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CROWDING, SATIATION AND SATURATION: THE DAYS OF TELEVISION SERIES' LIVES *

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Abstract

The performance of firms depends not just on the structure of the industries in which they compete but also on their relative positioning within those industries, in terms of operating within particular niches. We propose that demand for these niches depends endogenously on the historical ecology of the products offered: Niches become saturated – reduced in their ability to support products – as a large number of previous offerings allows the audience to satisfy its desire for products of a particular type. Analyzing the survival rates of television series aired in the United States from 1946 to 2003, we found that the survival rates of future entrants fell with the extensiveness of recent offerings in the niche, and that the negative association between crowding and survival also weakened with this saturation.

Keywords: categories, competition, niches, product demography, saturation

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INTRODUCTION

Strategy scholars have long recognized that firm performance varies systematically not just across but also within industries. Porter (1980), for example, proposed that firms differ in the generic strategies that they pursue and in the performance of those strategies. Research on strategic groups has since extended this insight, finding that firms within an industry often cluster into sets with similar product positioning, common business models and comparable internal operations (e.g., McGee and Thomas, 1986; Dranove, Peteraf, and Shanley, 1998; Zott and Amit, 2008). A related and parallel line of research, meanwhile, has characterized the product portfolios of firms along many dimensions and has connected the characteristics of those portfolios to firm performance (e.g., Sorenson, 2000; Sorenson, McEvily, Ren, and Roy, 2006; Zahavi and Lavie, 2013).

Though these streams of research have contributed substantially to our understanding of business strategy, they have at least one important limitation: By conceptualizing and measuring positioning at the level of the firm, they miss important variation in performance within firms and within industries – particularly in settings where firms offer multiple products or span regions – that could not only explain firm performance but also guide managerial decisions. Recent research therefore has sought to disaggregate both industries and organizations. Industries have been divided into niches and submarkets (e.g., de Figueiredo and Kyle, 2006; Barroso and Giarratana, 2013). Organizations meanwhile have been split into business units and into individual products and services (e.g., Helfat and Raubitschek, 2000; Eggers, 2012).

To study competitive dynamics at these more micro levels, researchers have collected complete information on all products offered in a range of industries and have shifted the unit of analysis to the product. By using product survival as the primary measure of performance (within firms), this stream of research – sometimes referred to as product demography (Carroll, Khessina, and McKendrick, 2010) – has demonstrated that product performance depends on the degree of crowding within the niches to which particular products belong (Cottrell and Nault, 2004; de Figueiredo and Kyle, 2006; Khessina and Carroll, 2008;

Barroso and Giarratana, 2013).

We advance this literature on product positioning and the evolution of niches in two ways. Although the theoretical literature on niches and submarkets has always portrayed these resource spaces as clusters of demand that emerge over time (Sutton, 1998; Klepper and Thompson, 2006; Hannan, Polos, and Carroll, 2007), the empirical literature has typically treated them as pre-existing and has (often implicitly) assumed that preferences among consumers within them remain stable over time (e.g., de Figueiredo and Kyle, 2006; Hsu, 2006; Barroso and Giarratana, 2013). We therefore introduce an empirical approach for constructing niches, on the basis of descriptions of products, that allows these niches to arrive over time.

We also extend this literature theoretically by arguing that demand for a particular niche depends endogenously on the historical ecology of product offerings. Our proposition draws on research in cognitive psychology, which classifies the features used to compare objects as being either alignable or non-alignable, depending on whether they share a common structure (Markman and Gentner, 1993). Alignable features on automobiles, for example, would include engine horsepower and cargo space. A navigation system or a novel body design, meanwhile, might serve as a non-alignable feature. These differences matter because audiences find it easier to compare objects on alignable features and therefore place less emphasis on non-alignable ones in their choices (Markman and Gentner, 1993). Building on these ideas, we posit that products with large proportions of non-alignable attributes experience strong satiation and saturation processes: Over time, consumers tire of the product, becoming satiated with it. Because buyers perceive little novelty when that originality depends mostly on non-alignable features, this satiation also extends to other, similar, products. Satiation, therefore, has a related niche phenomenon: saturation. Consumers gradually weary of an entire niche as it becomes overly common.

To test these ideas, we estimated the determinants of product survival among television series originally broadcast in the United States between 1946 and 2003. Because television programs vary primarily on non-alignable features, they offer an excellent setting for exploring our

proposition. Television also represents an important segment of the economy, with revenue of roughly \$36 billion and employing more than 88,000 people (IBISWorld, 2012). Consistent with our expectations, product mortality rose with product age and when series followed well-trodden conceptual themes. Saturation also appeared to moderate the effects of crowding, reducing its negative association with product survival. As in past research, crowding, particularly within niches, increased exit rates.

Our research contributes to the literature in multiple ways. First and foremost, we have developed and demonstrated support for a theory of endogenous demand, where firms themselves influence consumer interest in niches through the products that they offer. Second, we have introduced a method for identifying the emergence of those niches over time, through the clustering of product descriptions. Third, our estimation has incorporated multiple approaches for addressing potential endogeneity in entry into niches. In doing so, it has revealed that the increasing returns to product density in a niche, often interpreted as the positive effects of “legitimation” of the category, may instead reflect the fact that producers endogenously enter niches that they (correctly) perceive as having unmet demand. Finally, our research has further demonstrated the value of disaggregating firm-level performance into its components, in this case to the product level, to understand better the drivers of that performance.

The results also have implications for the managers of multiproduct firms. Most immediately, they demonstrate that managers should attend to the intensity of competition within a niche, as products perform better on average in less crowded regions of the product space. More novelly, our results also indicate that managers should consider not just the current offerings in these niches but also the recent history of offerings. Even if rivals abandon a segment of the market, if it has become saturated due to a glut of recent offerings, managers may need to avoid the niche for quite some time before interest in it recovers. Interestingly, this saturation effect also points to a potentially effective product strategy: To the extent that saturation creates an isolating mechanism against follow-on entry, innovators might effectively preserve their first-mover advantage by flooding the niche with a surfeit of similar offerings (cf. Lieberman and Montgomery, 1988).

POSITIONING, NICHEs AND PERFORMANCE

How does positioning influence firm performance? One approach to answering this question has been to assign firms to groups, based either on scope or on product similarity, and to examine how those groups differ in their behavior and performance (e.g., Carroll, 1985; McGee and Thomas, 1986; Mas-Ruiz, Ruiz-Moreno, and de Guevara Martinez, 2014). Another approach has been to characterize product portfolios – for example by rates of churn – and to explore how those portfolio characteristics relate to firm-level performance (e.g., Sorenson, 2000; Barroso and Giarratana, 2013; Zahavi and Lavie, 2013).

Although both of these lines of research have been fruitful, each remains limited in its ability to understand the performance of firms that offer multiple products or that operate across more than one region. The first approach finds it difficult to classify these firms, as multiproduct firms straddle niches and submarkets. And neither allows the researcher to capture and explore variation within the firm across its offerings. Yet, managers routinely rely on such information to guide their decisions of what kinds of products to develop and which current offerings to cull.

To address these limitations, researchers have begun to shift the unit of analysis to the level of the individual product or service. Although that shift has had the advantage of providing a more nuanced lens on positioning and the product portfolio, it has also necessitated a change in the measure used to evaluate performance. Firms often do not calculate – and, even when they do, almost never release – product-level profitability. Researchers therefore rely on product longevity as a measure of product-level success (Carroll *et al.*, 2010). This measure has face validity: Managers rarely shutter successful (profitable) products and services. Product exit due to firm failure, moreover, probably reflects poor performance on the part of the firm. But researchers must nevertheless exercise caution in moving from product-level results to firm-level implications.

Shifting to this level of analysis has allowed researchers to examine heterogeneity in the performance of products as a function of their positioning within niches—pockets of consumers with similar preferences. Although theoretical models have long treated industries as

heterogeneous spaces composed of numerous niches (Sutton, 1998; Klepper and Thompson, 2006), the empirical literature had little ability to explore and understand this variation until researchers began developing datasets with complete information on the product demography of industries (Carroll *et al.*, 2010). As these datasets have become available, researchers have documented a number of regularities, such as that exit rates rise with age and that products that enter niches near the technological frontier survive longer (Greenstein and Wade, 1998; Cottrell and Nault, 2004; de Figueiredo and Kyle, 2006).

Whether at the industry- or niche-level, the (often implicit) imagery of the buyer in these studies has been of someone with monotonic preferences, interested in getting the most on the relevant dimensions, such as processing speed and memory, for the lowest price. But the results to date have come primarily from studying products of a particular type—usually ones where manufacturers continually improve on earlier generations of offerings in relatively easy-to-evaluate ways. Consider computers (Stavins, 1995; Greenstein and Wade, 1998), disk drives (Ruebeck, 2005; Khessina and Carroll, 2008) and laser printers (de Figueiredo and Kyle, 2006). Computers and disk drives become faster, smaller and able to process and store ever-greater amounts of data. Laser printers gain in resolution and speed. Consumers therefore can easily compare offerings and understand why they should prefer the latest and greatest. In these settings, one would expect buyers to purchase products at or near the cost-efficient frontier, leading to the obsolescence of older offerings (de Figueiredo and Kyle, 2006).

Other classes of products, however, differ more on difficult-to-distinguish dimensions. Consider a typical cultural product: music. How can one compare songs by different artists, or different albums of the same artist? Audiences perceive these offerings as distinct and prefer one to the other but the basis for that preference often remains opaque, even to the listener. Researchers similarly find it difficult to determine which products might substitute for which others and therefore compete more intensely. But product turnover occurs in these settings, often at rates higher than in settings with easy-to-compare attributes. Fashion houses introduce new lines of clothing each season. Furniture designers change their colors and styles on a regular

basis. Restaurants update their menus. And entertainment companies constantly release new albums, books, movies and television series. What drives product mortality in these settings? To understand better how these distinctions might influence product-level dynamics, we draw on recent research in cognitive psychology to develop a more nuanced model of consumer preferences and choices (i.e. demand).

Behavioral assumptions

We first assume that consumers compare products on the basis of the attributes or features of those products to determine their relative preferences for one versus another (Tversky, 1977). We have a spatial imagery in mind, with consumers having some ideal point – or set of ideal points – in a multidimensional product space, each associated with generating some peak level of satisfaction that may vary across points (Lancaster, 1971). Consumers choose to consume the offerings located closest to their ideal points, subject to some reservation price. Clusters of consumers with similar preferences therefore create pockets of demand (i.e. niches).

We further assume consumers to have some sort of budget constraint, in terms of either their ability to purchase products or their time available for consuming them. At the level of the population, this constraint – aggregated across all consumers – places an upper bound on the carrying capacity of the niche. At the level of each product, because of this budget constraint, as more products become available, the average number of consumers that each attracts falls.

On these assumptions our perspective differs little from past research on positioning and product demography. In cases where consumers consistently prefer more or less on some attribute (e.g., for a laptop, its weight or the capacity of its hard drive), each new product that comes a little closer to these ideal points attracts consumers, displacing earlier – now inferior – offerings. Competition then leads to the non-viability and discontinuation of these inferior products. Consistent with these assumptions, exit rates have been found to rise with product age (de Figueiredo and Kyle, 2006; Fosfuri, Giarratana, and Luzzi, 2008) and to fall with product quality (de Figueiredo and Kyle, 2006; Khessina and Carroll, 2008).

We nevertheless depart from this prior literature, extending it, in two interrelated respects: First, we introduce the idea that, in many contexts, consumers have shifting preferences or even have a preference for novelty itself. Second, we distinguish between alignable and non-alignable features as the basis for product differentiation and derive predictions as to how this distinction influences the emergence and dynamics of niches.

Novelty: We assume that the appeal of any particular product declines over time. One could justify this assumption in two ways. On the one hand, consumers may simply have a taste for novelty, deriving less and less satisfaction from a particular product as they consume more of it (e.g., McAlister, 1982). Although the specific mechanism underlying this preference does not matter for our theory, psychologists have long thought of novelty-seeking as an innate characteristic that manifests itself in early childhood (Flavell, 1977). More recent research, moreover, has found a strong association between individual-level variation in novelty-seeking and genetic variation in dopamine receptors (Ebstein, et al., 1996).

On the other hand, the ebbing appeal of products might stem from shifting tastes. Consumers have generally been treated as having stable preferences. Product exit therefore has been interpreted as a result of the arrival of better and cheaper alternatives. But this assumption of stability seems too strict. Tastes change. That's true in high-technology industries; Christensen (1997), for example, argued that incumbents in the disk drive industry failed to recognize and respond to the changing preferences of consumers. That's true even in industries with little innovation; Albuquerque and Bronnenberg (2009), for instance, studying frozen pizza, demonstrated that drifting consumer preferences could create shifts in demand even in the absence of improved quality or reduced prices. To the extent that products match well with the preferences of the audience at the time of their introduction, one would expect them to become less appealing as they mature and as demand drifts away from these points (cf. LeMens, Hannan, and Polos, forthcoming).

Structural alignment: Both the consideration of products as potential substitutes and the assessment of their relative attractiveness depends of comparison. Structural alignment theory argues that some attributes systematically contribute more to consumers' comparisons (Gentner and Markman, 1994; Zhang and Markman, 1998). Alignment exists when attributes of a pair of offerings being considered have a common structure, cases where each has an attribute that appears to align (match) with the other (Markman and Gentner, 1993). Perhaps the most straightforward common structure exists when one can compare the pair on a continuous measure, such as the processor speed or hard drive capacity of two computers or the percentage alcohol by volume of two beers.¹ By contrast, non-alignable attributes represent cases in which two offerings differ on a feature that one has but for which the other has no apparent counterpart. If one computer but not another has multi-threaded processing or one beer but not another includes cinnamon, consumers might consider these attributes non-alignable. Although nearly all products include some mix of alignable and non-alignable attributes, the proportion of each varies.

These distinctions matter because the comparison of alignable and non-alignable attributes differ in their cognitive cost, with the comparison of alignable attributes requiring much less effort (Zhang and Fitzsimons, 1999; Zhang and Markman, 2001). Imagine the selection of a cellular phone. To compare alignable elements, such as speed, memory and screen size, one need not understand which of these attributes matters most or even how they affect the phone's operation. One can simply select the option that appears equal to or better than the others on each dimension. Complications only arise with tradeoffs, for example where the phone with the largest screen has a slower processor. Even then, the consumer needs only understand the relative importance of the factors involved. By contrast, the evaluation of non-alignable features first requires the evaluator to determine their values on some universal utility scale (Hsee, 1996), a cognitively demanding task. Consumers therefore tend to focus on alignable attributes and to ignore non-alignable ones.

Alignable attributes define niches. Audiences come to perceive sets of products or services as

¹Even non-ordinal features could become aligned if consumers perceive them as belonging to a common structure. For example, the introduction of a novel automobile transmission technology could become alignable to the extent that critics and consumers evaluate it in terms of its effects on acceleration or fuel efficiency.

similar because they share some common elements (Tversky, 1977; Mervis and Rosch, 1981). These groupings might never attain a label or the stability associated with more established categories (cf. Hannan *et al.*, 2007), but they reside in proximate locations in product space and consumers see them as substitutes. They therefore form the consideration sets for consumers and the relevant competition for producers. For expositional purposes, we refer to products with these common characteristics as belonging to a niche.

Even within these niches structural alignment plays an important role in consumers' judgments. Because alignment operates at a dyadic level, pairs of products within a niche often have a larger set of alignable attributes than those common to all members of the niche. Consumers therefore continue to focus on alignable features in assessing the relative attractiveness of offerings within the niche. Non-alignable differences, by contrast, come into play primarily in cases where two offerings appear roughly equivalent on alignable elements (Gentner and Markman, 1997). For example, in choosing the cell phones mentioned above, if two phones appeared identical on speed, memory and screen size, then one might favor the one that had an added (non-alignable) feature not available on the other.

Demographic implications

Saturation: The most direct implication of these assumptions is a “satiation” effect, the idea that the appeal of a product would decline over time and consequently that the odds of exit should rise with age—a frequent finding in the empirical literature on product demography (e.g., Greenstein and Wade, 1998; Cottrell and Nault, 2004).

We would expect this effect to prove particularly pronounced in a setting such as television, where audiences value variety both across and within products. Even from one episode to the next, part of a series' appeal stems from the introduction of novel characters, themes, and plot elements (while creating align-ability by incorporating characters and plot lines from earlier episodes). Finding features that audiences continue to find fresh can prove difficult. Producers exhaust early the variety available through the recombination of alignable attributes and must then

rely on non-alignable ones to distinguish their offerings. But because consumers focus on the alignable elements and discount the novel non-alignable ones, they may perceive the latest episodes as simply being reruns of earlier ones.

Note that we view this preference for novelty as a property of a consumer's ideal point in product space rather than of a particular product offering. In other words, satiation erodes the relative appeal of the attribute space surrounding the product being consumed. That distinction has an important implication: Repeated consumption of a good reduces not just the satisfaction associated with the product consumed but also with all products perceived as similar to it, such as those in the same niche. Over time, then crowded niches in the product space become saturated: So many consumers become satiated with products of a particular type – with a set of alignable features – that producers can no longer appeal to them. One would therefore expect product exit rates to rise with saturation.

Crowding: From the assumption of a budget constraint, it follows that the average number of consumers captured by each product declines with the number of products offered. Crowding therefore raises the probability that a product falls below the minimum number of consumers needed to justify its continued production and consequently increases its odds of being discontinued (Sorenson, 2000; de Figueiredo and Kyle, 2006). This crowding effect has been the most consistent finding to date in product demography. Both producer density – the count of manufacturers – and product density – the total number of products on the market – raise product exit rates (e.g. Greenstein and Wade, 1998; de Figueiredo and Kyle, 2006; Khessina and Carroll, 2008). Our baseline predictions regarding crowding therefore parallel those of past studies.

Given that consumers purchase the products closest to their ideal points, moreover, this crowding effect should prove particularly pronounced for products that occupy proximate positions in the preference space, those in the same niche. Some prior research has also examined whether products sold by the same firm – often referred to as product line extensions – generate more or less competition than those offered by competing firms. On the one hand, products sold

by the same firm vie for the same firm-level resources and therefore one might expect them to compete more intensely. On the other hand, coordination within the firm might allow producers to distribute their offerings more evenly across the product space, reducing the intensity of competition. In most studies to date, however, competition has appeared stronger within firms than across them (Carroll *et al.*, 2010).

How might these effects shift in settings where differentiation depends more on non-alignable attributes? We would expect more diffuse competition for two reasons. First, alignable features help distinguish more clearly one offering from another and therefore can prevent consumer confusion over offerings (Gourville and Soman, 2005). Products with larger numbers of alignable attributes therefore become more finely segmented into distinct niches (i.e. into categories with higher levels of contrast). Second, alignable features combined with vertical differentiation – one direction of improvement being preferred by the majority of consumers – should contribute strongly to the obsolescence of older offerings. Non-alignable features, by contrast, increase the difficulty both of comparing products and of creating comparison sets and therefore lead to less structured competitive rivalry.

Crowding in saturated submarket niches: How does saturation, in turn, influence the effects of crowding? At first blush, one might guess that it would intensify competition. Holding constant the population of consumers, saturation essentially depresses demand in one region of the product space. As the same number of products compete to attract the remaining consumers still interested in those sorts of offerings, one might expect the effects of crowding to become more intense.

But recall that audiences tend to evaluate entrants into a niche on the basis of the features of the earlier entrants. With alignable features, this asymmetry does not necessarily place entrants at a disadvantage vis-à-vis incumbents: Technological advances often allow entrants to deliver features more effectively and efficiently than incumbents (Lieberman and Montgomery, 1998). But with non-alignable features, a different dynamic emerges. To the extent that entrants do not offer the same non-alignable features as previous products in the niche, consumers may perceive

their offerings as inferior; to the extent that they differentiate them on the basis of non-alignable features, audiences often ignore them (Zhang and Markman, 1998). As a consequence, later entrants generate less competitive intensity than earlier ones. In settings characterized by a large proportion of non-alignable attributes, one would therefore expect the effects of crowding to become less intense with saturation.

TELEVISION SERIES

We explored these dynamics in the population of primetime television series in the United States, from 1946 to 2003. This setting fits our research question well. New product development and niche creation play central roles in the industry. Each of the major broadcasters introduces about 15 series per year (Vogel, 2001). Differentiation depends almost entirely on non-alignable attributes. Producers compete on finding novel themes, plot lines and genres that appeal to audiences. Relative to some other settings, moreover, these product introductions – even the failures – have been well documented.

Television also has the advantage of removing price from the equation, thereby simplifying the empirical analysis. Consumers do have a budget constraint in terms of their time and therefore the longevity of a series depends on its popularity. But viewers do not pay different prices for different programs, and therefore the models need not account for pricing.

Broadcasters and production companies have strong interests in maximizing series longevity for two reasons. First, developing a series requires substantial upfront investment. Producing an hour-long pilot episode could cost as much as \$10 million and require several months of planning. Promising pilots lead broadcasters to order an initial half-season, roughly ten episodes with costs of up to \$3 million each. But broadcasters rarely generate sufficient advertising revenue from these early episodes to cover their costs (Mermigas, 2007). Instead, they subsidize programs for the first season or two hoping to recover these losses in subsequent seasons.

Second, the value of a series itself increases dramatically if and when it goes into syndication. Syndication means that other channels purchase rights to rerun the episodes. Since these reruns

incur no incremental costs, the revenue they generate accrues almost entirely to the bottom line (Vogel, 2001). Historically, series have generally only become viable for syndication once they have reached a total of 100 episodes (roughly five seasons in length).

Although television executives have strong incentives to develop popular series, they still find it difficult to predict popularity. Both Fox and NBC, for example, initially passed on *Seinfeld* before NBC decided to give it a try. The development of series therefore involves a great deal of trial-and-error.

Despite this unpredictably, consumer tastes appear to follow some large-scale patterns. Kennedy (2002), for example, notes that Westerns proved popular in the 1960s, providing more than 10% of the primetime lineup. But interest faded in the 1970s, with not a single Western airing during primetime by the end of the decade. The familiar pattern begins with an innovator developing a novel concept that proves successful. Recognizing a previously unmet pocket of demand, both the innovator and imitators introduce additional series within the same theme (Owen, Beebe, and Manning, 1974; Bielby and Bielby, 1994). These shows, however, rarely reach the popularity of the original, with lower average ratings and shorter lifespans (Kennedy, 2002). At some point, interest wanes to the point that the theme nearly disappears.

Data

Drawing on information compiled in *The Complete Directory to Prime Time Network TV Series: 1946–Present* (Brooks and Marsh, 2003), our dataset covers all fictional television series broadcast in the United States during primetime, from October 1946 to July 2003.² We excluded both non-primetime fiction series and non-fiction series – such as reality programming, game shows, news magazines and talk shows – because they generally do not go into syndication and therefore may exhibit quite different dynamics (Hyatt, 1997). For each series, our records include entry and exit dates, a plot description, the network that aired it, the episode length, the day of the week and time of day that it aired, and the cumulative number of Emmy Awards it received.

²Because they fall outside the scope of our main data source, we excluded series developed by cable channels.

Although the first television network in the United States, NBC (National Broadcasting Company), began broadcasting in 1930, the idea of programming content in the form of a series with an ongoing storyline did not emerge until much later. Early programming revolved around Broadway plays, news, sports, game shows, travelogues and cooking programs. The industry began to broadcast made-for-television serials after World War II. In 1947, the DuMont Television Network notably aired one of the first series, “Mary Kay and Johnny”—a live comedy of 15-minute episodes about young newlyweds in New York. But television series really came into their own in the 1950s. During this decade, television series also quickly converged on a common format: 30- or 60-minute episodes aired once-per-week at the same time and on the same day of the week. Despite beginning in 1946, our dataset therefore does not have any meaningful left-censoring.

During this period, seven broadcast networks – NBC, DuMont, CBS, ABC, Fox, UPN and WB – aired 2,245 different series during primetime. We observed these series for a total of 40,855 series-months. For the purposes of sample construction, we defined primetime as a program aired between 7:00 pm and midnight (Eastern time). Primetime has long held a special position in television broadcasting. Initially, the major networks only aired programs regularly from 7:00 pm to 11:00 pm. To limit their costs, television stations would either go off-air or broadcast cheap, filler material during other times of day. But even as television stations have moved toward round-the-clock programming, primetime – still defined as 7:00 pm to 11:00 pm – continues to account for the bulk of audience attention and advertising revenue.

Figure 1 depicts the distribution of product lifetimes for the population of primetime fiction series. Although the average series runs for 1.5 years, the median only survives a single season, and only 7.5% passed the five-year threshold generally required for syndication. This short average lifespan also means that our data exhibit very little right-censoring—only 144 series (5.1%) remained active in 2003.

Figure 1 about here

Defining niches

Research on product demography has generally recognized that competition occurs most intensely among offerings with similar characteristics. With continuous data, one might capture this localized competition with weighted density measures (cf. Baum and Mezas, 1992; Sorenson and Audia, 2000). In practice, however, the research to date has typically grouped products into discrete niches, according to ranges on one or more dimensions. de Figueiredo and Kyle (2006), for example, used resolution and speed to define segments in their study of laser printers.

An emerging literature on categories has similarly sought to group products and organizations according to the audiences to which they attempt to appeal. For cultural products, these categories have generally been genres (e.g. Hsu, 2006). For food and wine, they have been styles of production and cuisines (e.g., Kovács and Hannan, 2010; Negro, Hannan, and Rao, 2011). But even within these categories, products often vary tremendously in their attributes and the audiences to which they appeal. Few, for example, would consider *South Park* and *Yes, Prime Minister* substitutes even though both are highly-rated comedies. Recent research, therefore, has begun to explore using detailed data on the attributes of products and organizations to define their relative positions in preference space. Kovács and Johnson (2014), for example, used menu items and ingredients as a means of classifying the positions of restaurants.

We follow a similar approach, clustering television series according to the similarity of the text used to describe them in *The Complete Directory to Prime Time Network TV Series: 1946–Present*. We inferred clusters (niches) from these descriptions using the SenseClusters package (Pedersen, 2003). Our approach essentially identified the words (and their synonyms) commonly used in the descriptions and combined that information with the genre classifications to form niches (see the Appendix for further details). The more, for example, that a drama series description included words synonymous with law or legal matters, the higher the probability that the algorithm would assign it to a cluster grouping programs with the law as an element. We call the clusters identified by this algorithm “conceptual themes” to distinguish them from genres.

Note, however, that our implementation of these conceptual themes has them nested within clusters. Thus, for example, the comedy genre includes conceptual themes that one might label: comedy-adult, comedy-family, and comedy-high school.

Because this clustering algorithm depends on overlapping common elements, our conceptual themes essentially identify groups of series with a set of common alignable attributes among them. Across conceptual themes, however, these same features may not have corresponding elements in other clusters and therefore may represent non-alignable features outside the conceptual theme. Also note that although series within each conceptual theme share some common (alignable) elements, differentiation within any conceptual theme depends primarily on non-alignable features.

In total, the clustering algorithm identified 59 distinct conceptual themes.³ These themes emerged at different points over the course of our observation window and more than one-third (22) of them also went extinct during this period. The most common pattern observed, roughly 25% of niches, involved a rapid increase in the density of series in the theme over the decade after its innovation followed by a decline to only one or two series with the theme.

To provide a better sense of the dynamics within these niches, Figure 2 plots the number of television series over time within four clusters of conceptual themes, numbered 0, 4, 8 and 18 by the SenseClusters package. Cluster 0 groups several drama series that align on the basis of being about police departments (e.g. *Columbo*, *The Mod Squad*, *Chips*). Cluster 4 pulls together dramas with the common feature of involving private investigators (e.g. *Barnaby Jones* and *Private Eye*). Clusters 8 and 18, meanwhile, capture nearly all Westerns, with the first group comprising those that have ranching as a theme (e.g. *Bonanza* and *Rawhide*) while the latter groups those that involve other aspects of the Wild West (e.g., *Lone Ranger*, *Maverick* and *Iron Horse*). As one can see from the graphs, each of these themes enjoyed a peak of popularity followed by a decline.

Figure 2 about here

³To assess the sensitivity of our results to the specific clusters chosen, we also forced the algorithm to create smaller and larger numbers of clusters and estimated the models using those theme definitions (see Table 3).

Estimation

To estimate the longevity of series as a function of its attributes and the ecology of other offerings, we adopted an event-history approach, with the television series-month as our unit of analysis.⁴ In this case, the “event” (dependent variable) is the removal of a television series from the primetime lineup. We coded an event as occurring in the month following the last reported primetime broadcast in Brooks and Marsh (2003). Because series frequently have a break between seasons, we only considered an exit to have occurred if the series did not air again in the subsequent season. Data limitations prevented us from following series after they had left primetime. Although, in theory, a show could move to a daytime slot, in practice, such shifts almost never occurred. One can therefore safely interpret our estimates as factors associated with the discontinuation of the production of a series.

One could estimate the correlates of exit using either continuous-time hazard models or discrete-time methods. We adopted a discrete-time approach, estimated as a panel probit, for two reasons: First, because our data have no left-censoring and a low level of right-censoring, the probit model generally provides more efficient estimates than continuous-time methods (Tuma and Hannan, 1984; Blossfeld and Rohwer, 1995). Second, the use of the probit allows for clearer comparisons across models with and without instrumental variables.

Independent variables

Satiation: The models included a flexible specification for series age. In addition to a count of the number of months (scaled to years) that the series has been in production, *SERIES AGE*, and its square, we included a dummy variable, *NEW SERIES*, for the first season (year) of a series. Given series-level satiation effects, we expected exit rates to rise monotonically with age. But, given that age captures a plethora of maturation and selection processes, we approached this expectation with caution.

⁴Series generally air once per week and therefore the series-week might seem the preferable unit of analysis. But almost none of the covariates change within any particular week. Analysis at the series-month level therefore more appropriately accommodates the serial correlation in the data.

Saturation: Saturation implies that consumer demand depends not only on similar products offered concurrently (t) but also on those that had been offered in previous periods ($t - 1, t - 2, \dots$). To capture this effect, we created a measure for the cumulative proportion of the schedule up to the current period that had been covered by a particular conceptual theme:

$$Saturation_{tj} = \sum_1^{t-1} \sum_{\Omega w/h} d_{j\tau}^{w/h},$$

where $d_{j\tau}^{w/h}$ represents a dummy variable that takes the value one if, in the weekday-hour (w/h) of period τ , at least one network aired a series of theme j . $\Omega w/h$ represents the set of all possible primetime hours ($5 \times 7 = 35$). In other words, we calculated the proportion of primetime slots in a month with a series of a particular theme and then summed that proportion over all prior months. Note that the numerator of this measure only increments by one for two (or more) series of the same theme aired in the same time slot. Because viewers could only watch one of them, we assumed that more than one simultaneously-shown series could not contribute to any particular individual's saturation with a theme. To examine the joint effects of crowding and saturation, we interacted this variable with the crowding measures.

One might expect this saturation effect to decay over time. For example, if no network has produced a Western for a decade, perhaps consumers would once again consider a Western fresh. Note that our measure does effectively incorporate a kind of discounting: To the extent that the intensity of programming in a theme falls below its historical average, our measure does actually decline. We nevertheless also test the sensitivity of our results to incorporating an explicit discount rate (see Table 3).

Crowding: We created multiple measures of crowding to capture differences in the effects of product density depending on whether crowding occurred within- or across-firms and on whether it occurred for conceptually-similar or conceptually-dissimilar themes.⁵ NUMBER OF SERIES

⁵We examined the possible existence of non-monotonic effects for each of these terms by introducing squared terms for each count. We nevertheless only report those estimated as being distinguishable from zero at $p < .05$.

counts all series currently being produced and broadcast by any television network in a month. We would generally expect crowding, on average, to accelerate exit. We then split this count to examine whether a series had been produced by the same firm or by a competitor. For ease of exposition, we use the term “product extension” to refer to crowding within the firm. COMPETITION therefore counts the number of series being aired during a particular month by competing stations while PRODUCT EXTENSION captures the number offered by the same network.

We then further segmented crowding according to conceptual themes (niches) using the 59 categories derived from the series descriptions. THEME COMPETITION counts the number of series within a particular conceptual theme offered by competing networks. NON-THEME COMPETITION meanwhile captures the number of series in any other theme aired by a competing network. PRODUCT THEME EXTENSION counts the number of series within a particular conceptual theme offered by the same network while PRODUCT NON-THEME EXTENSION refers to the number of series shown by the same network in any other conceptual theme. Although crowding, on average, should increase exit rates, one would expect this effect to hold even more strongly within similar series.

Control variables: We also included several control variables. To account for differences in production value, SERIES QUALITY counts the accumulated number of Emmy Awards won by a series. The Emmy Awards, determined by votes of the members of the *Academy of Television Arts & Sciences*, have been given every year since 1949.

We captured potential first-mover advantages associated with introducing a conceptual theme in two ways (Lieberman and Montgomery, 1988). NETWORK INNOVATOR is an indicator variable with a value of one if the network producing the focal series had been the first to introduce that particular conceptual theme (perhaps with an earlier series). SERIES INNOVATOR meanwhile indicates that the focal series itself had been the first in a theme.

To account for inertia and/or learning at the level of the broadcaster, we included both linear

and quadratic terms for NETWORK AGE. To avoid the inclusion of two simultaneous clocks, we defined this variable as the age of the network at the time of the introduction of the series.

Over this period, cable television also became increasingly important. Although these stations produced relatively few of their own series during the period analyzed, they did draw audiences away from the broadcasters. To account for this competition, the models included a control for CABLE SUBSCRIBERS, the number of households subscribing to cable (in thousands). Table 1 reports descriptive statistics for these variables.

Table 1 about here

We also included a large number of fixed effects to partial out any potential confounding effects that might stem from variation in demand for reasons unrelated to satiation and saturation. Time-slot (hour-of-day) and day-of-week fixed effects captured differences in the audience available in different time slots. Month and year fixed effects controlled for seasonal variation in the time spent watching television and competitive shocks, such as the entry of new channels and changes in industry regulation (Radas and Shugan, 1998). We also controlled for time-invariant differences across organizations through the inclusion of a set of indicator variables, one for each television network.

RESULTS

Table 2 reports the results of our probit models, with heteroskedastic-consistent standard errors in brackets. Model 1 represents the baseline model. Model 2 then distinguishes the number of series aired by the same network versus those broadcast by its competitors. Models 3 and 4 next examine variation in the crowding effects by whether they stem from series in the same or in different conceptual themes.

Focusing first on the control variables, we would note that the estimates appeared quite consistent across specifications, in terms of sign, significance and even magnitude. Beginning with the series characteristics, those of higher quality survived longer, as one would expect. At the organization level, although both the linear and quadratic terms for the age of the network had

significant coefficients, the inflection point falls far outside the range of our data. Television series from older producers had monotonically higher probabilities of exit (cf. Khessina and Carroll, 2008). At the industry level, the positive and significant coefficient associated with the number of cable subscribers suggests that cable eroded the audience available to broadcast networks.

In terms of the variables of interest, let us begin with the satiation effects. Series initially suffered from a liability of newness, as indicated by the large coefficient for NEW SERIES. Once they survived the first season, however, the odds of failure fell with series age, though at a decreasing rate. Across all models, saturation had the expected positive and significant effect on product mortality—the probability of exit rose with cumulative entry into the conceptual space surrounding a theme. Repeated consumption of a particular product appears to reduce consumer interest not just for the product itself but also for other similar products (those in the same niche).

Turning to the crowding results, the positive coefficient for the number of series (Model 1) indicates that series introduced into more competitive environments had shorter lifespans, a pattern found also in other settings (e.g., Greenstein and Wade, 1998; Cottrell and Nault, 2004; Khessina and Carroll, 2008). When split by producer, both the number of series aired by a focal network and by its rivals exerted a negative effect on series survival (Model 2). Although series aired by competitors seemed to generate more intense competitive pressure, the magnitude of this difference appears small. Models 3 and 4 then split crowding according to conceptual themes. Surprisingly, series introduced in the same conceptual theme appeared not to compete with the focal series. Meanwhile, series introduced in other conceptual themes seemed to increase the probability of series withdrawal, the canonical effect of competition. At face value, the results suggest that only series with different conceptual themes from the focal series generated competition for it.

Table 2 about here

One could interpret these results as implying that the number of series competing in a conceptual theme raises its legitimacy in the eyes of resource holders and consumers, much as researchers have made sense of positive density effects in organizational ecology

(Hannan and Carroll, 1992). But the need for legitimacy here seems surprising. Television series as a product have almost certainly been accepted as a form of entertainment since the 1950s. These effects, moreover, appear above and beyond the year fixed effects, which should capture any legitimation at the level of television series as a product category.

Another possibility is that product density varies in conjunction with some other factor. In particular, one might worry that conceptual themes with higher levels of product density also have greater inherent attractiveness and therefore may support a larger number of series (i.e. have greater niche-level carrying capacity). To the extent that these differences in popularity remain relatively constant over time, the inclusion of theme-level fixed effects can adjust for them. Model 5 therefore introduces theme fixed effects, eliminating the apparently beneficial effect of within-theme competition.

But these theme-level fixed effects still assume that differences in demand across conceptual themes remain relatively stable over time (except for the effects of satiation and saturation). That assumption seems strong. Anecdotal evidence, for example, suggests that comedies may become more popular during economic recessions (Brown, 2012). And, even if individuals remain relatively consistent in their preferences (except for satiation and saturation), the changing demographics of the population of the United States over such a long period may nevertheless have led to ebbs and flows in the popularity of particular themes.

Rather than trying to imagine all of the factors that might influence the relative popularity of one conceptual theme versus another, we adopted a practical but brute force approach. We created a large number of interaction terms between indicator variables for each of the themes and five different demographic and environmental variables: the share of the population under 18 years of age, the share over 65 years, the share caucasian, the share unemployed and the number of cable subscribers (295 terms = 59 themes \times 5 factors).⁶ To the extent that the demand for particular themes depends on the economy, a particular demographic segment, or competition from cable, these terms give our model considerable flexibility in capturing exogenous (to the product

⁶Data on demographics and cable penetration came from the *U.S. Census Bureau*.

ecology) variation in theme demand over time.

Model 6 adds these interaction terms to the model. Not only do they improve the fit of the model but also they deliver a more sensible set of product density effects. Series with the same conceptual theme now appear more strongly associated with product exit than those with other themes, as one would expect if these series competed more intensely for the same viewers. Only product theme extensions continue to have a positive and significant relationship to series longevity. Given that many of these line extensions share characters or branding, the existence of positive spillovers here seems reasonable. Saturation also appears far more strongly associated with the failure of series than in the models without these interaction terms.

Although the sheer number of interaction terms prevents us from reporting them, some of the coefficients hint at interesting relationships between demographic factors and the demand for particular themes. The popularity of police dramas and family dramas, for example, appeared negatively correlated with the share of the population over 65 years of age. And the popularity of science fiction varied inversely with unemployment, consistent with research that suggests that people prefer more realistic programming during tough economic times (McIntosh, Schwegler, and Terry-Murray, 2000).

Model 7 finally introduces an interaction between theme competition and saturation. The negative and significant coefficient indicates that crowding appeared to produce less competition in saturated niches, consistent with our expectation that later entrants operate at a disadvantage to earlier ones in settings with a large proportion of non-alignable attributes.

Robustness

Although the fixed effects and interaction terms eliminate a wide range of potential confounds, we nevertheless estimated additional models to test the sensitivity of our results to other factors as well as to our modeling assumptions. Table 3 reports the results of a sample of these estimates.

Dynamic panel estimates: An alternative approach to the fixed effects and interaction terms for addressing the potential endogeneity in entry into niches would involve the use of instrumental variables. Valid instruments, however, must predict the variables of interest – competition and product extensions – yet remain uncorrelated with the error term in our model of product exit, conditions that remain elusive in our setting. We therefore explored the sensitivity of the results through the use of a dynamic panel estimator. This method uses as instruments the differences, lagged by one or more periods, in the core variables of interest with respect to their individual (series) means: $x_{it}^{**} = x_{it} - \frac{1}{T_i} \sum_{\tau} x_{i\tau}$ —in our case, the differences in the mean levels of the variables lagged by six months (chosen as the length of a broadcasting season).

Bhargava and Sargan (1983) first proposed this approach; its moment restrictions have been studied by Arellano and Bover (1995). By differencing out the individual series means, this approach eliminates any time-invariant component in the relationship. Lags meanwhile allow the instruments to correlate with our covariates of interest while hopefully remaining uncorrelated with the error term.

Model 8 reports the dynamic panel estimates. Comparing the results with the probit estimates without fixed effects (Model 4), we note that the coefficient associated with competition from series with the same conceptual theme again becomes positive and larger than that associated with non-theme competition. More generally, the dynamic panel estimates appear broadly consistent with the results of the fixed effect models. However, as these dynamic panel instruments only satisfy the exclusion restriction when theme-level sources of endogeneity do not vary over time, we consider these results more supportive than conclusive.

Table 3 about here

Theme definitions: Our initial identification of conceptual themes allowed both the optimum number of themes and the clustering of series into themes to emerge from a clustering algorithm (see the Appendix). Although we have no reason to believe that these clusters do not capture meaningful sets of series – and indeed a visual examination of the cluster memberships suggest

that they seem sensible – we nevertheless wished to assess the sensitivity of our results to this choice. Perhaps audiences actually perceive a more fine-grained schema or perhaps they would not distinguish between some of our themes?

To address this issue, we forced the clustering algorithm to generate both smaller and larger numbers of conceptual themes. Table 3 reports two variants near the extremes on this dimension. Model 9 reports the results using the 90th percentile of the cluster distribution, in terms of the number of clusters identified by the algorithm, with a total of 109 conceptual themes. Model 10, meanwhile, reports the results using the 10th percentile of this distribution, with a total of only 35 conceptual themes. As one would expect, the magnitude of the coefficients – particularly for the saturation effects – increases as the definition of the themes becomes narrower and therefore the series within the themes become more similar. But the pattern of results remains consistent regardless of the number of themes chosen.

Another issue concerns whether a theme can disappear and then re-emerge. On the one hand, the clustering algorithm should handle this issue. To the extent that seemingly similar shows incorporate different elements in one period versus another, the algorithm would assign them to separate clusters. On the other hand, one might believe that these series differ in ways not captured in their descriptions. Models 11 and 12, therefore, treat themes that re-emerge from a period of hibernation as being novel. Model 11 re-sets the theme variables once a theme has been inactive for five years (and therefore has 138 themes instead of 59), while model 12 re-sets it after ten years (resulting in 79 themes instead of 59). These choices have little bearing on the results.

Time discounting: Finally, as noted above, one might expect the saturation of conceptual themes to dissipate over time, as consumers forget about past offerings. To test this possibility, we used various depreciation rates when calculating our saturation measure and re-estimated the model. In general, models using measures with discounting did not fit the data as well as those without but the results remained broadly robust to such discounting. Model 13 reports one example of these models, using a 0.5% monthly depreciation rate (equivalent to a roughly 6%

annualized rate).

DISCUSSION

We proposed that the performance of products – and consequently of the firms that offered them – would depend on the product demography of the niches (submarkets) to which those products belonged. Past research has demonstrated that niches vary in terms of their degree of crowding (competition) and that products perform better on average in less crowded niches (Greenstein and Wade, 1998; Cottrell and Nault, 2004; de Figueiredo and Kyle, 2006). Drawing on research in cognitive psychology, we argued that the demand for products within particular niches depends also on the historical product ecology of these niches, with a large number of recent offerings leading to a satiation of interest in similar products (a process that we refer to as saturation of the niche). We found strong support for these claims in an analysis of the survival rates of all non-fiction television series aired during primetime in the United States, from 1946 to 2003.

To test these ideas, we developed a novel means of classifying products into niches (referred to as “conceptual themes”). Research to date has generally used existing and established category definitions, such as genres, as the basis for constructing niches (Hsu, 2006; Kovács and Hannan, 2010; Negro *et al.*, 2011). But often these categories group disparate sets of products that few consumers would consider substitutes. In other cases, established categories may not even exist. We therefore developed our definitions of conceptual themes by using clustering techniques to identify similarity in the textual descriptions of television series. Differentiation on this dimension proved both systematic and economically meaningful. Given that textual descriptions also exist in a wide variety of other domains – from cultural products to job descriptions to organizations – this approach appears a promising means of segmenting differentiated populations.

Consistent with past research on product demography, we found that crowding at the level of the niche had a negative relationship with the survival rates of television programs. On average, series only had two competing offerings in their niches, and the entry of one additional one

corresponded to an increase of 0.2 percentage points per month in the probability of exit (based on the estimates from Model 7). Given the baseline exit rate of 6% per month, this effect implies a roughly 3% higher hazard rate. By contrast, the entry of a series with a different conceptual theme had an almost negligible relationship with product performance—raising the hazard rate by only 0.5%. We would nonetheless note that both the intensity of diffuse competition and the degree of localized competition appeared far less important to performance in this setting than they have been in past studies of product demography.

Interestingly, this negative relationship for within-theme competition only appeared once we used fixed effects or an instrument to account for potential endogeneity in entry into conceptual themes. The naïve estimates, by contrast, revealed a positive relationship between competition and survival. Given that research on organizational ecology has generally interpreted the positive effects of density as evidence of legitimation (Hannan and Carroll, 1992), one might find it tempting to do so here as well. But the estimation of density effects at the niche-level differs from that at the population-level because the estimates depend on both cross-sectional *and* longitudinal variation. Differences in demand (or intrinsic appeal) across niches can therefore become confounded with legitimacy. Future research that attempts to divide populations into niches should therefore pay careful attention to – and attempt to account for – potential endogeneity in niche-level density.

As expected, we also found that the survival rates of series declined with the saturation of the niche. Saturation, in fact, appeared to have a much stronger relationship with product performance. A one standard deviation increase in the saturation of the niche corresponded to a one percentage point higher probability of exit each month, a 17% higher hazard of exit. Saturation also appeared to moderate the magnitude of the crowding effects, though only to a small degree: The increase in the hazard rate associated with the entry of a series with the same conceptual theme declined from 3% to 2% with a one standard deviation increase in saturation.

Our results have at least three implications for managers in the industry. On the one hand, they provide guidance as to which niches managers might want to enter when considering the

development of series. Interestingly, the recent history of offerings appears a stronger predictor of product success than the current level of competition within a conceptual theme. Managers therefore should probably pay more attention to whether a large number of recent offerings may have saturated consumer demand for a particular sort of product than they should to rivals' current offerings. That should come as comforting news to managers, given that the production cycle in the industry requires nearly one year of lead time to put a new show on air (Granof and Sorenson, 2003).

But some firms have managed to shorten this cycle and being able to do so brings the possibility of benefiting from fast following. Fox, for example, has been experimenting with forgoing pilots (Adalian, 2013)—a risky endeavor but one that might open opportunities as well. If the follower can echo quickly a successful theme innovation, then it can exploit a niche with a relatively low level of crowding before it becomes saturated. On the other hand, if it cannot get there quickly, then managers might better simply attempt to innovate themselves or to revitalize a conceptual theme that has been dormant (Model 11 suggests that saturation may reset if the theme has been out of play for more than five years).

On the other hand, our results also suggest an interesting strategy for protecting the advantages associated with innovating (in conceptual themes). Note that product line extensions do not appear to hurt performance until a network airs seven or more of them during the same season. Producers therefore may have the ability to stave off competition by following successful theme innovations quickly with a number of similar series—effectively saturating the niche. CBS, for example, appears to have pursued this strategy with *CSI*, rapidly introducing spinoff shows following on the success of the original series. By doing so, the innovator may effectively erect barriers to successful entry into the niche; when differentiation depends primarily on non-alignable features, consumers find it difficult to assess the novelty of these imitators and prefer the original series – and perhaps the offshoots – that shaped their expectations for the conceptual theme (Zhang and Markman, 1998).

Our focus on the television industry allowed us to identify novel niche-level dynamics but one

might reasonably question whether these dynamics and therefore the managerial implications might extend to other settings. In answering this question, the nature of product differentiation within the industry seems crucial. In settings such as television programs where differentiation depends more on non-alignable features – those without obvious counterparts across products – than on alignable ones, we would expect similar dynamics to manifest. Many classes of products, such as food, clothing, movies, and music, appear similar in this respect. Saturation might also occur in settings, such as automobiles and computers, where differentiation occurs in large part on alignable differences. In those settings, however, technological progress on these alignable dimensions – such as becoming faster, being able to store larger amounts of data, and becoming more energy efficient – probably swamps any saturation effect.

More broadly, the existence of saturation processes may help to address larger issues in the literatures on corporate demography and on fads and fashions. To date, the focus in both of these fields has been on the adoption side. Legitimacy at an organizational-, industry- or category-level eases access to resources and to consumers, thereby increasing their viability (e.g., Hannan and Freeman, 1977; Strang and Macy, 2001). But products and industries do not last forever. What accounts for their demise? To a large extent, the assumption has been that their decline stems from the arrival of a better idea or product (e.g., Bikhchandani, Hirshleifer, and Welch, 1992) or from failure to meet the expectations assigned to them (e.g., Abrahamson, 1996). Saturation effects, however, suggest that in many cases popularity erodes from within – not from failing to meet expectations but from satisfying and shifting future preferences – paving the way for the next product or trend.

Indeed, these saturation effects may therefore represent an important factor in a variety of cycles—fads, fashions and the decline of certain sorts of organizations and industries. In large part, the focus of research on these cycles has been more on their emergence than on their decline. But many of the mechanisms identified as underlying these diffusion processes – awareness of an idea or product, information about its advantages, legitimation of its form – have an asymmetric character, they can explain adoption and proliferation but not decline. Those explanations of the

end of a fad or fashion have therefore generally relied either on the emergence of a better substitute or on the idea that the original adoption had been based on inaccurate information. Saturation – the idea that the audience’s preferences might systematically change as a result of their past consumption – therefore offers a novel and potentially interesting mechanism for explaining the ebbing of fads, fashions, products and organizational forms.

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Appendix: Identification of conceptual themes

We used the SenseClusters package to identify conceptual themes (Pedersen, 2003). The algorithms incorporated in this package cluster items by simultaneously maximizing the similarity among members of clusters and the dissimilarity across members of different clusters.

We drew on two pieces of information to form the clusters: (i) the genre classifications of the television series, and (ii) the descriptions of the series plot, setting, and themes found in Brooks and Marsh (2003).⁷ On average, each of these descriptions has a length of 188 words, though they vary greatly. By including the genre in the information set, we effectively generated conceptual themes nested within genres (though theoretically if genres grouped incoherent sets of series, the algorithm could have produced conceptual themes that crossed genres).

One of the particularly vexing difficulties in comparing free text stems from the availability of numerous synonyms for almost any important term. Two descriptions might describe almost identical themes without using any common words, other than perhaps articles, prepositions and some common verbs. The SenseClusters package addresses this issue by allowing one to create clusters on the basis of a second-order method. The program first replaces each word in a context with a vector of words with which that word commonly co-occurs. Thus, for example, if “law” tends to appear in the same descriptions with “legal” and “lawyer” more than one would expect by chance, the program would associate every instance of the word “law” not just with “law” but also with these two other related terms. In essence, it replaces each word with a set of synonyms. The program converts each sample of text, in our case, the series descriptions, into a term-frequency vector that sums these related term vectors: $d_{tf} = (tf_1, tf_2, \dots, tf_m)$, where tf_i denotes the frequency of the i^{th} feature in the description.

The CLUTO clustering algorithms (see Karypis, 2003) treat the clustering problem as an optimization process, maximizing or minimizing a particular clustering criterion function. In this

⁷To avoid associations based on relationships unrelated to similarities in conceptual theme, we excluded from the clustering sentences that explicitly referenced others series—for example, in the description of *Q.E.D.*, “The series was produced in England by John Hawkesworth, who was also responsible for the acclaimed PBS series *Upstairs, Downstairs* and *The Duchess of Duke Street*.”

case, our clustering used the cosine function, $\cos(d_i, d_j) = \frac{d_i d_j}{|d_i||d_j|}$, as a measure of the similarity of two descriptions d_i and d_j . To assess the fit of the clusters, we used the criterion function, which has produced excellent results in other settings and has outperformed most other objective functions (see Zhao and Karypis, 2003):

$$I_2 = \sum_{r=1}^k \sum_{d_i \in S_r} \cos(d_i, C_r), \quad (1)$$

where C denotes the centroid and S represents the set of k descriptions to be clustered. The clustering algorithm then maximizes the similarity between each description and the centroid of its cluster.

We did not set an initial number of clusters, instead allowing the program to determine endogenously the optimal number of clusters. The algorithm identified 59 clusters with an average of 39 series within a cluster. Each cluster also has an associated set of labels identifying the words used to classify the series.

To provide a better sense of this procedure, consider the cluster that groups spy/espionage series. The set of words defining this cluster and distinguishing these series from other clusters include: secret agent, government agency, top secret and foreign intrigue. Within this cluster, the algorithm identified 29 series, such as *The Wild Wild West* (CBS) and *The Avengers* (ABC). The first series within this cluster, *The Man from U.N.C.L.E.*, appeared in 1964 on NBC. It's description reads:

The Man from U.N.C.L.E was American television's answer to the very popular James Bond movies. Two super agents, Napoleon Solo and Illya Kuryakin, were teamed to fight the international crime syndicate THRUSH. U.N.C.L.E. (which stood for United Network Command for Law and Enforcement) had its secret American headquarters in New York. Running the office was Mr. Waverly, whose function was to assign agents to cases and coordinate their efforts...

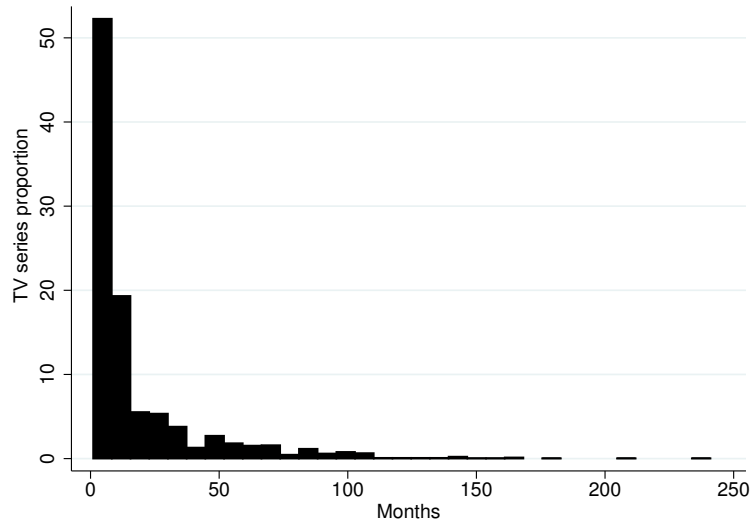


Figure 1: TV series age at exit

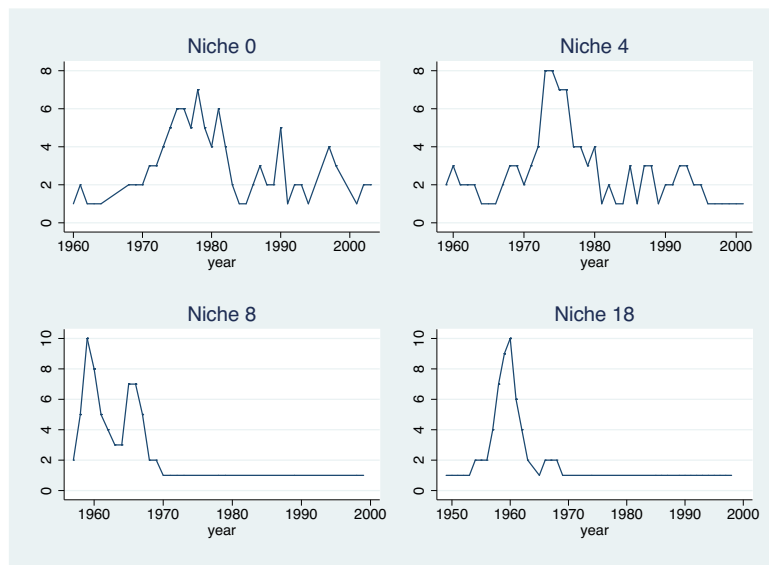


Figure 2: Number of TV series within submarket niches-year

Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
Exit	0.06	0.24	0	1
New series	0.42	0.49	0	1
Series age (in years)	2.33	2.50	0	21
Saturation	0.54	0.63	0.001	3.49
Number of series	60.43	15.07	1	96
Competition	43.38	14.49	0	87
Product extension	17.04	4.97	1	30
Theme competition	1.70	2.28	0	17
Non-theme competition	41.68	14.09	0	87
Product theme extension	1.72	1.23	1	11
Product non-theme extension	15.33	4.93	0	30
Series quality	0.12	0.51	0	5
Network innovator	0.28	0.45	0	1
Series innovator	0.05	0.22	0	1
Network age (in years)	24.40	15.50	0	56
Cable subscribers (in thousands)	28190	26897	0	66732

Note: Unit of measurement is series-month. N:40,608 observations

Table 2: Exit probit model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
New series	0.398*** (0.038)	0.396*** (0.038)	0.387*** (0.038)	0.387*** (0.038)	0.361*** (0.038)	0.330*** (0.041)	0.330*** (0.041)
Series age	-0.073*** (0.016)	-0.074*** (0.016)	-0.072*** (0.016)	-0.069*** (0.016)	-0.054*** (0.017)	-0.034* (0.020)	-0.033* (0.020)
Series age ²	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.003** (0.002)	0.003** (0.002)
Saturation	0.147*** (0.017)	0.148*** (0.017)	0.201*** (0.019)	0.211*** (0.019)	0.085** (0.041)	1.494*** (0.320)	1.556*** (0.325)
Number of series	0.015*** (0.003)						
Competition		0.016*** (0.003)					
Product extension		0.010** (0.004)					
Theme competition			-0.014** (0.007)	-0.013* (0.007)	0.009 (0.008)	0.045*** (0.010)	0.073*** (0.015)
Theme competition × saturation							-0.025** (0.010)
Non-theme competition			0.017*** (0.003)	0.017*** (0.003)	0.016*** (0.003)	0.012*** (0.003)	0.012*** (0.003)
Product theme extension			-0.009 (0.012)	-0.141*** (0.023)	-0.111*** (0.025)	-0.052* (0.028)	-0.051* (0.028)
Product theme extension ²				0.020*** (0.003)	0.015*** (0.003)	0.009*** (0.003)	0.008** (0.003)
Product non-theme extension			0.010** (0.004)	0.010** (0.004)	0.010** (0.004)	0.007 (0.005)	0.007 (0.005)
Series quality	-0.224*** (0.044)	-0.222*** (0.044)	-0.230*** (0.045)	-0.232*** (0.046)	-0.267*** (0.051)	-0.267*** (0.053)	-0.270*** (0.053)
Network innovator	-0.046 (0.028)	-0.047* (0.028)	-0.049* (0.028)	-0.047* (0.028)	-0.023 (0.031)	0.025 (0.037)	0.027 (0.037)
Series innovator	-0.049 (0.070)	-0.047 (0.070)	-0.090 (0.070)	-0.087 (0.070)	0.015 (0.077)	0.130 (0.119)	0.127 (0.119)
Network age	3.425*** (0.087)	3.437*** (0.087)	3.450*** (0.088)	3.408*** (0.088)	3.346*** (0.089)	4.633*** (0.174)	4.648*** (0.175)
Network age ² / 10	-0.003** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.006*** (0.002)	-0.006*** (0.002)
Cable subscribers	0.013*** (0.0001)	0.013*** (0.0001)	0.013*** (0.0001)	0.013*** (0.0001)	0.013** (0.0001)	0.018*** (0.002)	0.018*** (0.002)
Time Slot FE [3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE [7]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE [12]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE [57]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network FE [7]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Theme FE [59]	No	No	No	No	Yes	Yes	Yes
Theme×factor interactions [295]	No	No	No	No	No	Yes	Yes
Pseudo- R^2	0.114	0.115	0.117	0.119	0.131	0.135	0.136
Observations	40,582	40,582	40,582	40,582	40,578	40,578	40,578

Number of fixed effect groups in brackets

Robust standard errors in parentheses

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$

Table 3: Robustness checks - Exit probit model

Variables	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
	Instrumental variable	More themes	Fewer themes	Restart after 5yrs	Restart after 10yrs	Depreciation
New series	0.410*** (0.039)	0.302*** (0.045)	0.412*** (0.040)	0.308*** (0.043)	0.356*** (0.042)	0.286*** (0.041)
Series age	-0.078*** (0.017)	-0.038* (0.023)	-0.047** (0.019)	-0.073*** (0.021)	-0.049** (0.020)	-0.067*** (0.020)
Series age ²	0.006*** (0.001)	0.002 (0.002)	0.004*** (0.002)	0.006*** (0.002)	0.004** (0.002)	0.005*** (0.002)
Saturation	0.291*** (0.045)	10.15*** (0.769)	2.538*** (0.308)	4.602*** (0.494)	4.985*** (0.455)	3.508*** (0.551)
Theme competition	0.031* (0.018)	0.149*** (0.025)	0.055*** (0.011)	0.078*** (0.016)	0.098*** (0.015)	0.077*** (0.019)
Theme competition × saturation	-0.019** (0.010)	-0.101*** (0.038)	-0.015*** (0.004)	-0.021** (0.010)	-0.039*** (0.011)	-0.080*** (0.029)
Non-theme competition	0.020*** (0.005)	0.009*** (0.003)	0.011*** (0.003)	0.008** (0.003)	0.0139*** (0.003)	0.0115*** (0.003)
Product theme extension	-0.174*** (0.041)	-0.121** (0.050)	-0.048** (0.021)	-0.035 (0.029)	-0.057** (0.028)	-0.077*** (0.028)
Product theme extension ²	0.023*** (0.005)	0.028*** (0.010)	0.006*** (0.002)	0.006* (0.003)	0.011*** (0.003)	0.009*** (0.003)
Product non-theme extension	0.014** (0.006)	0.006 (0.005)	0.008* (0.004)	0.009* (0.005)	0.011** (0.005)	0.007 (0.005)
Series quality	-0.217*** (0.046)	-0.381*** (0.064)	-0.255*** (0.047)	-0.284*** (0.061)	-0.235*** (0.052)	-0.258*** (0.051)
Network innovator	-0.038* (0.022)	0.020 (0.033)	-0.032 (0.034)	0.069** (0.029)	0.051* (0.026)	0.069*** (0.026)
Series innovator	-0.106 (0.081)	0.376*** (0.114)	0.224 (0.166)	0.058 (0.089)	0.124 (0.117)	0.167 (0.119)
Network age	3.729*** (0.094)	9.474*** (0.655)	3.159*** (0.111)	-21.15* (12.440)	-95.27*** (3.271)	3.443*** (0.116)
Network age ² / 10	-0.003** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.008*** (0.002)
Cable subscribers	0.014*** (0.0001)	0.031*** (0.001)	0.012*** (0.001)	-0.072** (0.036)	-0.015*** (0.003)	0.014*** (0.0001)
Time Slot FE [3]	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE [7]	Yes	Yes	Yes	Yes	Yes	Yes
Month FE [12]	Yes	Yes	Yes	Yes	Yes	Yes
Year FE [57]	Yes	Yes	Yes	Yes	Yes	Yes
Network FE [7]	Yes	Yes	Yes	Yes	Yes	Yes
Theme FE	No	Yes [109]	Yes [35]	Yes [138]	Yes [79]	Yes [59]
Theme × factor interactions	No	Yes [545]	Yes [175]	Yes [690]	Yes [395]	Yes [295]
Pseudo- <i>R</i> ²	0.1258	0.1356	0.1211	0.1423	0.1300	0.1331
Observations	38,648	40,457	40,586	40,541	40,569	40,581

Number of fixed effect groups in brackets

Robust standard errors in parentheses

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$