Producer Exploration Generates Categories without Audiences*

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Abstract

Category theory finds that markets tend to partition producers into categories and that producers who do not fit one specific category—or who span multiple categories—perform worse than their single-category peers. The major thread of category theory argues that categorizations stem from the bounded rationality of market audiences, who are forced to impose categorizations and ignore miscategorized producers in order to efficiently interact with the market. I present an alternative model in which producers in a market segregate into categories and experience a miscategorization penalty without any reliance on an audience process: working in an uncertain world, producers tend to imitate past successful peers, and an *ex-post* rationalization process identifies such clusters as categories. Categories reflect, but do not cause, producer success. This model of dynamic exploration of an uncertain world not only accounts for the basic findings of category theory but further explains how categories shift and emerge over time, in ways consistent with recent extensions of the literature. In all cases, miscategorization results not from the limited knowledge of the audience but the limited knowledge of producers. I establish these results in a formal model and simulation.

*The latest version of this paper is available at tony.vashevko.com/research/#explore

Introduction

Category theory combines a theoretical proposition with an empirical observation. The dominant thread of recent theory relies on conformity pressure resulting from audience cognition (Zuckerman 2017; Zhao et al. 2017): it argues that people search for objects in a market by categorizing them, and find it difficult to evaluate or understand objects that are difficult to categorize (Zuckerman 1999; Hannan, Pólos, and Carroll 2007). The theory aims to explain an empirical pattern: objects in markets often come with categorical labels attached and objects with multiple or ambiguous labels face market penalties. Restaurants come with cuisine labels, and restaurants with a single cuisine (e.g. Korean, Mexican) earn higher reviews than restaurants that mix cuisines (e.g. Korean-Mexican, Kovács and Hannan 2015). Movie audiences prefer single-genre movies (e.g. romance, horror) to multi-genre movies (e.g. romance-horror, Hsu 2006). The path from theory to phenomenon appears straightforward: Evidence that individuals categorize is well-established in cognitive psychology (Rosch et al. 1976) and marketing (Shocker et al. 1991; Roberts and Lattin 1991). As such, the failures of miscategorized objects in a market presumably stem from failures in individual categorizations. Market objects that fall outside market categories fail because individuals find it hard to understand them.

An extensive empirical literature has grown up around this initial proposition (Hannan 2010; Durand and Paolella 2013; Vergne and Wry 2014). This literature largely relies on empirical work observing that poorly-labelled firms and products in fact suffer relative to well-labelled peers. Comparatively little work has tried to test the implicit claim that the consequences of categorization at the level of the market result primarily from the failures of audience categorization (Negro and Leung 2013 offer a notable exception).

This absence of research could be excused if there were little reason to doubt the theoretical claim. Empirical findings, however, raise concerns about the theory. First, producers appear to face multiple audiences, and these audiences exhibit not only different tastes (Kovács and Liu 2016), but different tastes for categorical ambiguity (Pontikes 2012)—venture capitalists, for instance, appear to punish category spanners less than general audiences do. Such findings raise questions of why different audiences differ in their ability to categorize a market as well as how researchers, let alone producers, are to know the number and kind of audiences that a particular producer faces.

The second, more critical concern, is that identification of market-level miscategorization relies on observation of instances of miscategorization. For instance, researchers can show that multi-genre movies underperform single-genre movies because they can observe both single- and multi-genre movies in the wild. This raises the question of why producers wind up in multi-genre rather than single-genre positions. While such production errors may be unintentional, they may also reflect conscious efforts to push the boundaries of the existing categories: in fact, recent work in category theory has both demonstrated empirically that miscategorized actors may outperform well-categorized actors (Smith 2011; Leung 2014; Sgourev and Althuizen 2014; Paoletta and Durand 2016) and has theorized on the conditions that might moderate the miscategorization penalty (Durand and Khaire 2016).

This article proposes an alternative explanation for the market-level phenomenon of categorization. This explanation examines the behavior and motivations of producers in complex world. Even in the absence of an audience that makes systematic categorizations to understand objects in a market, markets still force producers to make uncertain decisions. When producers enter a market, they face a situation of uncertainty (March, Sproull, and Tamuz 1991). The characteristics that lead to

market success are numerous and have complex interactions—an organization may succeed or fail due to its own internal capabilities, the idiosyncratic tastes of its customers, or even random events (Levinthal 1997). Success may stem from audience categorization too, but such categorizations may be ad-hoc and shift from person to person (Durand and Paoletta 2013). Similar organizations, though, will likely face similar pressures. In such an uncertain environment, an organization is wise to take cues from its peers. A new Chinese restaurant may want to offer popular dishes even if its chefs do not specialize in them. A movie sequel promises to bring in a similar audience to its prequel, reducing risk (Eliashberg, Elberse, and Leenders 2006). At the same time, perfect imitation of peers and predecessors may be both impossible (Rivkin 2000) and unwise—no restaurant is likely to fully copy the details and decor of a competitor, and two analogous restaurants in the same neighborhood may condemn themselves to a crippling price war. Organizations, then, likely seek some optimal level of differentiation—close enough to avoid the risk of an entirely novel business model but far enough to avoid dangerous competition.¹

This article argues that a process of optimal differentiation in a complex world reproduces the market-level phenomenon described by category theory. For fear of failure, new producers will congregate around the successful market positions of predecessors. When such clusters grow too dense, producers differentiate to distant positions. All such exploratory efforts begin isolated. Failures remain so. Successful exploration attracts imitators over time, generating new clusters. The outcome of such optimal differentiation generates dense islands of similar, successful products, sitting between lonely failures. If audiences tend to label clusters of objects (c.f. Hannan,

¹Contrast this with optimal differentiation research stemming from institutional theory, which argues that producers’ optimal distinctiveness involves a balance between competitive and institutional conformity pressures (Zhao et al. 2017). In the present article, producers balance competition against a generalized fear that excessive differentiation will lead to something going wrong.

Pólos, and Carroll 2007), it will appear that well-categorized objects outperform ill-categorized objects. The market will appear to feature a miscategorization penalty, even if audience cognition played no special role in producing the market.

Causality here flows in reverse: miscategorization does not cause failure; failure causes miscategorization. As this article further shows, miscategorized objects come in two kinds: those doomed to remain isolated, and those that will create categories around them in the future. This producer-level differentiation mechanism accounts for why organizations sometimes choose to take market positions outside of established categories, and it hints at why different audiences may differ in their taste for miscategorized objects.

The core of this article is a formal model and simulation. The model explores how producers react to uncertainty in their environment and exploration by their peers. This model describes a world in which producers sequentially explore a world while observing the behavior and outcomes of their peers. It solves for producers' optimal exploration behavior given their limited understanding of the world at any given point in time. Finally, it shows how this optimal exploration behavior generates differential clustering around prior successes that reproduces the basic pattern observed in the literature on market categories.

Theory and Model

To understand how this research stands in relation to category theory, it is helpful to break down the theoretical propositions made in existing work. Two foundational works are particularly informative here: Zuckerman's seminal 1999 article, and Hannan, Polos, and Carroll's book (2007) that helped shape the empirical strategy of much subsequent work.

The key arguments underlying an audience-side theory of categories rely on the relationship between three features of a market: (1) *market position*, (2) *audience categorization*, and (3) *market outcomes*. *Market position* denotes the characteristics of an object, including the ways it might appeal to various needs. Similar objects have close positions. *Audience categorization* is the way audience members perceive the characteristics of an object and the way they communicate these characteristics to each other through shared labels. Audience categorization may misrepresent ‘true’ characteristics of the object, so that audience members fail to understand what uses an object could be put to. *Market outcomes* measure object success in the market, translating an object’s characteristics into audience appeal, evaluations, prices, or sales.

The relationship of these three features in the dominant thread of category theory may be better understood by reference to fig. 1a. Characteristics of producer positions cause the audience to categorize them in particular ways. These categorizations then affect the outcomes that producers experience, with miscategorized producers suffering relative to well-categorized peers. The steps in this logic have been variously elaborated by different authors; empirical research has focused on identifying the second causal link in the diagram, on identifying whether outcomes are associated with audience categorizations.

Zuckerman (1999) argues that a market consists of an interface between producers and an audience evaluating them. The audience, consisting of intermediate experts, imposes a system of categorizations on producers and producers attempt to differentiate within this system in order to avoid excessive direct competition. Producers that differentiate so much that they fall outside established categorizations drop out of audience consideration and face worse market outcomes, as members of the audience direct less of their business to mis-categorized producers. In Zuckerman’s context,

Figure 1: Differing causal logics of past, present, and future work.

analysts specialize into industries and tend to overlook producers that fall outside established industry lines. In the terms of fig. 1a, markets feature some prior system of categorizations, producers position themselves in order to avoid competition while remaining within categorical bounds, and producers that step out of bounds face worse market outcomes. Audience categorization plays a primary causal role in producer outcomes: objects fail when they are miscategorized. Zuckerman (1999) only implicitly discusses the connection between market positions and market outcomes. He argues that producers differentiate to avoid competition, but does not draw out this argument further.

Hannan et al. focus on establishing a deeper understanding of how the system of categorizations works. A key observation of the book is that many markets feature a system of labels: movies and books come with genre labels, restaurants come with

cuisine labels, and software makers fall into labelled market segments. They offer an account for how such labels come about and what they may signify. In particular, Hannan et al. draw an explicit connection between the location of objects in feature space and the existence of categories and labels, between the market positions of objects and the audience categorization process. Hannan et al. argue that market objects occur in relatively tighter or relatively looser clusters in some underlying feature space, and that categories emerge to signify sufficiently dense and distinct clusters of objects in this space. Different clusters receive different labels. Objects that fall between clusters tend to receive multiple labels, and labels referring to loose clusters tend to be more ambiguous than labels referring to dense, highly-contrasting clusters. Hannan et al. provide two services for category theory: theoretically, they draw out the process by which producer positions generate categorizations (the first link of fig. 1a); empirically, they provide a formula for studying categorization through the use of market labels.

Empirical work in category theory relies on the structure provided by these two core pieces. The feature space model of Hannan et al. allows for increasingly sophisticated measures of producer categorization (e.g. Pontikes 2012; Kovács and Hannan 2015). Zuckerman (1999) establishes the plausible causal link from these categorizations to observable outcomes. Empirical work then proceeds by showing an association between measures of categorization and outcomes.

This article offers an alternative explanation for empirical findings of a link between categorization and outcomes. In fact, it argues that the link is spurious: categorizations and outcomes are jointly, but independently, determined by how producers choose to position themselves in the market (fig. 1b); correlation between the two stems from a common cause, not a direct connection. I argue that producer exploration generates a direct mechanism by which producers in tight clusters are more successful than those

outside them. To the extent that an independent process of categorization exists to rationalize and make sense of the market, this process reflects but does not affect the results of producer exploration.

If categorization does exert a direct role in producer outcomes, its effect must live alongside the direct effect of producer exploration. As they jockey for position in a market, the outcomes producers experience may be partially mediated by how an audience categorizes them (see fig. 1c); the role of empirical work is to measure the extent of this mediation. In more recent work, Zuckerman (2017) acknowledges that producers face such supply-side constraints and that excessive differentiation imposes strategic risks other than miscategorization; he maintains that categorization plays a primary causal role in producer outcomes. This argument does not, however, address the concerns of Durand and Paoletta (2013) that individual categorization processes may not aggregate to market outcomes insofar as individuals may rely on goal-dependent or ad-hoc categorization schemes. The goal of the present work is to establish that strong category effects appear even in a world dominated by such ad-hoc categorizations and market uncertainty.

Producer Exploration Generates Clusters of Success

Producers considering entry or expansion in a market face a difficult inferential problem. They can observe a set of peers or competitors that have made previous entries into the market. They can see the products their peers put into the market and some measure of how successful these forays were. But in general, producers have only a very limited understanding of what their peers are doing or how their behavior translates into observed levels of success (White 1981; March, Sproull, and Tamuz 1991; Levinthal 1997). Producers may even have a poor understanding of how and why their own

internal production processes work (Nelson and Winter 1982; Hannan, Pólos, and Carroll 2003; Bernstein 2012). Attempts to imitate dissimilar competitors may lead to crippling failures if producers fail to identify even a single key component of their competitor’s strategy (Rivkin 2000). Even if individual audience members rely on cognitive categorization to select partners, these categorizations may be idiosyncratic, ad-hoc, and unpredictable (Durand and Paoletta 2013).

Such uncertainty generates a critical tradeoff between imitation and exploration in market entry (c.f. March 1991): Close imitation of existing peers is likely to produce similar organizational outcomes; it comes at the cost of easy comparison and fierce competition against established peers. Differentiation, on the other hand, carries the risk of drastically misunderstanding a market or the production processes that lead to success in the market. An entirely novel business plan may end up being wildly successful, but it is just as likely to fail completely. Imitation offers a certain but more costly result. Exploration offers the chance of great success as well as great failure.

To the extent that organizations do attempt to imitate their peers, they will prefer to imitate successful peers rather than unsuccessful peers (c.f. Denrell and March 2001; Denrell and Le Mens 2007; Banerjee 1992; Strang and Macy 2001). On top of that, imitation of successful peers may reduce the burden of price competition: at similar levels of differentiation, a producer imitating a more successful peer should earn higher profits than a producer imitating an unsuccessful peer. Producers entering a market or changing their position then are likely to crowd around success and will crowd more around greater successes than around lesser successes. Over time, as producers enter a market, generally successful market positions will feature larger, denser clusters of producers than less successful positions.

Like Zuckerman’s (1999) argument, this argument relies on a process of optimal differentiation. But whereas Zuckerman’s producers fear differentiation because it

carries the risk of taking them outside of categorical boundaries, producers here fear any of the ways that differentiation can go wrong. Businesses may fail and succeed not just because of socially shared categorizations, but for idiosyncratic or ephemeral reasons. A Russian restaurant may discover that its prospective customers prefer more Americanized or conversely more traditional food than expected. The chef's unique take on latkes might be unusually appealing. Its tapwater might taste bad. Its owner might be absentminded or charismatic to key critics. Producers differentiate to avoid direct competition but fear differentiation because it robs them of control over how their product will land in the market. They differentiate until the risk of further differentiation becomes too high.

Categories and Labels

The above account offers no explanation for how categorizations and labels emerge in a market. Yet the ubiquity of labels and categories in markets would suggest that they serve some role. While cognitive theories of categories argue that social categorizations drive market outcomes, they may instead serve simply to facilitate communication about markets. As Hannan, Pólos, and Carroll (2007) argue, categories and labels may be most informative when they refer to well-defined, dense, and distinct clusters of similar objects. It is natural to assume that categories and labels emerge in ways that optimally fulfill this informative role.

Audience members need to communicate with each other, and to do so, they need to share a common language with common referents. Categories and labels serve as these common referents. Having a commonly understood set of restaurant categories makes the difference between inviting a friend to a potato, meat, and sour cream dinner, and inviting them for Russian food. It also helps the restaurant describe itself to me:

I understand Samovar Russian Palace more easily than Samovar Potato and Sour Cream Hut. Yet the absence of labels does not preclude meaningful communication: if I don't recognize the restaurant, I can look at their menu; if my friend is unfamiliar with Russian food, I can describe the dish.

Efficient ways to communicate appear to emerge easily and spontaneously in groups of people (Weber and Camerer 2003). I argue that categories and labels primarily serve this communicative role in markets: labels emerge in order to efficiently describe producer positions in the market and they tend to emerge around dense and distinct clusters of producers. The market positions of products generates both market outcomes and labels that describe those positions, but the labels exert no independent effect on market outcomes.²

Model

The arguments above lead to a set of simple propositions. Producers in an uncertain market environment take calculated risks as they push new products into the market. Producers attempt to imitate their peers to avoid risks of market exploration. Producers prefer to imitate successful peers rather than unsuccessful peers. Producers in successful regions of the market will be more similar to each other and more densely clustered than producers in unsuccessful regions of the market.

I establish these propositions with a formal model of producers entering an uncertain market. Producers operate in a market represented by the real number line: each point on the real number line represents some position in the market (c.f. Hotelling

²It must be pointed out that social classification is itself subject to interpretation as a strategic producer decision. Signalling is a well-established market dynamic (Spence 1973), and producers will adopt labels that aid their performance in the market (Podolny 2008; Etzion 2014; Pontikes and Kim 2017). This paper discusses the emergence of classification schemes in the absence of any market benefit to classification.

1929; Salop 1979). Some audience evaluates or consumes products in the market. For any given position in the market, there is some portion of the audience that would be willing to consume it, so that any position in the market is viable. Positions differ, however, in the extent to which they are appealing to the audience or the extent to which it is easy for a producer to offer a product at that position. Higher appeal positions command greater prices, sales volume, or evaluations for the producer, so that producers derive greater utility from placing themselves at high appeal positions.

Unfortunately, producers do not know what the appeal of a position is. The function defining the appeal of a position is given by a drift-free Brownian random walk (c.f. Callander 2011; Callander and Matouschek 2014). Using the notation that the appeal of a producer at position x is given by W_x , the basic property of this appeal function is that the difference in appeal between two positions in the market is given by a normal distribution with variance proportional to the distance between positions:

$$W_x - W_y \sim N(0, (x - y) \cdot \sigma^2)$$

Positions that are close together will have relatively similar degrees of appeal to producers. A position that is far apart from another is likely to have either much higher or much lower appeal.

For a producer, this environment is complex and difficult to search over, and bears great similarity to the N-K models typically used to model complex landscapes. In fact, many intuitions derived from N-K models of environmental complexity apply to the Brownian walk setting. In contrast, Brownian walks allow for continuous measures of producer distance and make it much easier to derive optimal producer behavior. Since the mechanism of this article relies on optimal differentiation by producers, both

of these features are critical to the analysis.³

In addition to the inherent appeal of a position, producers also face direct competition from neighboring producers. For simplicity, I assume that this competitive penalty depends only on the position of the nearest neighbors. Denoting the positions of all existing producers by in the market by X , the competitive penalty facing a producer at position x in the market is given by:

$$c(x, X) = \frac{1}{\min_{x < x_h \in X} |x - x_h|} + \frac{1}{\min_{x > x_l \in X} |x - x_l|}$$

The competitive penalty is nonlinear: as a producer becomes arbitrarily similar to her nearest competitor, the competitive penalty imposed by their proximity becomes arbitrarily high. Fig. 2 illustrates this penalty for a producer considering entry at a range of positions either to the right of a single competitor or between two competitors spaced one unit apart. The competitive penalty approaches infinity as a producer attempts to perfectly imitate their nearest neighbor.

Finally, producers are risk averse in their decision-making process, so that they evaluate the value of a given position using some risk-averse utility function u (Pratt 1964):

$$u(x, X) = u(W_x - c(x, X))$$

Stochasticity appears in this function in the form of W_x : for any position x that has not yet been attempted by some producer, W_x is a random variable whose value is determined by the Brownian motion described above.

Producer risk aversion is important to these results. Because the landscape is

³Appendix B further compares relative advantages of Brownian walks and N-K landscapes to model organizational search over complex landscapes. For an alternative use of Brownian walks in organizational research, see Levinthal (1991), Denrell (2004), or Le Mens, Hannan, and Pólos (2015).

Figure 2: Competitive penalty with competitors at $x = 0$ and $x = 1$

given by a Brownian walk, the distribution of risk is symmetric at any distance from existing points, and because the walk is drift-free, the distribution is symmetric about zero for producers at the edge of the landscape. A risk-neutral producer would be indifferent between taking on no risk by copying a competitor perfectly, and taking on arbitrary amounts of risk by differentiating. Competition, though, would induce risk-neutral producers to differentiate as much as possible from incumbents; a producer with competitors on only one side would attempt to differentiate by jumping infinitely far from incumbents.⁴

Producers enter the world one at a time. Some initial producer (or set of producers) begin at an arbitrary predetermined position in the space with some initial level of appeal. At every subsequent point in time, a new producer attempts to enter the

⁴N.B., in this model producers end up clustering more around successful positions than around unsuccessful positions, so that successful positions end up facing more future competition than unsuccessful positions. Forward-looking producers may expect greater competition upon success than upon failure. Such future expectation may have the effect of making risk-neutral producers act risk-averse in that imitative competition will reduce the net present value of successful positions more than it reduces the net present value of failed positions. In lieu of deriving these expectations, I simply assume risk aversion.

market in a way that maximizes their expected utility. These new entrants do not know the shape of the appeal function: they can only observe the positions and realized successes of incumbent producers. Given the positions of incumbent producers at time t , denoted $X^t = \{x_1, x_2, \dots, x_{t-1}\}$, and the observed appeal at those positions, denoted $W^t = \{W_{x_1}, W_{x_2}, \dots, W_{x_{t-1}}\}$, a producer enters at a position x that maximizes their expected utility:

$$\max_{x \in \mathbb{R}} E(u(x, X^t))$$

Uncertainty in this expected value calculation stems entirely from a producer’s uncertainty about the appeal of any given position. As an entrant considers positions arbitrarily far from any incumbent, the chance that the appeal of this position will be very low increases. As an entrant attempts to push out further from her competitors, she increases the chance that her position will be much worse than her most similar competitor. Fear of this risk pulls producers towards their competitors, while fear of competition pushes them away, so that producers end up taking positions at some intermediate distance from their peers.⁵

Once an entrant enters at their preferred position x they discover the true value of their position. Producers are not, however, able to move. This assumption may be consequential: If producers could move, we might expect them to preferentially migrate towards local peaks and depopulate local valleys. Results may depend on whether audience cognition reflects all producer attempts or only current positions: if producers

⁵This model is indebted to the Hotelling line model of a market. Hotelling (1929), however, predicts a ‘principle of minimum differentiation’: producers should end up imitating each other almost perfectly in such markets. As D’Aspremont, Gabszewicz, and Thisse (1979) show, this prediction cannot be sustained in equilibrium, and instead construct an example in which a ‘principle of maximal differentiation’ holds. Salop (1979) likewise constructs an equilibrium line market with maximal differentiation between producers. In general, it is not clear whether either principle represents the natural prediction (Biscaia and Mota 2013).

fully migrate out of local valleys, the difference between successful and unsuccessful producers would diminish, though it may not disappear entirely. Nevertheless, the fundamental mechanism driving the results of this model should remain: producers can better tolerate competition in successful positions than unsuccessful ones, allowing them to cluster more densely around high-appeal than around low-appeal positions.⁶

Simulation

Deriving the optimal behavior of individual producers in such a market is relatively straightforward. Deriving the properties of the market as a whole is much more difficult. Instead, I simulate multiple instances of such markets in order to describe their general properties. Appendix A discusses the full details of the simulation. In brief, I simulate 1000 markets, and simulate the entry of 250 producers into each market. I seed each market with an initial set of producers, identical across all markets. Subsequent entrants make optimal entry decisions given their knowledge of existing producers' appeal. Their own entry then provides additional information to the next generation. The appeal function ends up distinct in each market: if two entrants into different markets happen to enter at the same position x , they will almost certainly end up with different levels of appeal.

I use a specific functional form for utility, $u(m) = am - \exp(-bm)$. It can be shown that this utility exhibits risk aversion, with risk aversion increasing in b . Further, u exhibits decreasing absolute risk aversion (Pratt 1964), which ensures the existence of the expected utilities that producers must calculate for the present results to hold (Callander and Matouschek 2014).

⁶In addition, if producers are aware of their ability to move, they may use initial moves to learn about the environment in order to maximize the value of their future moves. This greatly complicates the derivation of optimal behavior, in that producers would now be solving a dynamic optimization problem, potentially in the presence of movements by competitors. Such problems range from difficult to intractable.

Producers must evaluate their utility either on ‘open’ intervals, in which they have only one competitor because they are searching on the very edge of a market, or on ‘bridge’ intervals, in which they have competitors on both sides. On ‘open’ intervals, producers maximize their expected utility by selecting Δ , the distance to their nearest competitor, at x . On ‘bridge’ intervals, producers maximize their expected utility by selecting Δ , the distance to their leftmost competitor, at x_l . For convenience, the distance from their rightmost competitor, at x_r is given by $\bar{\Delta} = x_r - x_l - \Delta$. The expected utility takes the form:

$$E(u(\Delta)) = aM(\Delta) - \exp\left(-bM(\Delta) + \frac{1}{2}b^2V(\Delta)\right)$$

where $M(\Delta)$ is the expected appeal at Δ , and $V(\Delta)$ is the contribution of variance to the expected utility. On open intervals, these equal:

$$M(\Delta) = W_x + c(\Delta)$$

$$V(\Delta) = \Delta\sigma^2$$

On bridge intervals, these equal:

$$M(\Delta) = W_{x_l} + \frac{W_{x_r} - W_{x_l}}{x_r - x_l} \cdot \Delta + c(\Delta) + c(\bar{\Delta})$$

$$V(\Delta) = \frac{\Delta \cdot \bar{\Delta}}{x_r - x_l}$$

Entrants evaluate their expected utility at all available intervals and enter market in the interval and with a Δ that maximizes their expected utility.

Modeling the Categorization Process

The model described above only encapsulates the positions and outcomes of producers in the market. To model the behavior of audience cognition in these markets, I attempt to identify dense clusters of producers. Each cluster would likely represent a distinct category of producers, with producers falling outside such clusters representing producers that are difficult to categorize or that fall into multiple categories.

I identify such clusters by fitting a finite Gaussian mixture model to the positions of producers in each market (Dempster, Laird, and Rubin 1977; Xu and Wunsch II 2005). A finite Gaussian mixture model is a general tool for classifying points into similar clusters. Characteristics of this model make it particularly appealing for modeling category membership.

This model assumes that the positions of a set of points are given by some set of normal distributions, $\{N(\mu_1, \sigma_1^2), \dots, N(\mu_k, \sigma_k^2)\}$, centered at different means and with potentially different variances. Roughly, the model assumes that each point is generated by first randomly selecting one of the k distributions, proportionally to its probability p_i . The position of the point is then drawn from the chosen distribution. Such mixtures tend to place the centers of clusters at particularly dense parts of the set. I select the number of clusters k using the Bayesian Information Criterion (Schwarz 1978; Steele and Raftery 2009).

There are two major advantages to modeling clusters with a probabilistic mixture model, as here. Unlike hierarchical or partitioning (e.g. k -means) cluster models, a probabilistic model estimates the likelihood of each point being in each cluster. This allows for a measure of each point’s grade of membership in each cluster—high grade-of-membership positions are those close to the center of the cluster and which the cluster is likely to generate. In addition, it allows for the identification of points

that straddle clusters, points whose grade of membership across clusters is roughly equal.

Fig. 3 gives an example of one simulated market, the clusters identified in it by the Gaussian mixture model, and the associated measures of category membership described below. Panel **A** shows the positions of producers and the appeals W of their positions; the bottom of the panel shows the local density of producers across the market. Panel **B** shows the probability density functions of the two clusters identified in the market: the two clusters align with the peaks seen in Panel **A**.

I define the grade of membership GOM of a point x in cluster i as the logarithm of a point's predicted likelihood of being in a cluster, $p_i(x)$, normalized by the peak predicted likelihood of the entire cluster:

$$\text{GOM}_i(x) = - \left(\max_z [\log p_i(z)] - \log p_i(x) \right)$$

where z is the point with the highest grade of membership in the category. Comparison against the peak-likelihood point controls for differences in cluster width: points in more diffuse clusters have lower likelihoods on average. Panel **C** of fig. 3 shows the grade-of-membership functions associated with each cluster identified in the example market: even though Cluster 2 is more diffuse than Cluster 1 (panel **B**), the most central producers in each clusters have identical grades of membership.

I also construct measures of the extent to which a point lacks categories or spans multiple categories. For every point, I consider the two clusters in which the point has its highest grades of membership. Taking $p_1(x)$ and $p_2(x)$ to be the highest and second highest predicted likelihoods for the point, I first define a measure of miscategorization and a measure of spanning, as depicted in Panel **D** of fig. 3:

Figure 3: Example of a simulated market, estimated clusters, and measures of category membership

$$\text{Miscat}(x) = 1 - (p_1(x) - p_2(x))$$

$$\text{Span}(x) = \frac{p_2(x)}{p_1(x)}$$

Under these definition, points are miscategorized either if they are unlikely to belong in any cluster or if they are about equally likely to belong to multiple clusters. On the other hand, points are spanners if they are similarly likely to belong in multiple clusters. Next, I reduce these to binary measures, so that a point x is considered miscategorized if $\text{Miscat}(x) > 0.5$, and it is considered a spanner if $\text{Span}(x) > 0.01$. The particular thresholds were chosen by inspection, but analysis is robust to variation around these specific values. Finally, I construct a third binary measure of non-categorization if a point is miscategorized and is not a spanner. This allows me to examine the effects of spanning and non-categorization separately.⁷

Results

Existence of a Miscategorization Penalty

The aim of this article is to show that a process of optimal market entry under uncertainty can generate the market-level categorization phenomenon described by category theory. As described above, the prediction made by category theory is that well-categorized producers are generally more successful and appealing than

⁷The regressions I consider below include *Spanner* and *Non-Categorized* as predictors. Using *Spanner* and *Miscategorized* as predictors instead causes the coefficient on spanner to reflect the effect of spanning net of the underlying effect of miscategorization. All else equal, spanning points tend to occur in denser, higher value regions in which two clusters exist close together, which causes *Spanner* to predict a positive effect of spanning relative to the miscategorization alone. Treating spanning and non-categorization as mutually exclusive allows for closer comparison to prior research.

ill-categorized producers. Well-categorized producers tend to fall into dense clusters of similar producers, whereas ill-categorized producers tend to fall outside of or between such dense clusters.

There are three ways of examining this proposition in the markets simulated here. First, if the categorization penalty holds, then category-spanning positions will tend to be less appealing to the audience than non-spanning positions. More fundamentally, positions with lower grade of membership in any category should be less appealing to the audience than positions with higher grade of membership in any category. That is, positions which generally do not fit in any category should generally underperform positions that fit in some category. Most fundamentally, the miscategorization argument can be applied directly to positions in feature space. Insofar as categories signify dense clusters of positions, the miscategorization penalty should be stronger for more isolated positions, and weaker for positions in dense clusters. The miscategorization penalty would predict that a producer's distance from his predicts lower appeal. The propositions below summarize these three arguments:

Proposition 1 (Category spanning)

Positions spanning multiple categories will have lower appeal than positions that do not span multiple categories.

Proposition 2 (Grade of membership)

Positions with a lower grade of membership in their nearest category will have lower appeal than positions with a greater grade of membership in their nearest category.

Proposition 3 (Distance)

Positions with greater distance to their neighbors will have lower appeal than positions with lower distance to their neighbors.

I test these relationships with linear regressions estimating the effect of each measure of category membership on the appeal of the position. I estimate the effects within each period of each market. Specifically, within each period t and each market i , I estimate the regressions

$$W_{x,i,t} = \alpha + \beta_{1,i,t}NoCategory_{x,i,t} + \beta_{2,i,t}Spanner_{x,i,t} + \epsilon_{x,i,t}$$

$$W_{x,i,t} = \alpha + \beta_{i,t}GOM_{x,i,t} + \epsilon_{x,i,t}$$

$$W_{x,i,t} = \alpha + \beta_{i,t}Distance_{x,i,t} + \epsilon_{x,i,t}$$

where x indexes all producers within a market during the period, and each regression considers one of the measures of category membership: distance to nearest neighbor; grade of membership; or distance to nearest neighbor. Thus, in each market and each period, I estimate three separate β coefficients representing how miscategorization predicts producer appeal.

In each case, larger β represents a larger effect of category membership on producer appeal. Propositions 1-3 predict negative β for distance to nearest neighbor and category spanner status, and positive β for grade of membership: category-spanningness, decreasing grade of membership, and increasing distance all reduce producer appeal.

Fig. 4 plot these coefficients across all markets over time. Fig. 4a shows the difference between category spanning and non-spanning positions; fig. 4b shows the effect of increasing grade-of-membership; Fig. 4c shows the effect of an increasing distance to neighbor on producer appeal. Pale lines track how the relationship evolves within each individual market over time, as more entrants come into the market. The thick middle line show the average value of the coefficient across all markets within a period, with a 95% confidence interval represented by a white band around the line.

Finally two thin gray lines show the relationship at the 10th and 90th percentile of markets in each period.

Each of the figures supports the predicted relationships. Category spanners generally have lower appeal—the estimated effect of spanning is generally negative within markets and it is negative when aggregating across all markets. Positions with high grade of membership in some category generally have higher appeal. Most fundamentally, isolated positions generally have lower appeal. These relationships appear to strengthen over time as markets approach something like their equilibrium state.

Within the context of these models, these effects may be better termed as a correlation between clustering and appeal than as a miscategorization penalty: the correlation reflects producer tendency to imitate success instead of the limits of audience cognition. Markets in which producers imitate success naturally generate a positive correlation between density and appeal. When audiences assign high category membership to dense clusters, ill-categorized producers tend to also have low appeal, reproducing an apparent miscategorization or category spanning penalty.

This correlation between clustering and appeal, however, is not absolute. As a close look at the thin lines of fig. 4 suggests, many individual markets experience periods in which the correlation between clustering and appeal disappears. Looking at markets at least 50 periods away from initial conditions, 32 percent of markets and 2 percent of market periods experience an inversion of the penalty as measured by grade-of-membership; 62 percent of markets and 4.7 percent of market periods experience an inversion as measured by category-spanner status. A fair amount of the time, the most successful producers in a market will be those outside of major clusters or categories. Such inversions occur entirely because the appeal function is unknown: as producers discover highly appealing regions outside of existing clusters,

(a) Effect of category spanning. $W = \alpha + \beta_1 \cdot NoCategory + \beta_2 \cdot Spanner$

(b) Effect of increasing grade of membership. $W = \alpha + \beta \cdot GOM$

(c) Effect of increasing distance to neighbor. $W = \alpha + \beta \cdot distance$

Figure 4: Effect of position characteristics on position appeal, 1000 simulated markets, 250 periods.

they find themselves simultaneously outside of existing categories and in positions of high appeal. If many producers discover success, enough producers may wind up outside existing clusters that the overall positive correlation between clustering and appeal disappears or reverses.

It bears repeating that the appeal function, and the audience members and production processes which generate it, do not depend on the categorical structure of the market. Categories reflect producer positions but do not influence where producers choose to enter the market. The correlations reported here arise entirely from producer willingness to imitate success, no matter the sources of that success. It may be tempting to interpret areas of high appeal as representing latent categories. Producer appeal may stem from audience evaluation and may, in the extreme, even result entirely from an audience's cognitive inability to evaluate certain kinds of producers. It remains the case that producers have no awareness of these categories above and beyond their knowledge of the appeal function. Audience members, too, have either a limited understanding of such latent categories or a very limited ability to convey their understanding to producers. Neither producers nor the audience can predict the appeal of a novel object, above and beyond its similarity to prior examples.

The categories and labels that exist in practice have a limited ability to predict these latent features. More importantly, while the clustering-appeal correlation is a typical feature of markets, it is not an absolute but a probabilistic relationship: miscategorized producers experience lower appeal only when existing categories closely align with peaks in the appeal function. The process of producer imitation tends to reinforce this alignment. When the alignment breaks down, the clustering-appeal relationship, and any apparent miscategorization penalty, attenuates or disappears. The analysis below explores this dynamic instability of the categorical system further.

Change and Emergence of Categories over Time

The cluster model estimated here not only estimates the position of clusters but the number of clusters as well. This allows for an investigation of category dynamics in markets.

The literature on categories has a mixed record of dealing with category emergence. Much of the formal theory treats categories as *a priori* constructs in the market (e.g. Zuckerman 1999; Hannan, Pólos, and Carroll 2007). A separate strand of the literature has discussed category and form emergence as a highly intentional process. Some research discusses the role of social movements in creating new categories (Lee, Hiatt, and Lounsbury 2016; Weber, Heinze, and DeSoucey 2008; Carroll and Swaminathan 2000). Some discusses the role of influential vanguards (Koçak, Hannan, and Hsu 2014; Rao, Monin, and Durand 2005; Ruef 2000). Scholars are generally pursuing mechanisms of category emergence (Glynn and Navis 2013). What these approaches share is an emphasis on the intentionality of category emergence and a stress on category existence as a prerequisite for market action. If the existing system of categories is a poor fit for the market, some group of actors in society must typically create the category before producers can take advantage of it.

In the model presented here, categories follow producers instead of leading them. The category system shifts to reflect the reality of producer behavior as it changes over time. This allows for a specific prediction for the timing of category change. The number of categories in a market may increase as new categories emerge, or may decrease if two existing categories combine into one. As discussed above, though the clustering-appeal correlation is a common feature of markets, it is not ubiquitous, and markets often undergo periods in which this correlation weakens or reverses. A weakening (or reversing) clustering-appeal correlation indicates that the existing

system of categories poorly describes the set of positions that producers have found to be appealing to the audience. Such situations are ripe for categorical reconfiguration and emergence.

Proposition 4 (Category Change)

The number of categories in a market is more likely to change when the clustering-appeal correlation is weakening.

If the proposition holds, the number of categories in a market is more likely to change when the clustering-appeal correlation has experienced a sustained negative trend. I evaluate the relationship in each period of each market as described in the previous section, measuring the effect of decreasing grade-of-membership and the effect of spanning multiple categories. I measure trend by the overall change in the estimated β coefficient for each effect across the prior 25 periods, with appropriate sign changes to reflect the discussion here. A negative trend implies that the correlation between clustering and appeal is weakening (i.e. the miscategorization penalty is weakening); a positive trend, that the correlation is becoming stronger. I then predict the probability that the number of categories will change this period as a function of trend.

Tbl. 1 presents the estimates of these logistic regressions. The table shows that a recent positive trend (increasing clustering-appeal correlation) strongly predicts stability in the number of categories in a given period. If instead producers discover success at the borders of existing categories, weakening the penalty, the category system will change to reflect their discovery.

The theoretical implications of this proposition are straightforward: changes in the set of categories will naturally track the exploratory and imitative behavior of producers, even if producers are ignorant of the category system. There are interesting empirical implications in this proposition as well insofar as the miscategorization

	(1)	(2)	(3)	(4)	(5)
(Intercept)	−2.840*** (0.010)	−2.855*** (0.009)	−2.968*** (0.012)	−2.970*** (0.012)	−2.969*** (0.012)
Penalty Trend (Distance)	−1.720*** (0.125)				
Penalty Trend (GOM)		−1.464*** (0.121)			
Penalty Trend (No Cat.)			−0.515*** (0.071)		−0.466*** (0.073)
Penalty Trend (Spanner)				−0.440*** (0.096)	−0.307** (0.098)
Num. obs.	219000	219000	151837	151837	151837

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 1: Trends in the clustering penalty predict category change

penalty is observable in markets. Markets with a weaker miscategorization penalty likely offer opportunities for further innovation, or already feature a set of innovating producers. This proposition also offers an alternative way to understand the market-maker/market-taker distinction drawn by Pontikes (2012). Pontikes argues that different audiences may have different tastes for categorical ambiguity, showing that venture capitalists are more favorable to category spanners than are general audiences. The mechanism described here instead suggests that venture capitalists may be operating in systematically different markets than the general audience. More specifically, VCs may have identified a set of markets in which innovation and categorical reconfiguration are within reach, and existing clusters do not strongly predict successful or appealing market positions. VC preferences do not lead them to ignore miscategorization, nor do their abilities enable them to overcome the cognitive limits of categorical thinking. Instead, their preferences and skills lead them to identify and invest in markets in which categorical boundaries are misaligned. Similar dynamics may cause the preference for atypical hedge funds identified by Smith (2011).

Stability of Categorical Boundaries

Producer exploration affects not only the system of categories as a whole but also the categorical fit of individual producers. The categorical system described here reacts to the explorations of producers. As producers explore the environment, some end up luckier than expected, and others less lucky. Subsequent entrants end up facing a substantially similar set of market opportunities as their immediate predecessors but for the lessons learned by those predecessors. If their predecessors were unlucky, subsequent entrants will pursue the next-best opportunities available in the market. Lucky predecessors, however, inform the market of a new set of available opportunities. When an entrant is luckier than expected, she will inspire a flow of close imitators. Since the category system moves to reflect dense clusters of producers, unexpectedly lucky producers will pull nearby categories towards themselves or will generate entirely new categories.

Proposition 5 (Category Seeding)

Unexpectedly successful entrants will become more categorically central following entry.

A formal model can offer a deep view into the decision-making of actors in a market. In particular, the model is aware of each producer’s expected appeal at the position they chose to enter at. Once they enter, producers observe the position’s true appeal. I construct a measure of the difference between realized and expected appeal:

$$\Delta W_x = W_x - E(W_x)$$

I estimate the effect of ΔW on a producer’s grade of membership in the nearest category as well as the likelihood of the producer being a category spanner over the

	GOM	10 Per.	25 Per.	Miscat.	10 Per.	25 Per.
(Intercept)	-0.421*** (0.000)	-0.772*** (0.001)	-0.677*** (0.000)	-0.840*** (0.000)	-0.036*** (0.002)	-0.232*** (0.002)
ΔW	0.091*** (0.000)	0.078*** (0.001)	0.115*** (0.001)	-0.214*** (0.001)	-0.132*** (0.003)	-0.226*** (0.002)
Time		0.031*** (0.000)	0.012*** (0.000)		-0.069*** (0.000)	-0.030*** (0.000)
Time $\times\Delta W$		0.010*** (0.000)	0.001*** (0.000)		-0.028*** (0.000)	-0.004*** (0.000)
Num. obs.	31354000	2674000	6154000	31354000	2674000	6154000

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 2: Effect of unexpected appeal on category centrality

10 or 25 periods subsequent to producer entry. I truncate the tracking period because the long-term effect of success is more ambiguous than the short-term effect: over long periods of time, successful entrants may spawn yet more successful imitators, so that a category that at first moves towards the successful entrant later ends up moving away from them. In the real world, consider how MySpace become the prototypical social network before its more successful competitor Facebook took that spot.

Tbl. 2 presents estimates of this proposition. Positive ΔW indicates unexpected success, while negative ΔW indicates unexpected failure. The *Time* variable measures the number of periods since producer entry. The first three models show the effect of unexpected success on grade of membership, and the second three models show the effect on the likelihood of being a category spanner. The interaction term shows how these effects evolve over time. The models show that unexpectedly high appeal raises grade of membership in the immediate future and lowers the likelihood of category spanning.

Like the dynamics of category emergence, this result has several theoretical and empirical implications. It strongly suggests that categorical boundaries and categorical

prototypes may not be stable over time. As producers test the boundaries of existing categories and end up successful, existing categories will migrate towards their success and new categories will emerge around them. This reflects a process of passive sensemaking, as audience members learn which positions in a market convey peak performance (Antonio et al. 1999; Yanfei Zhao et al. 2018). Moreover, the model suggests a potential, albeit difficult, empirical test of the proposition. Although prospective entrants' expectations are difficult to observe, it may be possible to identify natural experiments within potential entrants, or to estimate the expected appeal of novel product configurations, before observing their realized appeal. Successful entrants should inspire imitation and categorical change. Failed entrants should inspire caution and stability.

Discussion

The model described here should be understood as an alternative explanation to category theory that is both able to reproduce its results and that makes several distinguishing predictions. In principle, it should be possible to distinguish the producer exploration theory described here from an audience cognition theory of a market categorization penalty. At the very least, the model described here raises the empirical bar that an audience cognition theory of categories must meet.

To summarize the argument, the model examines producer entry decisions in a complex, uncertain environment. Producers enter the market with a limited set of information: they know the outcomes of prior entrants along with their market position or the strategy they pursued. From this, new entrants can venture a guess on how successful a new strategy might be, based on how similar it is to prior attempts. Producers fear both failure and the threat of competition. They choose to enter the

market with some differentiation from incumbents. In doing so, the stream of entrants slowly explores the environment, learning which positions are successful and which not.

Key to the result is that producers imitating highly successful peers are more willing to tolerate close competition: losing profit to a competitor is easier when there is much profit than when there is little. As such, entrants tend to cluster more densely around successful, appealing positions, and less densely around unsuccessful positions.

Categories emerge to rationalize the outcome of this process. Categorization processes recognize existing clusters of producers and so correlate with dense positions. Because dense clusters form around appealing positions, categories also come to indicate successful positions, so that ill-categorized producers will tend to underperform well-categorized producers in the market. Markets generate a correlation between producer clustering and producer appeal, which may be appear as a miscategorization penalty or a category spanning discount. These penalties are only side effects of the interaction between producer exploration and an automatic categorization process. Categories play no causal role in the creation of a spanning penalty—they are merely an instrument for measuring it.

So far this argument reconstructs the predictions of category theory under an alternative mechanism. It makes at least two additional predictions that distinguish it. First, because categories track the success of producers, their meaning tends to migrate towards successful producers, especially as their success attracts imitators. The only description of categorical boundary drift under an audience cognition theory of categories makes a different set of predictions (Pontikes and Hannan 2013). Second, the producer exploration mechanism identifies conditions under which the mis-categorization penalty weakens. This helps explain previous findings about differential audience preference for categorical ambiguity (e.g. Pontikes 2012), by arguing

that such audiences engage in market selection, favoring markets where the penalty happens to be weaker. It also makes a specific prediction on the timing of category emergence—it occurs when category spanners start to perform relatively well.

The alternative formulation of categories described here can also help explain several puzzles in existing work on category theory. First, empirical identification of the category spanning penalty relies on observation of successful single-category producers as well as unsuccessful multi-category producers. Category theory gives no explanation for why such multi-category failures exist, or more precisely, for why they chose to enter the market with their specific poorly designed configuration. The mechanism here explains the motivation of such producers: they took a risk and failed.

Second, the producer-focused described here bears at least a nominal resemblance to the production-side category penalty described by Hsu (2006). The argument there goes that producers have limited resources to spread across multiple efforts. Because markets reward specialists, producers that specialize in a single category outperform generalists that spread their efforts across many domains. The puzzle here comes from the definition of a specialist. Hsu gives no means by which researchers could identify a “pure-type” market domain. That is, it is not clear whether romantic comedy films should be considered a specialist genre or a blend of romance and comedy: their success argues for the former and their name for the latter. The model described above provides a general way to avoid this problem: there are no inherent specializations in a market. Producers generalize when they attempt to bridge islands of success. Such bridging tends to fail precisely because islands of success sit atop the *most* successful possible positions in a market. If producers instead attempted to generalize by bridging islands of failure, we would expect generalists to outperform specialists.

The last point of discussion concerns a potential counterargument to the proposed model. One of the critical components of this model is the stochastic appeal function

describing the terrain that producers explore. This terrain abstracts away from the details of why one producer’s strategy succeeds and another’s fails. A critical reader could object that this model simply takes the logic of category theory and buries it in a mysterious function with a different name. Cognitive limits on categorization may be a major or even a dominant contributor to the appeal of a given position.

This abstraction should instead be understood as a critical empirical challenge to category theory. An established literature in organization theory, with traces through recent work, argues that nobody really understands how organizations work, including the people that run them (March and Olsen 1976; March, Sproull, and Tamuz 1991; Levinthal 1997; Hannan, Pólos, and Carroll 2003). Many idiosyncratic factors feed into the success or failure of a particular strategy, so that a random model of organizational outcomes may be the appropriate approach. In particular, any latent effect of categories must exist alongside all of the other factors feeding organizational success. Given that a theory of producer exploration of a random terrain generates the same empirical predictions as the existing category theory, category theory must look for ways to distinguish itself above and beyond the empirical finding of a mis-categorization penalty (see Fig. 1c).

More fundamentally, if audience-side conformity pressure plays a major role in determining product appeal in the model presented here, this would generate a category theory entirely alien to the one understood in existing work. Intuitively understood categories may well determine why audience members appreciate some products and avoid others. Audience members, however, appear to have very little ability to communicate their internal preferences to the producers that must fulfill those preferences. Whether this stems from some barrier to communication between producers and the audience, or whether it stems from an inability by the audience itself to know what it wants, it is hard to see what predictions such a theory of categories

could make.

Conclusions

The model presented here describes a world in which producers take risks in order to explore an uncertain world. This world reproduces many of the key empirical predictions of category theory. This suggests at the very least that category theory must look for additional empirical patterns in order to support its theoretical mechanisms. It appears as though the null hypothesis of category theory has been that categorical penalties should not exist in markets. This research resets the null: category penalties and apparent pressures to conform will randomly appear throughout the world.

While this may appear to be a hostile conclusion to a theory of categories relying on audience categorization, the model described suggests avenues to advance a category theory further. Such efforts may in fact be more fruitful than an attempt to adjudicate which model of the world is more correct. First, one of the key processes in this model is that producers maintain and react to an information set about the opportunities available in the world. In the model presented here, this information set is accurate. A category theory may instead advance arguments on how categories bias and shape producer exploration efforts, and prevent spanning from occurring in the first place. It is important to note that such advances will still find it difficult to distinguish categorically-constrained information from unbiased information sets. It will be difficult to discern the social construction of opportunity from an objective perception of opportunity (Zuckerman 2012).

Perhaps the more fruitful path forward is a reconfiguration of category theory from a cognitive to a political theory of the market (c.f. Fligstein 1996). While the mechanism presented here argues that coalitions and social movements are not

required for category formation, in practice, social movements seem to be involved in the creation or maintenance of categorical boundaries (e.g. Carroll and Swaminathan 2000; Rao, Monin, and Durand 2005; Weber, Heinze, and DeSoucey 2008). Such movements may be necessary precisely in order to prevent or encourage producer willingness to push categorical boundaries. Actors may use categories as organizing symbols to advance their material ends. Categories in such a world would serve not as an indicator of cognitive failure but as a coordinating device for recognizing and reacting to market threats. Expansion of the theoretical structure of a category theory will build a stronger theory.

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