and non-specialists, the general line of argument can be extended to the continuous case, where producers of differing levels of generalism in category-membership and engagement are compared. We choose to focus on the binary case for the sake of conceptual simplicity. Significant complications arise in extending the formal machinery to the continuous case. For example, to compare the expected total appeal of generalists of differing niche widths in a particular category, we must specify whether the focal category is one in which each generalist has its maximal category membership or engagement for any prediction to be warranted about the difference in expected appeal of offerings.

While the formal details are complicated, the informal extension of our theorems to the case of varying degrees of generalism is straightforward. As an extension of Theorem 2A, for example, one can expect the offerings of a producer with narrower category-membership niche to have higher appeal within its maximal category relative to the offerings of a producer with a broader niche. It then follows that a producer with a narrower category-membership niche will have higher overall appeal of offerings as contrasted with more generalized counterparts. Similarly, one can expect a producer with narrower engagement niche to have higher appeal of offerings in its maximal category as well as higher overall appeal relative to a producer with a broader niche.

Two Empirical Tests

Now we turn to examining empirical implications. We do so by testing the key Theorems 3 and 4 (rather than the postulates), because these theorems depend on the interplay among all of the definitions, postulates, and auxiliary assumptions. We also present results supporting the argument behind Theorem 1B. We examine the relationships entailed in these theorems in two empical contexts: the U.S. film industry and the online auction market eBay. The comparison of the two settings provides some indication of the generality of the argument.[13]

Producers in each context can choose to specialize or generalize across categories, and we witness variation in the extent to which they do so. This allows us to measure niche width on the two relevant dimensions: category membership and category engagement.

The settings differ in how categorization is made. In the case of films, the categories of interest are genres. Altman (1999: 128) observes that film studios prefer to "imply generic affiliation rather than actually to name any specific genres. . . The goal is of course to attract those who recognize and appreciate the signs of a particular genre, while avoiding repulsion of those who dislike the genre." Public assignments of a film to one or more genres are typically made by critics, distributors, and directories rather than by the production studios. As a result, the genre categorizations reflect assessments made by audiences regarding a film's GoMs in a set of genres. For these reasons, the film case is conducive to testing the audience-side mechanism. The film industry setting provides clear evidence about the relationship between category spanning and appeal to an audience (the audience-side process claimed in Theorem 3A) and success (Theorem 4A).

In the eBay setting, however, sellers must formally declare the categories that they engage by selecting to list their items in specific categories. Association with a category is the producer's choice, an aspect of engagement. Therefore, the eBay case appears better tailored for testing its the argument based on producer-side considerations: the relationship between breadth of engagement and success (Theorem 4B). However, as we detail below, the eBay case also provides an opportunity to examine an aspect of the audience-side process as well.

[13] We test the argument behind Theorem 1B using the eBay data, where we are able to measure sellers' level of engagement in each category independently of engagement niche width. We do not test the argument behind Theorem 1A because neither setting allows for a clear test. We cannot directly assess sellers' category membership niche width in the eBay case. In the film case, membership-niche width is based on the producer's grades of memberships in categories; given this, a test of the impact of category-membership niche width on category grade of membership would not be meaningful.

Setting 1: U.S. Feature Films

We analyze the contemporary U.S. film industry during 2000–2003. This setting appears compatible with the principles of allocation in total engagement and total category membership. Films are produced by temporary, single-project organizations (Faulkner and Anderson 1987) that are unlikely to build significant economies of scale.[14] Moreover, we introduce controls for a variety of attributes that might affect total engagement, such as the total size of a film's budget and whether its distributor was a major or independent studio.

It is also unlikely that the sum of category memberships will vary systematically with niche width (contrary to our assumptions) net of controls for attributes that likely affect the amount of energy that audiences will devote to identifying film projects, such as the box office draw of the film's stars and directors and whether a film is a sequel. Our controls also address differences in promotional resources devoted to films by controlling for the total size of the film budget, the number of opening exhibition sites, and whether the film's distributor is a major or independent studio.

In film, as in cultural arenas more broadly, cultural works are partitioned into genres (DiMaggio 1987). Reliance on genres facilitates both the production and consumption of films. On the production side, genres provide clear frameworks for selecting film projects, organizing projects' development, guiding studio resource-allocation decisions, and coordinating film project personnel (Altman 1999; Schatz 1981). On the consumer side, genres provide frameworks for recognizing and understanding individual films (Neale 2000) and thus influence how films are experienced and evaluated (Austin 1988).

Because assessments of genre classifications are made and reported by external agent, we measure generalism from the perspective of key agents in the audience. We gathered information about the genres assigned to each film from three archival sources: the Internet Movie Database (IMDB), RottenTomatoes.com (RT), and Showbizdata.com (SBD).[15] In these sources, films were classified in 17 genres: "action," "'adventure," "animation," "comedy," "crime," "documentary," "drama," "family," "fantasy," "horror," "musical," "mystery," "romance," "science fiction," "thriller," "war," and "western."[16]

[14] In markets where environmental resources are highly concentrated, resource partitioning theory holds that generalists occupying high-resource positions (market centers) often come to enjoy scale advantages (Carroll 1985). Hannan, Pólos, and Carroll (2007: Ch. 9), in integrating resource partitioning theory with niche theory, postulate that in markets that allow scale advantage, the principle in allocation in engagement is overridden by a postulate that holds that expected total engagement increases with scale.

[15] In constructing the genre measures, we included only the genres recognized by all three sources. For example, while RT regards "romantic comedy" as a genre, IMDB and SBD do not. In such hybrid cases, films were treated as classified under both higher-level genres. For example, films categorized as "romantic comedy" by RT were coded as "romance" and "comedy." If "romantic comedy" is indeed a broadly accepted genre (and if there are other similar cases), then our results will understate the effect of spanning categories.

[16] When a label was a clear subgenre of a single commonly-recognized genre, we classified it as part of the larger genre. For example, SBD uses the comedy subgenre labels of "black comedy" and "satire" in addition to the general label of "comedy." So we treat any film labeled by SBD as a "black comedy" or "satire" as having the SBD label of "comedy."

We set a film's GoM in a genre to the proportion of entries in each of the three archival sources that classify the film under that genre. The greater the agreement among sources that a film should be classified under a particular genre, the greater the film's GoM in the genre. The films in our sample, on average, are categorized as belonging to more than three genres. It seems more appropriate therefore to examine the consequences for producers of differing degrees of generalism rather than for a binary comparison of specialists versus non-specialists. We calculate the width of each film's category-membership niche using the following equation:

$$wd(\boldsymbol{\mu}(x,y,t)) = 1 - \textstyle\sum_{l \in \mathbf{1}_p(m,t)} \widetilde{\mu}^2_{i(l)}(x,y,t),$$

where $\widetilde{\mu}_{i(l)}(x,y,t) = \sum_y \mu_{i(l)}(x,y,t)/N_y$, where the summation runs over the agents who provide the GoM assessments, whose number is denoted by N_y. This treatment adjusts the definition of category-membership niche in D.5 to reflect the collective assessment made by the three archival sources.

The sample of films used in this study consist of those that (1) ran at least one day in any U.S. theater, (2) had an original release date between April 16, 2000 and December 31, 2003, and (3) are listed in all three of the archival sources. In total, 397 films meet these criteria. Data on financial success, production, and distribution comes from the Internet Movie Database (IMDB).

We capture the appeal of a film to the (typical) audience members using film critics' and consumers' assessments of quality. Research on the film industry suggests a strong association between critics' evaluations and the preferences of typical film consumers. For example, a number of studies have found a significant positive relationship between favorable critical reviews and theatrical rentals or revenues (e.g. Litman 1983; Wallace, Seigerman, and Holbrook 1993; Eliashberg and Shugan 1997). Because critics publish evaluations for a significant proportion of films, such ratings are a good proxy for the appeal of films to typical audience members.

We collected critics' ratings from RT, a web site that archives reviews of films from a diverse array of critics. RT divides its critics into "cream of the crop"—those that review for top newspapers by distribution as well as popular magazine, Web, TV, and radio critics—and all others. Because many cream-of-the-crop critics do not provide numerical ratings of films, we measure the appeal of a film as its proportion of positive reviews ("fresh" tomatoes).[17] To assess appeal among all RT critics, we measure the average of numerical ratings submitted by critics to the web site for each film.

We also assess appeal using ratings submitted to IMDB by its users. Registration at IMDB is free of charge, and registered users can enter ratings for any of the films listed. The appeal of each film to IMDB users is treated as the

[17] A number of critics indicate whether their overall evaluation is positive (a "fresh" tomato) or negative (a "rotten" tomato) for each film they review. When critics do not provide this overall assessment themselves, RT editors make this assessment. The editors state that they "take into account word choice, rating (if any), tone, and who's the critic in their determination of whether a review is positive for not" (http://www.rottentomatoes.com, 12/21/06).

average of its IMDB ratings. We assess the fitness of films by their economic returns in U.S. theaters: the box office gross (gathered from IMDB).

Our analyses control for a variety of producer-specific factors. A commonly mentioned factor in film research is star power, the ability of a film's stars to draw a large audience of film-goers. Our measures of star power come from the *Hollywood Reporter*'s 1999 and 2002 Star Power surveys, in which film industry insiders ranked actors in terms of their ability to ensure financing, major studio distribution, and wide theatrical release, as well as to open a film, on the strength of their name alone. Each film's star power was set at the maximum Star Power ranking of all the actors on its cast. Films that did not have any actors who were listed Star Power rankings were assigned a score of 0 for this measure. Similar measures of film's director power were created using data from *Hollywood Reporter*'s Director Power survey.

Other control variables gathered from IMDB are: (1) the breadth of each film's theatrical exhibition during its opening weekend (measured as the natural log of its number of opening screens), (2) total size of its budget, (3) whether it was a sequel, and (4) whether it was backed by a major or independent distributor.[18]

We also control for crowding within a film's targeted genres. The more saturated the market becomes with a certain type of film, the less the appeal of films of that type. In support of this, Hsu (2006) finds that greater niche overlap decreases films' appeal among film audiences. The niche overlap between two films is operationalized as the fraction of the total genres in which the focal film is classified that the alter film is also classified in (MacArthur 1972). Niche crowding is the sum of a film's niche overlaps with all other films exhibited during the length of its exhibition.

Finally, we include variables reflecting a film's GoM in each of the 17 genres to control for the effects of differences in the popularity or niche volume of individual genres on the film's appeal. (This is a fuzzy-membership analogue to using dummy variables for genre memberships.)

Results

Table 1 presents descriptive statistics for key variables in the feature film analyses. Films in our sample, on average, are categorized under 3.2 genres across the three archival sources. This yields 1,270 observations at the film/genre level. As this table shows, information on budget is missing for a subset of films. Rather than drop films with missing budget information from the analyses, we include a binary variable ("any budget information") that equals 1 when this information is present and equals 0 otherwise; and we coded the budget to zero for observations with missing information. RT critics also did not review all of the films in our sample. Analyses of appeal use the subset of 377 films for which critic ratings are available. Supplementary analyses conducted on all 397 films

[18] We classified as major those distributors that accounted for more than 2 percent of total yearly market share during the period preceding this study (1997–99).

for box office gross and IMDB ratings show results similar to those presented here.

[Table 1 about here]

We analyze the effect of the width of the (category-membership) niche on total appeal and fitness. Film appeal is reflected in three variables: (1) average RT critic rating, (2) proportion of positive evaluations from top RT critics, and (3) average IMDB user rating. The fitness of films is reflected in (the natural logarithm of) U.S. box office gross. We estimate equations predicting these four variables simultaneously using Zellner's (1962) seemingly-unrelated regression estimator, which accounts for correlation among the error terms of the equations for a set of dependent variables.

[Table 2 about here]

As Table 2 shows, niche width generally has a significant negative effect on the three measures of appeal. For each measure, the effect of niche width becomes stronger when the GoMs of films in each genre are included in estimation (results in columns 1b, 2b, 3b, and 4b). This suggests that some generalists might fare better than some specialists in unpopular genres because they span popular ones. However, when the profiles of genre memberships are taken into account, the cost of generalism in terms of appeal become clearer, which agrees with Theorem 3A. Similar patterns obtain for our measure of fitness: U.S. box office gross, which agrees with Theorem 4A.

Because we estimated the sets of four equations as a system, we also calculated joint tests of the effect of niche width on the four outcomes. These null hypothesis that niche width has no effect on these outcomes can be rejected decisively ($X^2(4) = 12.51$ for the specification without genre effects, $X^2(4) = 15.87$ for the full specification).

For the control variables, we find that greater niche crowding during a film's run and a greater number of exhibition sites on release significantly decrease a film's appeal. Director power generally increases appeal. Backing by a major distributor has a positive impact on the appeal of films to RT critics, while star power and budget have a significant positive effect on appeal to IMDB users. For box office returns, we find that a greater number of opening sites, backing by a major distributor, and star power increase returns while greater niche crowding decreases them.

Setting 2: eBay Auctions

Our second set of analyses focus on the success (fitness) of sellers who auction listings on eBay. As in the film setting, the economies of scale that many traditional organizations enjoy appear to be modest among eBay sellers. While some sellers list considerably more items than others, we control for volume of items auctioned. Moreover, we do not suspect that niche width is correlated with total engagement. Examination of partial correlations shows that total number of items a seller auctions and the number of categories in which the seller participates are not correlated. In our analyses, we also control for the reputations of sellers (the posted feedback scores), because a positive reputation generally increases a seller's appeal.

The nature of eBay's online interface also minimizes concern that total category membership of its sellers will vary systematically with niche width. eBay pushes sellers to list their items in the appropriate category and claims on its web site that items that do not fit the category in which they are listed will be removed from the site. eBay's guide to sellers also advises them to search for items similar to theirs and take note of their category assignments. This set-up makes it unlikely that sellers will list goods in categories that are at odds with the other goods in that category and therefore intrinsically unappealing relative to the other goods in the category.

The data that we use for our analyses are a sample of auctions that ended on August 31, 2001 in a diverse set of 23 categories: "antique furniture," "antiquities," "folk art," "US coins," "digital cameras," "camera lenses," "dolls," "antique dolls," "health," "model trains," "Elvis memorabilia," "drawings," "prints," "antique prints," "art photographs," "other art," "Pokemon," "printers," "printer supplies," "watches," "antique watches," "tickets," and "weird stuff." We analyze a random sample of 1,444 auctions in these categories, stratified by the number of items sellers auctioned and the number of categories they auctioned in during the previous seventeen months for which we have data. These data, which were provided by eBay, Inc., include item titles, feedback scores posted for users, number of bids, whether the auctions ended with a sale, and masked identifiers for buyers and sellers. In order to measure the strength of collective identity shared by market participants in a category, we use a second data set consisting of downloaded auction descriptions and IDs of sellers and bidders associated with these auctions (see Koçak 2006 for more information about the data).

As noted above, sellers must pick a category of goods among a predefined set that matches their item. Because eBay's interface encourages buyers to browse for items in specific categories, the chosen category corresponds to a defined target audience. We use a binary measure of the category-engagement niche: sellers who list items in two or more categories are marked as having a wider niche than those who focus their engagement in one category. In contrast to the film case, the proportion of specialists to non-specialists within eBay is relatively high—70% of the sellers specialize in a single category during the relevant auction period. In this case, a comparison of specialists to non-specialists appears more appropriate.

We distinguish between current and past category engagement. Current generalism likely reflects limits on the amount of attention that the seller can devote to items in any category at a time point. Past generalism speaks to variations in the category-specific expertise obtained in prior auctions (holding constant the number of prior auctions entered) as well as the identity the seller might have built in previous transactions with category buyers.

We investigate whether sellers with wider category-engagement niches do an inferior job of engaging their target audiences relative to their more specialized counterparts. When listing their items, sellers write a short title describing the item, which is then listed alongside other item titles in the same category. Prospective bidders browse these titles or search for keywords in them to find an item that they might want to buy. eBay's web site reminds sellers that their item titles should be informative and use descriptive keywords. The use of quality indicators and category-specific acronyms in item titles provides useful information for buyers but requires sellers to possess some familiarity with conventions within the category. Therefore, we analyze the use of quality indicators and acronyms in item titles to measure seller's engagement within each category. We code item titles that describe an item as "Good" or "Fine" as well as those that use more sophisticated descriptors of quality such as "certified MS63" as having quality indicators. We code item titles as having acronyms that describe the items if we find any acronyms that are not quality indicators, such as in, "print cartridge NIB [New In Box]," "Jesmar CPK [Cabbage Patch Kids] violet eyes," or "VAM [Van Allen–Mallis] 8 Morgan Dollar."

Because a seller's fitness increases monotonically with the success of each of their auctions, we treat a positive outcome on an auction (making a sale) as a measure of fitness. We assess the success of each offering with two measures: whether an item attracts any bids and whether an item is sold. Both measures lead to the same pattern of results. To save space, we only report results for models estimating the likelihood that auctions ended with a sale.[19]

We control for sellers' reputation, measured by the feedback scores listed for them on the eBay web site on the last day of the auction, and sellers' previous experience in the focal category and in other sampled categories. These controls allow us to rule out the possibility that specialists outperform generalists because they have better reputations, have learned more about the focal category, have more experience with eBay, or are simply better known. Finally, we include a set of dummy variables indicating the category in which the focal item has been classified to control for any category-specific effects.

Results

We use maximum-likelihood logistic regression to estimate the probability that (1) the item title includes an acronym, (2) the title includes a quality indicator, and (3) the auction results in a sale. To control for demand and supply and other category-specific unobservables, we include dummy variables for categories in all of our models. This led to the loss of some observations in the regressions for sellers' use of acronyms and quality indicators in titles. Because none of the auctions in the "antique dolls," "antique furniture," "other art," "drawing," "health," and "printers categories" used acronyms or quality indicators to describe the items, none of the auctions in "tickets," "camera lenses," "art photo," "antique watches," or "antique prints" used quality indicators, and none of the auctions in the "antiquities" category used acronyms, the auctions

[19] Results of regressions predicting the likelihood of getting a bid are available from authors upon request.

in these categories were dropped from the corresponding analyses (because we analyze specifications with category-specific effects). We end up with 1,267 auctions in the analyses predicting use of acronyms in item titles and 1,146 auctions in those predicting use of quality indicators.

[Table 3 about here]

The 1,444 items in our sample were put on auctions that ended on August 31, 2001 by 935 sellers: 49 had no prior selling experience, 270 had engaged only in one category, 130 had engaged two categories, and the rest had engaged more categories, with the most extreme generalist having listed items in 22 of the 23 categories over the previous 17 months. Of the sellers with these auctions, 783 sellers engaged only one category on the focal day, 111 engaged 2 categories, 27 in 3, 6 in 4, 5 in 5, and 1 in 8. Some of the generalists spanned categories that share some characteristics, for instance the seller of dolls, folk art, and model trains that may appeal to hobbyists. Others span categories that seem quite unrelated, like the seller of digital cameras and folk art, the seller of printers and model trains, and the seller of antique dolls, antique prints, and weird stuff. The descriptive statistics in Table 3 show that half of all auctions ended with a sale, about 12% had quality indicators in item titles and 7% had acronyms that described the items.

[Table 4 about here]

Table 4 presents ML estimates of logit specifications for the three outcomes.[20] The first two columns in Table 4 provide evidence about the relationship of engagement-niche width and the GoM in engagement. Recall that we have two measures of the degree of engagement within a category: the use of acronyms in titles and the use of quality indicators in titles. In column 1 we see that sellers that engaged two or more categories on the focal day are less likely to use acronyms to describe their items in the auction titles. In the second model, we see that they are also less likely to use quality indicators to describe their items. These results are consistent with the view that a principle of allocation applies to engagement. Both of these results accord with the expectations from the argument behind Theorem 1B.

The width of the category-engagement niche over the previous 17 months does not have a significant effect on either indicator of engagement. The difference in the effects of current and past niche width in these regressions might point to the different constraints increased niche width imposes on sellers' allocation of resources across categories, on the one hand, and the distribution of their category specific assets, on the other hand. We explore these ideas further below.

Neither the seller's feedback score nor the total number of auctions listed by the seller has a statistically significant effect on sellers' estimated engagement in these models.

[20]To adjust standard errors for the clustered observations, we use robust Huber-White sandwich standard errors.

The results in the third and fourth columns speak to the main claim, that niche width lowers appeal and, therefore, fitness (as claimed in Theorem 4B). These specifications allow a direct effect of the width of the category-engagement niche (measured by category listings) and of the two concrete measures of engagement (use of acronyms and quality indicators). Three possibilities of interest are (1) that neither niche width nor the degrees of engagement affect the probability of completing a sale, (2) that niche width has only an indirect effect on the probability of completing a sale (niche width has no effect but the degrees of engagement do), and (3) that niche width has both a direct and indirect effect. In column 3 we consider a reduced form, which contains an effect of niche width but not of the degrees of engagement. It shows that sellers that engaged two or more categories on the focal day as well as sellers that engaged multiple categories over the previous 17 months are significantly less likely to sell their items.

The model whose estimates appear in the fourth column of Table 4 adds effects of indicators of whether sellers used acronyms to describe their items and whether they used quality indicators. The use of quality indicators in titles significantly increases the likelihood of a sale; however, the use of acronyms does not. Net of these effects, the widths of the category-engagement niches (current and past) continue to exert significant negative effects on the probability of completing a sale, suggesting that niche width has both direct and indirect effects on fitness.

The coefficient estimates for the control variables have the expected signs. The total number of auctions by the seller on the same day has a negative effect; and sellers with higher feedback scores are more likely to sell their items.

To investigate why the width of the category engagement niche over the previous 17 months has a negative effect on fitness although it does not appear to affect engagement, we performed some supplemental analyses. We propose that increases in current niche width will limit the attention that sellers can devote to engaging multiple audiences; this therefore decreases the likelihood that they craft appropriate item titles (and descriptions, which we do not measure) to describe their auctions in the focal category. A wider historical niche, on the other hand, indicates sellers that are likely to possess fewer category-specific assets, such as category-specific knowledge about how to engage the audience, relationships with the audience, and a category-specific identity. We reason that a way to tease these alternatives apart is to study the differential impact of increased engagement-niche width in categories where audiences put greater value on category-specific identities. Note that this approach turns from considering only engagement to an analysis of the degree to which audience members attribute category membership to the sellers. In other words, it introduces the audience-side considerations addressed in our analysis of films.

Using the same data source on eBay auctions, Koçak (2006) finds that bidders in categories for goods with greater symbolic value are more likely to use eBay-user IDs that signal identification with the category (such as "elvis*fan," "trainman1," and "print27"), indicating the existence of a stronger collective identity shared by market participants. She argues that bidders in these categories are also more selective about the sellers they buy from. We extend this argument here and propose that bidders in categories where a collective identity has formed among market participants place more demands on sellers. Therefore, non-specialist sellers who auction in these categories will suffer reduced fitness.

We test this argument with regressions that add an interaction between niche width and proportion of bidders in the category that use category referencing IDs, which we label the *strength of the collective identity in the category*, to the models reported in Table 4. We do not estimate a main effect for collective identity because we include effects of category-specific dummies. The estimates appear in Table 5. In column 1, we see that past generalists (sellers who auctioned in multiple categories in the past) are less likely than past specialists to use acronyms to describe their items in categories on the focal day in categories of high symbolic value (where a prevalence of category-specific bidder IDs indicate the existence of a collective identity). In column 2, the effect of current niche width on the seller's likelihood of using quality indicators is no longer statistically significant.

The results reported in column 3 show that the effect of past generalism on the likelihood of a sale operates mainly in categories with strong collective identities. However, the estimated effect of current generalism on fitness does not change with the addition of this interaction term. This indicates that sellers that auction in multiple categories on the focal day suffer from a wide engagement niche regardless of audience demands for a focused identity; however, sellers that fail to specialize in the past get penalized strongly in categories where the bidders themselves display focused identities.

To learn whether these effects might be due to learning about the audience's expectations about members of a category, whether they may be due to specialists having more clients in the category, or whether bidders penalize non-specialists for their lack of a focused identity regardless of their experience in the category, we perform further analyses.

In a specification reported in column 4 in Table 5, we include a measure of sellers' experience and an interaction of this variable with past generalism. We measure sellers' experience with the number of items that the seller sold in the focal category over the previous 17 months. Although experience in the category has a significant positive effect on the likelihood of a focal-day sale, as would be expected, the negative effect of generalism and the stronger negative effect of generalism in categories with strong collective identities persist. In column 5, we report estimates of a specification where we include a measure of the number of repeat buyers that a seller had in the focal category and an interaction of this variable with past generalism. While the greater the number of past clients in the category, the greater likelihood of success for the seller, the negative effect of generalism in categories with stronger collective identities persists. Therefore, we conclude that the experiences or client bases of specialists in these categories cannot explain the penalties for generalists in categories with stronger collective identities.

Discussion

This paper draws attention to two alternative paths by which penalties for generalism emerge. Whereas prior research has tended to focus on one type of process versus the other, we develop a formal theory that integrates accounts based on audience perceptions of fit to categories and on engagement.

The results from our empirical studies provide support for our theory and suggest that both processes contribute to the overall patterns that have been documented in empirical studies. Our analysis of films demonstrates that an increase in the width of a producer's category-membership profile lowers the appeal and success of the producer's offerings. As the breadth of the genres assigned to a film project increases, the appeal of the film to audience members decreases as do box office revenues.

In the eBay setting, we analyze the impact of increases in the width of a producer's engagement niche. Consistent with the intuition behind the principle of allocation, engagement generalist sellers do not engage their targeted categories to the same extent as specialists, as evidenced by lowered usage of category-specific acronyms and quality descriptors for products. Further, we find that a wider category-engagement niche and use of quality indicators makes a seller's auctions less likely to end successfully in a sale. Importantly, we also find evidence of penalties associated with poor fit to schemata in this context: sellers who have generalized in the past have substantially lower odds of success in categories where audiences place greater value on category-specific identities.

Our theory considers memberships in categories, defined as labels for which the audience has achieved a high degree of consensus on its meaning (intensional consensus). A possible further step is that a category gets legitimated in the sense that audience members fill in, as defaults, category-consistent feature values for objects that bear the category label (Hannan, Pólos, and Carroll 2007: Ch. 5). If a set of market categories are forms in this sense, then the theory obviously still applies (because the labels are category labels). The negative consequences of multiple memberships on appeal and fitness should be stronger in this case. Audience members do not need to observe a producer's feature values to see inconsistencies with category codes. Knowledge that a producer bears a set of category labels causes audience members to attempt to fill in the relevant schemata-conforming feature values. If, as we assume, the schemata differ, then there is no way to fill in all the defaults consistently. The result is that the producer is difficult to interpret and appears to violate at least some of the constraints imposed in the applicable schemata. Audience members likely respond by avoiding interaction with the uninterpretable producer and devaluing its offerings.

There are a number of promising paths for extending the theory we have presented here. Perhaps the most important is to consider heterogeneity within the audience. We mentioned in passing that we abstracted away from the differences in tastes that typically characterize different social positions in an audience (e.g., the classic opposition of "high brow" and "low brow" taste) that is the central focus of standard niche theory. Moreover, the audiences for the various categories in a market might not overlap so strongly that it makes sense to characterize the typical member of the set of audiences. Addressing such cases requires attention to the ecology of the audience and the patterns of communication interaction among audiences. Developing an ecology of the overall audience would set the stage for formal treatment of the coevolution of populations of producers and audiences.

Another area for further investigation concerns relationships among the schemata audience members hold for categories. Significant overlap between the features emblematic of different categories is likely to shape the way in which audiences perceive and make sense of the producers who straddle them. One possibility is that the upper bound on the sum of GoMs for producers may be raised, increasing a producer's total intrinsic appeal. A related avenue concerns incompatibility in the schemata for particular categories. A number of researchers illustrate how incompatibility or opposition between categorical identities restricts the ability of producers to successfully cross categorical boundaries (Carroll and Swaminathan 2000; Zuckerman and Kim 2003; Rao, Monin, and Durand 2003; 2005). It is likely that producers who attempt to incorporate features from incompatible categories will be perceived as a poor fit with any one of them. This may be particularly damaging to producers when categories achieve a highly taken-for-granted status.

Examining such issues will help establish understanding of factors that determine the strengths of the penalties associated with both aspects of category spanning (those involving fit to category schemata and those involving diffuse engagement) in different contexts. Our investigation points to several other possible factors. The eBay results suggest that penalties paid for category spanning increase when audiences place greater value on category-specific identities. And, as suggested in our discussion of the empirical settings, concentration in environmental resources might significantly weaken the penalties for engaging more than one category. In addition, whether producers span categories with a single product (as in the film case) or with multiple products (as in the eBay case) might affect the degree to which generalists suffer from poor fit to category schemata. A comparative study of the relative strength of each process in different settings would broaden understanding of the constraints imposed on producers by market categories.

Appendix: Proofs of the Theorems

This appendix provides proof traces of the theorems. In the nonmonotonic logic used (Pólos and Hannan 2004), a proof involves collecting the "rule chains" (links of postulates, auxiliary assumptions, and definitions) that connect the antecedent and consequent in the theorem. A theorem is proven if a rule chain can be found that makes the claimed connection and there is no rule chain leading to the opposite inference[21] that is more specific or incomparably specific. In the case of these theorems, all of the rule chains point in the same "direction." Therefore, we sketch the minimal rule chain that constitutes a proof.

Theorem 1. Part A. By Definition 4A, $wd(\boldsymbol{\mu}(x, y, t)) < wd(\boldsymbol{\mu}(x', y, t))$ and $\mu_{i(l)}(x, y, t) = 1$ imply that there is some category $l' \neq l$ for which x' has nonzero membership from y's perspective (otherwise the niche widths could not differ). The principle of allocation, Postulate 2A, imposes the restriction that the sum of category memberships is the same for all producers in the market. Then the consequent in the theorem follows immediately.

The proof of Part B parallels that of Part A; but it uses Definition 4B and Postulate 2B.

Theorem 2. Part A. The only rule chains that connect the antecedent and consequent using the available premises yield the theorem. The minimal rule chain builds on the rule chain supporting Theorem 1A (a specialist has higher GoM in its focal category than any category generalist) the definition of a positively-valued category, Definition 1 (expected actual appeal of a producer's offering increases with a producer's GoM in a category for typical audience members), and Postulate 1B (expected actual appeal of a producer's offering increases with intrinsic appeal, given nonzero engagement).

The proof of Part B parallels that of Part A; but it uses Theorem 1B and Postulate 1C.

Theorem 3. Part A. Again the available premises yield only rule chains that connect the antecedent and consequent as stated. The definition of diversity, Definition 5, guarantees that there is a category-specialist in each category from the perspective of each typical member of the audience and that this specialist engages the category. It also restricts the scope to typical audience members. Given that the focal producer is a generalist, in the sense that the width of its category-membership niche exceeds zero, then (the rule chain warranting) Theorem 1A applies. It states that any category specialist has higher GoM in the category than the focal generalist. The definition of a positively valued category, Definition 1, states that expected actual appeal of a producer's offering increases with a producer's GoM in a category for typical audience members. Finally, Postulate 2A tells that, given nonzero engagement, the expected actual appeal of an offering with higher intrinsic appeal exceeds that of an offering with less intrinsic appeal.

[21]The theorems in this paper claim a positive monotonic relationship between function: the larger the ϕ, the larger the ψ. The opposing claim would hold either that there is no relation between ψ and ψ or that there is a *negative* monotonic relationship between them.

The proof of Part B exactly parallels that of Part A, except it uses the rule chains warranting Theorem 1B.

Theorem 4. The minimal rule chain that connects the antecedents and consequents uses (the rule chains that warrant) Theorem 3 along with Definition 6 and Postulate 3 (and summation over the typical members of the market).

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Table 1: Descriptive statistics for films

Variable	N	Mean	S.D.	Min.	Max.
Niche Width	397	.55	.2	0	0.8
Ln(budget)	289	16.91	1.3	11.8	19.0
Ln(no. of opening sites)	397	5.63	2.9	0	8.2
Top star power	397	48.36	30.4	0	100
Top director power	397	21.38	26.9	0	100
Sequel	397	.90	.29	0	1
Major distributor	397	.77	.42	0	1
Niche crowding	397	17.43	7.3	1.4	50

Table 2: Determinants of film outcomes: ratings and gross sales (Seemingly unrelated regression estimates)

	RT Top Critic		RT All Critic		IMDB Users		Ln(film Gross)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Niche Width	−16.54**	−27.41**	−.57*	−1.03**	−.43	−.77*	−.74*	−1.92**
	(6.62)	(10.28)	(.32)	(.51)	(.29)	(.46)	(.36)	(.57)
Ln(no. of opening sites)	−5.13**	−3.63**	−.28**	−.21**	−.25**	−.19**	.37**	.40**
	(.68)	(.68)	(.03)	(.03)	(.03)	(.03)	(.04)	(.04)
Budget information	−10.90	−32.17	−.66	−1.63	−1.67	−2.45**	−1.60	−3.07**
	(26.29)	(25.94)	(1.28)	(1.28)	(1.14)	(1.15)	(1.41)	(1.43)
Ln(budget)	.98	2.21	.06	.12	.13*	.17**	.17*	.25**
	(1.62)	(1.61)	(.08)	(.08)	(.07)	(.07)	(.09)	(.09)
Top star power	.04	−.03	.01*	.002	.01**	.003	.01**	.01**
	(.06)	(.05)	(.003)	(.003)	(.002)	(.002)	(.003)	(.003)
Top director power	.12*	.12**	.01**	.01**	.01**	.004	−.001	−.001
	(.06)	(.06)	(.003)	(.003)	(.002)	(.003)	(.003)	(.003)
Sequel	−.30	4.13	.02	.22	−.08	.18	.27	.26
	(4.62)	(4.65)	(.23)	(.23)	(.20)	(.21)	(.25)	(.26)
Major distributor	8.94**	7.33*	.47**	.39**	.25	.23	1.25**	1.13**
	(4.05)	(3.77)	(.20)	(.19)	(.18)	(.17)	(.22)	(.21)
Niche crowding	−1.05**	−1.42**	−.05**	−.07**	−.03**	−.05**	−.06**	−.11**
	(.21)	(.27)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Genre GoMs included	No	Yes	No	Yes	No	Yes	No	Yes
Constant	88.02**	73.38**	7.22**	6.58**	7.21**	7.05**	13.25**	13.73**
	(6.23)	(8.32)	(.30)	(.41)	(.27)	(.37)	(.33)	(.46)
Root MSE	24.83	22.70	1.21	1.12	1.07	1.01	1.33	1.25
Adjusted R-square	.23	.36	.26	.37	.24	.33	.70	.73
X^2	114.57	210.95	129.85	220.50	119.72	189.01	878.22	1043.53

* $p < 0.10$, ** $p < 0.05$ (two-tailed tests); N(films)=377.
Note: Numbers in parentheses are robust standard errors.

Table 3: Descriptive statistics for eBay auctions (N=1,444)

Variable	Mean	S.D	Min.	Max.
Item title includes acronym	.075		0	1
Item title includes quality indicator	.123		0	1
Auction ends with a sale	.503		0	1
Current generalism	.255		0	1
Past generalism	.724		0	1
Ln(no. of seller's auctions ending on the focal day)	2.19	1.64	0	6.15
Ln(seller's feedback score)	6.84	1.86	0	10.3
Ln(no. of items sold in focal category, previous 17 mos.)	4.76	2.91	0	10.2
Ln(no. of repeat buyers in focal category, previous 17 mos.)	2.82	2.54	0	8.30
Strength of collective identity in the focal category*	.082	.063	0	.204

* Measured at the category level (N=23)

Table 4: Determinants of the probability that a seller uses of acronyms in item titles, quality indicators in item titles, and success in auctions (Maximum likelihood logit estimates)

	Item title includes:		Sale	
	Acronym	Quality		
	(1)	(2)	(3)	(4)
Current generalism	−.883*	−1.17*	−.575*	−.539*
	(.383)	(.485)	(.173)	(.174)
Past generalism	.417	.141	−.534*	−.538*
	(.309)	(.281)	(.204)	(.209)
Ln(seller's auctions ending on the focal day)	−.017	.174	−.404*	−.416*
	(.101)	(.103)	(.059)	(.060)
Ln(seller's feedback score)	.017	−.113	.237*	.242*
	(.087)	(.095)	(.053)	(.053)
Item title includes acronym				−.114
				(.254)
Item title includes quality indicator				.627*
				(.228)
Dummies for categories included	Yes	Yes	Yes	Yes
Number of observations	1,267	1,146	1,444	1,444
Log pseudo-likelihood	−341.0	−347.7	−897.8	−893.5
Wald X^2			147.3	151.5
Degrees of freedom	18	15	26	28

Note: Numbers in parentheses are robust standard errors.
* $p < 0.05$ (two-tailed tests)

Table 5: Determinants of the probability that a seller uses of acronyms in item titles, quality indicators in item titles, and success in auctions (Maximum likelihood logit estimates)

	Item title includes: Acronym (1)	Quality (2)	Sale (3)	(4)	(5)
Current generalism	−1.12	−1.06	−.769*	−.664*	−.638*
	(.607)	(.840)	(.298)	(.298)	(.302)
Past generalism	1.72*	.434	−.002	.437	.303
	(.625)	(.545)	(.314)	(.401)	(.364)
Ln(seller's auctions ending on the focal day)	−.024	.174	−.407*	−.456*	−.465*
	(.102)	(.103)	(.058)	(.073)	(.074)
Ln(seller's feedback score)	.020	−.113	.231*	.160*	.165*
	(.093)	(.095)	(.053)	(.060)	(.058)
Strength of collective identity in focal category × current generalism	2.32	−1.23	2.34	2.13	2.08
	(4.48)	(6.51)	(2.58)	(2.56)	(2.57)
Strength of collective identity in focal category × past generalism	−11.4*	−2.81	−6.20*	−6.03*	−5.94*
	(4.58)	(4.20)	(2.81)	(2.77)	(2.77)
Ln(items sold in focal category, past 17 mos.)				.124*	
				(.059)	
Ln(items sold in focal category, past 17 mos.) × past generalism				−.079	
				(.052)	
Ln(repeat buyers in focal category, past 17 mos.)					.142*
					(.071)
Ln(repeat buyers in focal category, past 17 mos.) × past generalism					-.082
					(.063)
Dummies for categories included	Yes	Yes	Yes	Yes	Yes
Number of observations	1,267	1,146	1,444	1,444	1,444
Log pseudo-likelihood	−337.4	−347.4	−894.6	−891.6	−891.7
Wald X^2			152.1	153.5	155.24
Degrees of freedom	20	17	28	30	30

Note: Numbers in parentheses are robust standard errors.
* $p < 0.05$ (two-tailed tests)