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**Abstract.** Because differentiation matters in most markets, populations of competing producers are commonly subject to dual challenges of getting noticed. Producers that do not fit existing market categories have a hard time getting noticed as a viable market, but once they do, getting noticed individually is also difficult. Market audience awareness of relations among producers’ differentiated positions constitutes a network whose increasing density initially attracts entry by heightening perceptions of opportunity, but later deters entry by intensifying competition for attention. Analyses of 1980s computer workstation producers support this hypothesis. Results also show market network density offers accurate estimates of population size and an index of progress toward supplier saturation, the point at which market consolidation begins. These findings extend organization theory by linking the dynamics of markets and related organizational populations to the logic and limits of human categorization and cognition.

(140 words)
It is ironic that density dependence (Carroll and Hannan, 1989b), one of organization theory’s most widely replicated findings (see Hannan and Carroll, 1992; Carroll and Hannan, 2000), is arguably also one of its most divisive. Drawing on organizational ecology (Hannan and Freeman, 1977) and institutional theory (Meyer and Rowan, 1977; Zucker, 1977; DiMaggio and Powell, 1983), density dependence integrates institutionalists’ interest in legitimacy and prevalence (Tolbert and Zucker, 1983: 35) with ecologists’ interest in the population-culling effects of competition. In brief, this thesis states that organizational founding and survival rates are positively related to initial increases in population size because they contribute to a strength-in-numbers sort of legitimacy, but this relationship reverses as continued increases eventually intensify competition for resources needed to survive. Although institutionalists acknowledge density dependence findings as advancing knowledge about how organizational populations grow and decline, they also critique it for inferring legitimacy from population counts; they argue this violates the spirit of institutional theory (Baum and Powell, 1995) by “simply missing” a satisfactory measure of legitimacy, the construct of greatest interest to them (Zucker, 1989: 542). Ecologists, on the other hand, defend density dependence findings as evidence to be taken seriously, even if it infers complex constructs from simple variables (Carroll and Hannan, 1995).

In this paper, I address the important yet unanswered question raised by the debate over density dependence: if population counts do not measure legitimacy, what explains their widely replicated effects on the growth and decline of various kinds of organizations?
The growing literature on organizations and markets offers partial answers to this question. Drawing on institutional theory and ecology, this literature links markets and organizational populations to categories, identities and related networks. For example, Zuckerman (1999) shows that corporate securities get overlooked by financial analysts and discounted by investors when based on business portfolios that are poor fits with widely institutionalized market categories. This finding integrates institutional isomorphism with ecology’s principle of allocation, the idea that diffuse identities undermine fitness with the environment by forcing organizations to allocate limited capacities for conformity across multiple niches (Hannan and Freeman, 1989). Consistent with Hannan, Pòlos, and Carroll’s (2007) move to refine this principle by linking fitness to audience perceptions of how well organizations fit multiple socially constructed categories, studies show that organizations generally do worse when they fit several categories imperfectly rather than fitting one very well (Hsu, 2006; Hsu, Hannan, and Koçak, 2009; Leung and Negro, 2009). Overall, however, these advances relate fitness to counts without exploring how a growing group of misfits gets noticed as a category of their own.

Studies of market formation and change provide further clues about how counts affect producer populations. Extending White’s (1981; 2002) conceptualization of markets as categories and networks, Porac and collaborators offer a sociocognitive view of markets (Porac, Thomas, Wilson, Paton, and Kanfer, 1995; Rosa, Porac, Runser-Spanjol, and Saxon, 1999; Rosa, Porac, and Saxon, 2001), but this view does not yet address producer population dynamics. Although Haveman and Rao (1997: 1607) show that thrift organizations co-evolved with related institutional logics (Friedland and Alford, 1991), their account of form emergence does not explore how categories and counts are constructed. Reflecting the idea that both meaning and
social structure are dually constituted (Mohr, 1998), institutionalists link field evolution to the
dynamics of interorganizational networks (Powell, White, Koput, and Owen-Smith, 2005) and
public discourse about markets (Lounsbury and Glynn, 2001), but these advances stop short of
relating field or market emergence to categorization or cognition. Leveraging work that links
media coverage to corporate visibility and reputations (Deephouse, 2000; Rindova, Petkova, and
mutual fund categories to product innovations that tweak existing categories by “reconstituting”
their elements in new ways, but this work does not attempt to relate category change to counts of
similar deviants. While these studies do much to explain category formation, they do not theorize
links to the origins or effects of population counts as observed in density dependence.

Toward a deeper understanding of the effects of population counts seen in density dependence,
this research relates the dynamics of producer populations in monopolistically competitive
markets to aspects of categorization and cognition that govern audience capacity to see markets.
Specifically, I argue that producer populations are affected by dual challenges of getting noticed:
getting noticed as a viable new market is hard for producers that do not fit existing categories,
but getting noticed individually eventually becomes difficult for producers that do. Building on
the sociocognitive view of markets (Porac, et al., 1995; Rosa, et al., 1999; Rosa, et al., 2001) and
the idea of cognitive embeddedness (Zukin and DiMaggio, 1990), this argument relates both
kinds of getting noticed to cognitive embedding, a mechanism for populating market categories
by building up a market audience’s knowledge about both who competes with whom (Porac and
Rosa, 1996; White, 2002; Kennedy, 2005) and what a category means (Mohr, 1998). To model
this knowledge and relate it to producer population dynamics, I use the connections news stories
make among market entrants to build a panel of networks I call market networks, and I hypothesize an inverted U-shaped relationship between entry and market network density. That is, increasing market network density initially attracts entry by heightening perceptions of opportunity, but it eventually deters entry by intensifying competition for attention.

After developing this argument, I test it in a study of 1980s computer workstation producers. Controlling for density dependence, results support the hypothesized relationship between entry rates and market network density. Also, they show that market network density offers accurate estimates of population size and a potentially practical measure of progress toward supplier saturation, the point at which producer populations begin to consolidate. These findings extend organization theory by linking the dynamics of markets and related organizational populations to counts and their micro-foundations in human categorization and cognition.

**HOW POPULATING CATEGORIES AFFECTS MARKETS**

In monopolistically competitive markets (Chamberlain, 1933; Robinson, 1933) where differentiation matters, audiences allocate demand—the most basic resource for organizational survival (Tushman and Anderson, 1986: 448)—according to both categories for making sense of markets (Rosa, et al., 1999; Zuckerman, 1999; Hsu, 2006; Hannan, et al., 2007) and appreciation of producers’ distinctive capabilities (Penrose, 1960; Barney, 1991; Helfat and Peteraf, 2003). Thus, while tangible resources and operational routines are obviously important factors in market and industry evolution (Nelson and Winter, 1982), competing producers must also get noticed in two ways: for belonging to a category people understand, and for standing out within it.
Therefore, populating a nascent market category has competing effects on its attractiveness to potential entrants. While filling a category conveys credibility that attracts new entrants, it also leads to competition for attention that eventually deters entry. Getting noticed would not affect the growth and decline of producer populations if market audience capacity to follow within-category differentiation were unlimited, but this capacity is limited. To explain this, I turn now to sociocognitive facts that govern the dual challenges of getting noticed and explain how they affect producer population dynamics.

**Categories and Cognitive Embedding**

The shared interest in categories seen in organizational studies of markets and industries owes much to White’s (1981) argument that markets emerge from social comparison in which rivals see an image of consumer demand by watching each other’s commitments to varying volume and price points. To know whom to watch, however, producers must first understand who their rivals are (Kennedy, 2005) and where they fit in the category they define together (Porac, et al., 1995). Thus, categories set cultural standards of legitimacy (DiMaggio, 1997; Scott, 2001) and the context for competitor analysis (Porter, 1980; White, 2002).

For competitors not yet seen as a recognizable type of organization, getting noticed as a category requires a macro-level analog of organizational sensemaking, as defined by Weick (1995: 3). As public speculation about such misfits notes their similarities, it recasts them as instances of a new social entity—that is, as having the property Campbell (1958) called entitativity. For misfits to be seen as examples of a new reality in the natural order of things, they must overcome their
tendency to be overlooked (Zuckerman, 1999), and for that, it is necessary to take a name and reach general agreement about what it means (Quine, 1960; Kripke, 1972). Thus, categories depend on shared recognition of instances’ relatedness. These observations reflect Peirce’s (1992: 141) notion that people theorize concepts not by deductive or inductive logic, but by “hypothesis”, a style of reasoning Peirce also called “abduction” and “retroduction” because it involves capturing patterns by reasoning backward from cases to categories. Organizational scholars are increasingly using abduction to explain both theorizing and the process of discovery more generally (Van Maanen, Sørenson, and Mitchell, 2007).

To get noticed as constituting a legitimate market category, competing producers must become embedded in socially shared schema for what it means to be a particular kind of organization—Zukin and DiMaggio call this cognitive embeddedness (1990). Although research shows that cognitive embeddedness affects organizational performance in monopolistically competitive markets (Porac and Rosa, 1996), less is known about how producer population dynamics relate to the process of creating and populating new categories by embedding them in shared knowledge structures. Prior analyses show that organizations can shape categories to their advantage by publicizing links to a limited number of rivals, but this strategy’s positive effects reverse as a market category develops (Kennedy, 2008). This suggests links between cognitive embedding and producer population dynamics that have not yet been developed.

Because collective awareness of new market categories is essential to populating them, the media is a crucial venue for market sensemaking. Since journalism’s norms protect reporter independence (Schudson, 2001), news stories offer “social proof” of new categories (Rao, Greve,
and Davis, 2001) and help new kinds of businesses to develop reputations that attract resources (Pollock and Rindova, 2003; Rindova, et al., 2007). News stories about new categories contribute to market formation (Lounsbury and Glynn, 2001). As Rosa et al. (1999:69,68,74) show in their analysis of the emergence of the market for minivans, stories do this by building “consensus around product representations” and making “connections among products” (and producers) that shape “conceptual systems of consumers and other producers.”

Linking market categories to media-based sensemaking about connections among producers makes it possible to define cognitive embedding more tangibly. Market networks are built up by media coverage every time a news story mentions two or more producers together. Co-mentioning competing producers calls public attention to them and the connection between them. As a market news story co-mentions two or more competitors, it effectively expands a market network by adding a node for any previously unmentioned organization, and it fills it in by adding pair-wise links between all co-mentioned producers. Of course, market audiences forget some connections, which can be modeled by dropping connections that are not repeated. As this process creates and populates categories, it builds market networks that model a market audience’s collective view of producers’ differentiated positions and how they are related.

As media-enabled cognitive embedding builds up a growing collection of connections among firms, it produces market networks that reflect not only who competes with whom, but also what a category means (Mohr, 1998). Using networks to model meaning follows similar work in cognitive science that builds “semantic networks” to reflect how humans encode, retrieve and manipulate meaning (for an overview, see chs. 2-4 of Stillings, Weisler, Chase, Feinstein,
Garfield, and Rissland, 1995). In organization studies, Carley and collaborators captured teams’ mental models of concepts using semantic networks (Carley and Palmquist, 1992; Carley, 1997; 2002; Carley and Diesner, 2004).

**Perceived Opportunity and Competition**

Cognitive embedding offers a theoretical link between producer population dynamics and the process of populating a market network so that it becomes larger and more connected. Making use of the idea that a network’s connectedness is its density, or the ratio of actual to possible connections among items whose relations are being modeled (see Wasserman and Faust, 1994), I argue that increasing market network density initially helps a nascent group of competing producers get noticed as a category by heightening perceptions of opportunity, but it eventually makes it harder for any single producer to get noticed individually by intensifying competition for attention. Because cognitive embedding constructs the categories that enable population counts, the market network density it produces should have the same inverted U-shaped relationship to entry that population density does. To avoid confusion, I henceforth refer to population density as a population’s size, or count, and I use symbols for market network density as defined below, in Methods. The following sections elaborate this argument.

*Perceptions of Opportunity.* In a study of alliance networks in biotechnology, Powell, White, Koput and Owen-Smith (2005) show that increasing network density supported field formation and perceptions of opportunity by “suggesting a more connected field” (Powell, et al., 2005:
As the number of organizations connected by the alliance network grew, the density of the network grew at a faster rate, making the population more visible as a coherent identity.

A similar logic applies to media-based market networks. As a population of competing producers expands, the density of market networks based on producers co-mentioned in the media grows at a faster rate. By broadcasting connections to market audiences, the media heightens cognitive availability of covered firms. This availability makes the nascent producer population more visible and plausible as a distinct entity (Weick, 1995), which helps producers attract resources (Pollock, et al., 2008). This argument mirrors work in computer science that links the evolution of networks to their “densification”, or increasing density (Leskovec, Kleinberg, and Faloutsos, 2007). Thus, increasing market network density heightens perceptions of opportunity.

More familiar non-network arguments offer similar predictions. Growth in sales and producer population suggest opportunity and invite entry (Porter, 1980: 18), so when a nascent market is seen as growing, increasing size initially attracts entry by conveying legitimacy (Carroll and Hannan, 1989b). In nascent markets, the legitimating benefits of stories about the category go to all entrants, not just those covered most (Lounsbury and Glynn, 2001).

*Competition for Attention.* As producer populations and related market networks grow in size and density, producers have to work harder to get noticed individually for their unique capabilities. Despite the well-known cognitive limits of individuals (Simon, 1947; Miller, 1956; Simon, 1974), one might expect larger audiences to have fewer limitations when it comes to being aware of how producers’ differentiated positions relate to each other, but there are two
reasons this is not so. First, just as the number of connections a network can contain grows exponentially with its size (see Wasserman and Faust, 1994: 101, 103), the number of competitor interactions to be aware of in a producer population also grows exponentially with its size. Second, categorization focuses attention on producers that best represent a category rather than distributing it among all of them. Together, this makes for the “wealth of information” that, as Simon famously observed, “creates a poverty of attention” (1982: 40).

To elaborate, the logic of categorization makes competition for attention a central feature of monopolistically competitive markets. Whereas organizations overcome individual cognitive limits by employing hierarchical divisions of labor to distribute attention (Simon, 1982), market audiences cope with overwhelming volumes of news and information by using categories as filters. Because categorization economizes cognition by organizing attention around prototypes (Rosch, 1978: 261; for a nice overview, see Rosch and Lloyd, 1978), categorical divisions of labor focus attention rather than distributing it (Zuckerman, 1999: 1404). Studies that ask participants to classify objects show they are faster and surer at it for items that are more typical of a category (Mervis and Rosch, 1981), and participants asked to list members of a familiar category list prototype-like items first and fastest (Rosch, Simpson, and Miller, 1976). These findings suggest prototypes are highly central in network models of categories, so links in a market network should follow the distribution seen in many naturally occurring networks: an inverse power law that focuses links on a few prominent nodes (Barabási and Bonabeau, 2003). Competition for attention thus arises as contests to define market conceptions (Fligstein, 1996) confer advantage on producers identified with categories (Lieberman and Montgomery, 1988).
This idea that market audience attention is limited may appear to clash with Fama’s (1970) efficient market hypothesis, the proposition that prices in securities markets incorporate all relevant information, but I am not arguing that categories blind audiences to data relevant to valuing the stocks of companies they are inclined to follow. Rather, I follow Zuckerman (1999) in arguing that deviating from category prototypes will make it harder for competitors to attract audience attention. As mentioned, one might think a large enough market audience should have no reason to struggle following how even a growing number of differentiated positions relate to each other, but that depends on audience heterogeneity. In an audience whose members think exactly alike, everyone would follow the same competitors, so the audience’s view of the market could be no different than an individual’s. Conversely, if tastes are so diverse that producers all have an equal chance of being seen as the category prototype, the number of unique competitor-to-competitor interactions an audience can follow cannot exceed the number of possible prototypes—population size—times the number of producers a member can follow. This assumes audience members make similar judgments about which competitors are alike.

Furthermore, market segmentation might appear to expand a market audience’s capacity to track interactions among competitors’ differentiated positions. In a sense, this is true: large audiences can and do split into viable subgroups based on common interests in subsets of larger producer populations. Even when market segmentation does not produce clearly nested subcategories, however, this mechanism for breaking categories down is consistent with the idea that there are limits to a market audience’s capacity to track within-category differentiation. As noted above, this argument is specific to markets where differentiation matters, so things are likely to be different in markets that are defined around commodities or driven by automated purchasing.
HYPOTHESES

I now translate the foregoing argument into hypotheses that relate market network density to periodic entry rates, overall producer population levels and supplier saturation.

Market Entry. Consistent with the argument above, market network density should have an inverted U-shaped relationship to periodic entry rates. That is, entry should be positively related to initial increases in market network density, but negatively related to continued increases. Since market networks supports categorization and related counts, this leads to a first hypothesis:

Hypothesis 1: Controlling for the competing effects of population size, the increasing density of a market network initially attracts market entry but later deters it.

Extensions of density dependence argue and show that “perceptually focused” de novo organizations help a nascent group of competing producers get noticed as a category, but de alio entrants already operating in other businesses do not (McKendrick, Carroll, Jaffee, and Khessina, 2003). Thus, I also test H1 with controls for the competing effects of de novo producers.

Producer Population. In markets where differentiation matters and geographic scope is wide (national or global), changes in market network density should also be closely related to changes in overall producer population levels. The geographic scope of competition matters because location is likely to trump audience awareness of producers’ differentiated positions in markets with smaller trading areas and more commodity-like competition. In markets with far-reaching distribution channels, however, awareness of a firm’s differentiated position plays an important
role in its viability. In such markets, increasing market network density should have competing effects not only on entry rates but also on population levels. This leads to a second hypothesis:

**Hypothesis 2:** Initial increases in market network density are positively related to producer population levels, but continued increases reverse this relationship.

This may not apply in markets where specialized human resources are scarce or hard to move. For example, Stuart and Sorenson (2003) show that founding of biotech companies rose in cities with existing firms that recently raised initial public offerings of stock or were sold, but not in states with laws that permit employers to sue employees for joining or founding competitors. Similarly, Marquis and Lounsbury (2007) show that bank acquisitions led to new foundings in cities whose labor markets offered an ample supply of experienced banking professionals.

*Category Saturation.* Because producer populations peak at different maxima from market to market (Freeman and Audia, 2006), specific values of population size are not useful indicators of progress toward supplier saturation even though competitive intensity generally increases with the number of competing producers (Porter, 1980). Recall that supplier saturation is the point at which market consolidation begins because competition forces weaker producers to exit while strengthening surviving organizations (Barnett and Sorenson, 2002; Barnett, 2008).

Unlike population counts, however, market network density is subject to a predictable maximum. To explain why a market audience’s capacity to track relations among competitors’ differentiated positions does not scale with its size, consider how a market entrant’s ability to attract audience attention is like a new group member’s ability to attract friends from a clubby group. When a
group’s members already have as many friends as they can each make and maintain, a newcomer seeking friends must steal them, so to speak. Similarly, when a market audience is already aware of as many rivalry relationships as it can observe and retain, the only way new entrants can attract the attention needed to find demand is, again, to steal it. Both market and friendship networks have conventional network densities that peak at far less than 1, but conventional network density can be rescaled so that values near 1 correspond to maximum connectivity based on theory about the relations being modeled—whether friendships or audience awareness of market rivalries. I use the term saturation density to refer to this theory-driven re-scaling of network density. As defined in the methods section and Appendix A, saturation density dampens conventional density’s interaction with network size (Anderson, Butts, and Carley, 1999) so that it follows the S-shaped pattern of producer population trends. This leads to a final hypothesis:

**Hypothesis 3:** Trends in saturation density and producer population are closely related.

To be clear, I am not arguing that market network saturation density causes producer population growth, nor the reverse. Not every growing population gets noticed and counted as a category, and vice versa—categories are often defined around populations imagined but not yet observed. Rather, producer populations and categories co-evolve in monopolistically competitive markets. Obviously, a single market category cannot address the generality of the theorized link between population counts and market networks, but it can at least inform further research that may do so.
METHODS

I test this study’s hypotheses in analyses of producers of computer workstations, a distinct product market category that emerged in the 1980s. These analyses use data developed from new methods for going from a large media corpus—over 40,000 single-spaced pages—to market networks based on producers mentioned together in the news. Stories range from short blurbs about earnings or management changes to brief coverage of product news to longer stories comparing products and strategies. As argued above, the media provides a mirror of demand (White, 1981), and entrants get their information about market developments more from media coverage than from the direct public statements of producers (Kennedy, 2005). This fits with the argument that attention limits make media coverage important in markets (Hoffman and Ocasio, 2001). Analyzing entry and market population provides the opportunity to test whether and how media-based market sensemaking affects market dynamics, as predicted.

Site and Period: Computer Workstations from 1980 to 1990

Reflecting research at SRI and Xerox PARC in the 1960s and 1970s, Apollo Computer introduced the first commercial workstation in 1981. The first computer workstations put power previously seen only in a cupboard-sized minicomputer into end table-sized carts still too large to be mistaken for suitcase-sized box of a personal computer (PC). Though workstations were neither cheap enough to be personal computers nor powerful enough to serve departmental computing needs, they quickly found a following among scientists and engineers whose demanding computing needs were poorly served by shared minicomputers or mainframes. For
further background, see Bell (1986) for an overview of the evolution of different categories of computing machinery, Goldberg (1988) for a history of workstations, and Sorenson (1997; 2000) for analyses of changing forms and strategies of workstation producers.

Following the first media coverage of workstations in 1980 and Apollo’s first product in 1981, the early 1980s saw a stampede of entry. By the late 1980s, however, the producer population began consolidating until Intel Corporation released the 80486 in 1990, a microprocessor that enabled high-end PC manufacturers to produce machines with workstation-like power. As this blurred the lines between workstation and PC categories, the resulting re-definition of the market led to a new wave of entry (see Sorenson, 1997). As illustrated by this development, category-blurring is important to defining markets (Hannan, et al., 2007), but this research focuses on a simpler case to understand how connections among items within a single category affect the formation and consolidation of markets and related producer populations. Therefore, I limit analysis to 1980-1990, the period before differences between the workstation and PC categories began to blur. For this period, Figures 1 and 2 show annual total market revenue in billions of dollars and quarterly producer population with entries and exits.

**Data Sources and Collection Methods.** Using the industry catalog *DataSources* and LexisNexis, I assembled the quarterly producer population data shown in Figure 2 by counting producers that had entered by shipping workstations, but not yet exited, sold or failed. Yearly market revenue were obtained from the U.S. Industrial Outlook (1991) and Afuah (2000). From 1980-1990, there were 107 market entrants and 54 exits. While population size follows the S-shaped curve seen in diffusion of new types of organizations, total revenue growth was still growing steeply in 1990.
I collected the corpus of roughly 20,000 news stories from Lexis-Nexis archives. These stories were pulled from publications ranging from daily newspapers to national business magazines to specialized trade publications. To ensure each story mentioned computer workstations, I used a search term that distinguished computer workstations from furniture and personal computers. The corpus is organized into quarterly volumes for analysis.

To extract quarterly market networks based on producer co-mentions in corpus stories, I adapted the idea of relational content analysis (Carley, 1990) to develop new techniques and a custom software tool. From a list of terms for each organization, the tool finds mentions by story and uses them to create a co-mention network; for an illustrative example of this method, see Kennedy (2008), Appendix A. As argued above, market networks produced in this way provide models of how a market audience sees both relations among competitors and, therefore, the market overall. This approach offers a tractable way to reduce large amounts of text to market networks that can be analyzed quantitatively.

**Independent Variables.** This study’s main independent variable is market network density. In addition to using the conventional measure of network density, or ω (Wasserman and Faust, 1994: 101), I developed a new measure more suitable for assessing progress toward the saturation of a market audience’s capacity to track differentiated positions within a single category. I call this new measure *saturation density*, or Ω. As explained in detail in Appendix A, Ω re-scales ω to dampen ω’s interaction with network size (Anderson, et al., 1999) and produce the value “1” when network connectivity reaches an expected maximum level based on by the cognitive limitations of individuals and the overall market audience.
Since the hypothesized effects of market network density are curvilinear, I also created squared versions of $\Delta$ and $\Omega$. Because a variable’s linear and quadratic versions are typically highly correlated, including both in models can lead to estimation problems that require techniques for reducing factor correlations so that multi-collinearity diagnostics fall within acceptable ranges. Looking ahead to the descriptive statistics, Table B1 in Appendix B shows high correlations that raise these concerns. Since model diagnostics from analyses of market entry further suggest the possibility of multi-collinearity problems, I used mean-centering and residualization to transform both measures and their squares. As explained below, this eliminated multicollinearity problems. The primary results tables use these transformed variables, but results obtained from untransformed variables are also reported in Appendix B.

Market network density measures are lagged by one quarter. Lags of 2, 4 and 8 quarters were also used in sensitivity analyses.

**Dependent Variables and Estimation Techniques**

The dependent variables are quarterly observation of entry rates and market population. For the period 1980-1990, this gives 44 observations, but that amount is reduced in analyses by the lag used for independent variables. Since the data show no evidence of over-dispersion ($p=.50$), I used Poisson regression for analyses of period counts of entry events. As expected, negative binomial regressions produced the same results. All models were estimated in Stata.
In addition, non-linear regression is used to assess the fit between population density and the saturation of the market networks. Stata provides a non-linear regression routine that is used to fit the following function:

\[ N = b_1 \cdot \Omega_{t-x} + b_2 \cdot \Omega^2_{t-x} + b_3 \cdot \Omega^3_{t-x} + \varepsilon \]

where \( N \) is population density; \( b1-3 \) are model coefficients for the linear, quadratic and cubic effects of \( \Omega \), or saturation density; \( t \) is the analysis period; and \( x \) is the lag used for \( \Omega \), in quarters. I used lags of 1, 2, 4 and 8—that is, lags from one quarter to 2 years.

**Controls**

Because larger, highly concentrated markets generally offer less opportunity, I control for market revenue (in billions of US dollars) and 4-firm concentration ratio in analyses of market entry. Also, the total size of the market was controlled for using the log of the total number of full-time employees in all entrant organizations. Though this is a noisy control of industry size, it follows past precedent and makes the most of limited data.

To control for density dependence (Carroll and Hannan, 1989b) and its breakout into entries by dedicated startups versus established companies (McKendrick, et al., 2003), entry analyses also control for prior period levels of overall population and its square (test of H1) and its breakout into linear and quadratic versions of the prior period count of \textit{de novo} and \textit{de alio} producers (test of H2). Analyses were also run with only linear terms, and were significant in both cases.
Because controlling for the curvilinear effects of total population provides the more stringent control, results are reported with both linear and quadratic terms.

In the simpler analyses of producer population levels, controls include period, and the log of total market size, in employees. Because the non-linear regressions of population density on saturation density are meant to measure the fit between these two variables, no controls are used.

RESULTS

Table 1 shows descriptive statistics for the entry analyses. For 43 period observations, entries range from 0 to 9 per period, with the high mark occurring in period 16, which is the fourth quarter of 1983. From 0 in 1980, producer population peaked at 74 in the second quarter of 1988. The number of dedicated workstation producers peaked much earlier, reaching 28 in the fourth quarter of 1984; the number of *de alio* producers did not peak until 1988. From that point, the population declined steadily through 1990, but, as noted earlier, Figure 1 shows that total market revenue continued growing rapidly even as the market population began to decline.

Entry rate, population level, and market network density were observed for each quarter. From no firms and no connections, the market network density hit its maximum in the first quarter of 1988. Conventional network density, or $\Delta$, peaked at .31; saturation density, or $\Omega$, peaked at just over 1. Figure 3 shows the expected interaction between $\Delta$ and population size as an early peak, but $\Omega$ dampens this peak, as predicted. When $\Omega$ is smoothed by a 2-year moving average, it is nicely S-shaped, or sigmoidal, flattening out around .75. Sensitivity analyses of values of $\Omega$'s
tunable parameter $\omega$ show that smaller values (3-5) inflate $\Omega$’s maximum but show more of $\Delta$’s interaction with size, which worsens results. Larger values of $\omega$ (6-9) do more to dampen this interaction while also shifting the maximum down toward and below 1. For these larger values, changes do not alter the patterns of statistical significance reported in the results, below.

As mentioned above, linear and quadratic versions of several model factors are highly correlated; see Appendix B, Table B1. In analyses using untransformed factors, variance inflation factor (VIF) scores exceeded 100—well over guidelines that suggest keeping them below 10 (Greene, 2000) or, in certain situations, below 40 (O’Brien, 2007). Therefore, I mean-centered and residualized key independent variables$^1$. With these transformed factors, VIF scores dropped below accepted guidelines (see Snee and Marquardt, 1984). Also, coefficient standard errors were reasonable; and removing single observations did not change results. To be conservative, I report results based on transformed factors, but because results using untransformed factors do not show signs of multicollinearity other than VIF scores, report those also in Appendix B.

**Analyses of Market Entry**

Table 2 shows results of the analyses of market entry. Model 1 includes controls for the total market revenue in billions of US dollars, a 4-firm concentration ratio, and a mean-centered version of producer population size and its square, divided by 100 to ensure non-zero digits in

$^1$ Mean-centering subtracts individual observations from a factor mean; this lowers correlations between a factor’s linear and quadratic versions and reduces the likelihood of multi-collinearity problems. Residualization uses one factor to estimate another and subtracts estimated values of the second factor from the first to leave a ‘residual’ not explained by the first. This zeroes correlations between the first factor and the residualized second factor.
the reported coefficient. The revenue coefficient is significant and negative, indicating that entry rates fall with sales growth, as expected. Because market leaders emerged quickly, the 4-firm concentration ratio varies over a limited range and therefore is not significant. Model 1 results show the expected opposite signs for mean-centered producer population size and its square, but coefficients are not significant. Because using raw versions leads to VIF scores near 50 (well over the reported condition index of roughly 38), I mean-centered these factors by subtracting each observation from the mean; for the quadratic term, these values are squared. This drops the top VIF score to 3.50, well below the condition index of about 14. While this eliminates multi-collinearity concerns, it also eliminates significance of the producer population coefficients. As explained below, however, the untransformed factors are significant; see Appendix B, Table B2.

Models 2 and 3 show two tests of H1, the predicted inverted U-shaped relationship between market network density and entry. The first test uses Δ; the second, Ω. As mentioned, both measures are residualized. This lowers correlations and drops VIF scores from well over 100 to 22.8, comfortably under the model’s condition index of 28. While some texts suggest 10 as a threshold for VIF scores (Greene 2000), values of 30 or higher are acceptable if condition indices are higher (O'Brien 2007). As a baseline test of H1, Model 2 uses Δ. Results show that adding Δ and Δ² produces the expected opposite signs (Model $\chi^2 = 14.34$, d.f. = 2, $p < .01$) with marginal significance on the linear term ($p < .10$) and stronger significance on the quadratic term ($p < .01$). Model 3 uses Ω instead of Δ, which is the primary test of H1. Coefficients for prior period Ω and Ω² are significant ($p < .05$ and $p < .01$), as is model change (Model $\chi^2 = 15.80$, d.f. = 2, $p < .001$). These results show strong support for H1.
Models 4 and 5 show results of a replication test of the McKendrick et al. (2003) finding that the legitimating effects of producer population growth are driven by “perceptually focused” de novo producers (i.e., dedicated startups), not de alio producers also active in other markets. Model 4 shows results for mean-centered versions of the lagged count of de alio producers and its square. Coefficients are not significant, but model improvement is (Model $\chi^2 = 10.79$, d.f. = 2, $p < .01$). When residualized versions of de novo producers and its square are added, coefficients are significant at the $p < .05$ levels, albeit with marginal model improvement (Model $\chi^2 = 5.11$, d.f. = 2, $p < .10$). This offers encouraging support for McKendrick et al. (2003). Results based on untransformed factors follow the same pattern of significance; see Appendix B, Table B2.

Models 6 and 7 show results for two tests of H2, the prediction that the inverted U-shaped relationship between market network density and entry should hold when controlling for breakouts of population density into separate counts for de novo and de alio producers. The first test uses $\Delta$; the second, $\Omega$. In the baseline test, Model 6 shows that adding $\Delta$ and $\Delta^2$ yields significant model improvement (Model $\chi^2 = 11.14$, d.f. = 2, $p < .01$) and produces the expected opposite signs with marginal significance on the linear term ($p < .10$) and stronger significance on the quadratic term ($p < .01$). Replacing $\Delta$ with $\Omega$, Model 7 shows results for the main test of H2. With significant model improvement (Model $\chi^2 = 13.31$, d.f. = 2, $p < .01$), coefficients for prior period $\Omega$ and $\Omega^2$ are both significant, though the linear term is only marginally significant ($p < .10$). Taken together, results for Models 6 and 7 provide encouraging support for H2. Table B2 shows the same pattern of results for H1 and H2 using untransformed independent variables.
Analyses of Producer Population

Table 3 shows two tests of H3, the hypothesis that producer population levels follow an inverted U-shaped relationship to lagged market network density. While coefficients for conventional market network density are not significant (Model 2), the primary test of H3 is supported. Model 3 shows results for adding period $\Omega$ and $\Omega^2$ to the control model; both coefficients are significant ($p < .01$; Model $\chi^2 = 13.69$, d.f. = 2, $p < .01$). Thus, producer population has the predicted relationship to a market network’s saturation density, but not to its conventional density.

A close look at Figure 3 helps explain why market population has an inverted U-shaped relationship to $\Omega$, but not $\Delta$. Note that $\Delta$ features an early peak that is a poor fit with the producer population line’s S-shaped curve. This peak is an artifact of the interaction between size and conventional network density (Anderson, et al., 1999). In contrast, the line for $\Omega$ dampens this interaction, largely eliminating the early peak.

Figure 4 and Table 5 show support for H4’s predicted relationship between overall producer population levels and a cubic function of $\Omega$. A visual inspection of Figure 4 shows that $\Omega$ plateaus just after producer population begins to consolidate. As predicted, $\Omega$ and producer population follow very similar patterns. As a statistical test of the goodness of fit between the two, Table 5 tests shows results of a non-linear regression that estimates producer population as a cubic polynomial function of $\Omega$ at lags of 1, 2, 4 and 8 quarters (Models 1-4, respectively). Results show that $\Omega$ is an excellent predictor of market population. With strong statistical significance ($p < .001$), adjusted $R^2$ values remain very high even as the lag is increased from
one quarter to two years. At a 1-quarter lag, the adjusted $R^2$ is 0.98; at a 2-year lag, the adjusted $R^2$ drops to a still high 0.90. As this analysis includes only one market that succeeded, even this very strong relationship is still weak evidence that $\Omega$ values are clearly related to the onset of consolidation, but it does lend plausibility to the theorized linkage.

**Robustness Checks**

I also performed a number of additional analyses to explore the robustness of the results reported above. As described above, the primary independent variables in Model 2 were mean-centered and residualized to rule out the possibility of spurious significance due to potential multicollinearity problems. These results show coefficient significance for the variation in $\Omega$ and $\Delta$ that is uncorrelated with conventional population density, but this is not the same as the effect of the untransformed versions of $\Omega$ or $\Delta$. In Appendix B, Tables B1 and B2 show the correlations among factors and results for the same set of analyses when run using the untransformed versions of $\Omega$ and $\Delta$. The pattern of significance is the same, but the coefficients for the linear and quadratic versions of $\Omega$ and $\Delta$ are, of course, larger. Besides the high VIF scores obtained after linear regressions, the Poisson regressions did not show other signs of multi-collinearity such as large coefficient standard errors or susceptibility to deletion of select data points.

Also, I performed sensitivity analyses to explore the robustness of $\Omega$’s relationship to entry. Specifically, I used Poisson regression to estimate producer population size as a function of $\Omega$ and its square at varying lags. Controlling for total market size (in employees) and period, results
showed effects at lags of 2 and 3 periods, but not at 4 or more. This result fits the view that firms base their entry decisions on new information as it becomes available, even if not perfectly.

To further explore H3’s predicted relationship between $\Omega$ and population size, I also ran regressions on the first-differences of population counts and periodic exit rates. Controlling for period and lagged $de\ novo$ producer population size and its square (i.e., $de\ novo$ density dependence), results of tobit regression showed that lagged $\Omega$ and its square have a significant effect on period market exit rates ($p < .05$). In the models of first differences of population size ($n$), results of non-linear regressions of $n$ on a cubic polynomial function of first differences in $\Omega$ are highly significant, just as in Table 5, though with considerably lower explained variance (adjusted $R^2$ of 0.36). Also, in a tobit regression of population size on first differences in $\Omega$, results show a significant relationship to population size ($p < .05$ and $p < .01$, respectively).

DISCUSSION

For monopolistically competitive markets, this research offers a partial answer to institutional theorists’ critique of density dependence by offering a deeper explanation of why counts affect producer population dynamics. In particular, I argue that both market entry rates and producer population levels are affected by the dual challenges of getting noticed. Because market audiences tend to overlook would-be market pioneers not yet recognized as constituting a proper market or industry category, such organizations face the challenge of getting noticed as a category. With success at that, however, comes a second challenge: it invites entry that grows the producer population and makes it harder for each one to get noticed individually.
I test this argument using the density of market networks based on producer co-mentions in the media to measure how noticeable producers are, both as a category and individually. This builds on two ideas: increasing connectedness among competing producers makes them more socially salient, but it also intensifies competition for attention. Analyses of market entry rates show support for the hypothesis that entry has an inverted U-shaped relationship to market network density. Also, analyses that estimate producer population rather than using it as an independent variable show that market network density is an excellent predictor of this important variable.

**Contributions to Theory**

This study offers something to both sides of the debate about whether counts offer a reasonable proxy for legitimacy. To ecologists, it affirms the importance of population counts and replicates findings that refine density dependence by showing that more “perceptually focused” *de novo* entrants do more to attract entry than *de alio* ones (McKendrick, et al., 2003). To institutionalists, it offers a deeper explanation of why counts have the widely replicated effects seen in density dependence findings, particularly by linking the dynamics of networks to the formation of a new market category (Powell, et al., 2005). In particular, it links the competing effects of population counts as observed in density dependence to individual cognitive limits and the shared focus that categories produce because they are defined around collectively agreed upon prototypes. These aspects of cognition and categorization explain not only why shared awareness of increasing connectedness among competing producers initially attracts market entry by helping them get noticed as a category, but also why it eventually makes it hard for organizations to get noticed for their unique skills and capabilities. Overall, this study joins with recent research in
organization theory that links the macro-level behavior of organizations and markets to its micro-level foundations (Bothner, Kang, and Stuart, 2007; Kennedy and Fiss, 2009).

This argument sheds light on a puzzle not addressed by existing theory: why do producer population counts decline even as the demand they feed on continues to grow? Figure 1 shows demand for computer workstations continued growing steeply through 1990, but Figure 2 shows the producer population began to decline in 1988. In studies that relate the population of biological species to key resources such as food supplies, however, competition for food leads to population decline when the food supply declines, not while it is increasing. By linking cognitive embedding to the challenges of getting noticed as a category and differentiated producers, this study’s argument about cognitive embedding explains how a population of competing producers could begin to decline even while demand is moving in the opposite direction.

Also, this study introduces concepts potentially useful for predicting when market populations will begin to consolidate. Unlike population counts, the density of market networks based on media co-mentions can be re-scaled so that values near 1 indicate the number of connections being made is as much an audience can be expected to make and maintain. As described below, this also holds potential implications for practice that should be explored with further research.

What does this mean for the critique that counts are too simple to be acceptable proxies for the kind of legitimacy that interests institutionalists? The answer is, it depends on what is being counted, and who is doing the counting. As a general mechanism for categorizing and learning to count something unfamiliar, cognitive embedding applies regardless of whether it helps people
become aware of new things that are uncontroversial or widely seen as clearly heinous. Calling attention to growth of something heinous—take the sale of children into sexual slavery for example—is more likely to inflame resistance than to put a wet blanket on it. Without accounting for how new things fit what people already think of as legitimate, the most that can be safely said of cognitive embedding and its effects on categories and counts is that it makes new social realities out of things that were formerly overlooked (Kennedy, 2008).

**Limitations**

Market network density should not affect producer population dynamics in markets for commodities or markets restrained by significant regulatory, physical or cultural barriers to movement of finished goods or critical production factors. In regulated markets for pharmaceutical products, for example, competition is governed more by intellectual property rights than by cognitive embedding. Also, cognitive embedding is less likely to affect producer populations in markets where standards make differentiation difficult or undesirable. Even in monopolistically competitive markets, cognitive embedding may not affect producer populations once consolidation begins. Population declines are likely to be affected by technical aspects of production, not just producers’ relative share of market audience attention.

As already mentioned, analyses of a single market do not assess the generality of the market-level hypotheses tested in this research. For that, many more markets must be analyzed, and studies should include markets that clearly emerged and ones that never really came together (Denrell and Kovács, 2008). Also, reducing counts to connections that define categories
overlooks details of entrepreneurial action that could potentially moderate this study’s findings. For example, the politics of establishing particular market conceptions (Fligstein, 1996) could be used to enact the boundary conditions just described. Also, adopting particular approaches to organizing could produce technical advantages that shape nascent market categories (Santos and Eisenhardt, 2009) in ways that either accelerate or delay the onset of consolidation.

While cognitive embedding offers a deeper explanation of the origins and effects of counts, some institutionalists may still be dissatisfied with this study’s analyses because they use market network density as a proxy for constructs that are hard to measure directly—perceptions of opportunity and competition for attention. In defense of density dependence for its use of counts as indirect measures of legitimation and competition, Carroll and Hannan (1989c: 545) argue that testing it “does not hinge on direct measurement of legitimation and competition.” Because all measures involve some inference, I agree; the same logic applies to test cognitive embedding.

**Contributions to Method**

This study extends methods for using public discourse to understand meaning construction. These techniques fit the family of methods known as content analysis (Krippendorf, 2004), particularly the variety referred to as relational content analysis, or RCA (Carley, 1990; Roberts, 1997; Popping, 2000). Rather than focusing on qualitative analyses of themes or quantitative analyses of term frequencies, RCA emphasizes patterns of association among terms of interest. Compared to Carley’s (1993; 1997) methods for extracting models of shared meaning from archives of meeting transcripts, this study’s methods seeks simpler patterns in a larger,
longitudinally organized corpus. Compared to the use of similar techniques for relating organizational performance to market networks (see Kennedy 2008), this study emphasizes the market- or network-level features of shared maps of competition, not firm-level measures.

Also, this research introduces saturation density ($\Omega$), a new measure of network density that re-scales conventional density ($\Delta$) to base peak values on social theory, not graph theory. In models of producer population, $\Omega$ explains 90% of variance across periods of population growth and decline at lags of up to eight quarters. Because $\Omega$ dampens $\Delta$’s interaction with network size, it gives significant estimates of market entry and population levels, but $\Delta$ does not. Also, when $\Omega$’s tunable parameter is set by theory about the logic and limits of categorization and cognition, it performs as expected by peaking at around 1 (see Figure 4). That this occurs after the market began to consolidate suggests $\Omega$ follows changes in population size rather than causing them, but because $\Omega$ is based on theory that predicts it will peak at around 1, population declines that occur as $\Omega$ nears 1 are likely to be consolidation, not just negative moves in a random walk.

**Implications for Practice**

For markets where differentiation matters, $\Omega$ could be adapted to support real-time measures of progress toward supplier saturation, the point at which consolidation begins. Executives considering new market entry routinely rely on trends in sales, but these trends misrepresent opportunity when producer populations decline well before sales do. Even if executives had good data on the number of producers already in the market, the fact that producer populations peak at different sizes from market to market makes it hard to say when entry can only be successful for
new producers capable of displacing more established ones. This study’s findings tentatively suggest media-derived market networks hold information that gives a clearer assessment of how close a market is to supplier saturation. In this single study, the saturation density ($\Omega$) of market networks based on media co-mentions leveled off and peaked at values near 1, as predicted. Further study is needed to assess whether this pattern is general enough to be practically useful.

**Future Research**

Future research should explore how this study’s findings are affected by status, geography, and community ecology; also, it should conduct multi-market studies to test their generality and refine the proposed measure of a market network’s saturation density.

Status should affect both how audiences perceive opportunity and how competition for attention affects producers. Compared to other media outlets, for example, The Wall Street Journal has considerable influence on technology markets (Tellis and Johnson, 2007); all else equal, firms covered there are likely to have a greater effect on perceptions of opportunity and to attain greater prominence in market networks. At the same time, however, less is known about how lower status trade publications feed the higher profile outlets’ agenda-setting influence on public discourse (McCombs and Shaw, 1972). Based on prior studies of intermediary status (e.g., Podolny, 1993; Podolny, 1999), outlet and reporter status could affect cognitive embedding. Also, an organization’s ability to attract media attention should be affected by size and its executives connections (Higgins and Gulati, 2003), and status in complementary markets may transfer to other markets (Jensen, 2003), helping firms to get attention (Jensen, 2004).
Geographic features of markets should change how cognitive embedding shapes them. Just as in Hollywood or Silicon Valley, geographic concentration affects the emergence of regional economies (Sorenson and Audia, 2000; Audia, Freeman, and Reynolds, 2006; Freeman and Audia, 2006), and interorganizational ties interact with geographic concentration to establish fertile clusters (Zhang and Li, 2009). Also, the density of market networks based on *de novo* versus *de alio* producers could have different effects on these identities, much as breakouts of population density counts do (McKendrick and Carroll, 2001; Romanelli and Khessina, 2005).

More fundamentally, market analysis is shaped by the interactions of a wider community of organizational populations (Ruef, 1999) whose complementarities can be seen as instituting market and industry architectures (Jacobides, Knudsen, and Augier, 2006). For example, Monge, Heiss, and Margolin (2008) argue that communication networks are shaped by community-level interactions. In technology markets, news and analysis are supplied by a collection of complementary outlets and related types of organizations. Besides the trade and mainstream business news media, other media types include custom market research reports, targeted newsletters, specialized events, online publications, and blogs. This community serves not only producers and customers, but also all kinds of investors.

Finally, future research could extend the theory and methods developed here to produce richer models of categories, identities or concepts, and patterns of association that make new things seem real could be gathered to analyze the meaning of ideas behind social movements. With resurgent interest in the sociology of ideas (Camic and Gross, 2001; Camic and Gross, 2002; Frickel and Gross, 2005), relating models of concept meaning to movements and organizations
could offer insights into situations where practices, organizational forms or markets are affected
by broader cultural changes (Weber, Heinze, and DeSoucey, 2008), innovations in style or
product design (Rao, Monin, and Durand, 2003; Lounsbury and Rao, 2004), controversy and
advocacy about diffusing practices, (Fiss and Zajac, 2004; Briscoe and Safford, 2008), changing
arguments about legitimacy (Green, Li, and Nohria, 2009), or threats from activists (King, 2008).

Further research could also refine $\Omega$ to create a version of saturation density useful for analyzing
the dynamics of more mature markets. This holds the potential to shed light on resource
partitioning (Carroll and Swaminathan, 2000) and firms’ attempts to erect barriers to competition
and create distinct “strategic groups” (Porter, 1980; Peteraf and Shanley, 1997). For example,
incorporating the extent of clustering could explain how market segmentation affects producer
populations. As segmentation develops prototypes for emerging sub-categories, audience
capacity to follow differentiated positions should expand. As categories develop, the emergence
of hierarchy disperses attention that was previously focused around a central prototype. In more
mature markets, the limit of market network connectivity should be a function of network size,
individual cognitive limits, and the extent of category clustering. Furthermore, at the population
level, further study could explore “density delay” effects (Carroll and Hannan, 1989a)—i.e., the
effects of population size (niche density) at the time when organizations are founded. For
example, an organization that planned to enter the workstation market in early 1982 would have
seen only 10 producers at that time, but assuming it takes a year or two to ship its first product
(18 months was the average), it would face between 20 and 40 competitors. These changes both
confirm opportunity and intensify competition.
CONCLUSION

Because organization theorists are often placed into academic departments with social psychologists studying organization behavior, they are well positioned to relate macro-level market behavior to its micro-level foundations in social cognition. As markets are produced by many minds (Sunstein, 2006), analyzing audiences promises to identify systemic patterns to events historically treated as anomalies. In particular, market bubbles and their destructive bursts are related to the cognitive limits not only of individuals, but also whole audiences. Even many minds working together—the mind of the market, so to speak—cannot possibly live up to the mythical powers widely attributed to markets through misapplications of two of economics’ most influential ideas: the invisible hand and the efficient market. Until the links between social cognition and markets are better understood, magical thinking about their capacity for self-regulation will lead to periodic crises that ought to be viewed as normal accidents (Perrow, 1984). Rather than shackling the invisible hand, studying the interface between minds and markets will free minds to think in new ways about how to make the most of one of these important social constructions.
FIGURES AND TABLES

Figure 1

Total Revenue ($B), Market for Computer Workstations
Entry, Exit and Total Population Size
Figure 3

Conventional vs. Saturation Density of Market Networks

Period: Calendar Quarters (1 = Q1 1980)

Conv. Network Density
Saturation Density
Figure 4

Saturation Density and Predicted Population Size

Pred. Pop. Size  Saturation Density  2 yr. Moving Average
Computer Workstation Producers Co-mentioned in News Stories Q2 1988

Figure 5
Figure 6

Proportion of Media Mentions by Proportion of Producers
Computer Workstations, Q2 1988

Proportion of Mentions

Proportion of Producer Population
### Table 1: Descriptive Statistics for Variables in Analysis of Market Entry

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>1 Entries (Periodic)</td>
<td>43</td>
<td>2.49</td>
<td>2.38</td>
<td>0.00</td>
<td>9.00</td>
<td></td>
</tr>
<tr>
<td>2 ln Market Sales&lt;sub&gt;t&lt;/sub&gt;, ($B)</td>
<td>43</td>
<td>2.29</td>
<td>2.79</td>
<td>0.00</td>
<td>8.50</td>
<td>-.37</td>
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<tr>
<td>3 4-Firm Mkt. Concentration&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>43</td>
<td>0.75</td>
<td>0.28</td>
<td>0.00</td>
<td>1.00</td>
<td>.30</td>
</tr>
<tr>
<td>4 Producers&lt;sub&gt;t&lt;/sub&gt;</td>
<td>(a)</td>
<td>43</td>
<td>0.00</td>
<td>26.68</td>
<td>-43.30</td>
<td>.01</td>
</tr>
<tr>
<td>5 (Producers&lt;sub&gt;t&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt; / 100</td>
<td>(a)</td>
<td>43</td>
<td>6.954</td>
<td>5.68</td>
<td>.20</td>
<td>18.75</td>
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<tr>
<td>6 Δ&lt;sub&gt;t&lt;/sub&gt;</td>
<td>(b),(i)</td>
<td>43</td>
<td>0.00</td>
<td>0.06</td>
<td>-0.10</td>
<td>0.16</td>
</tr>
<tr>
<td>7 (Δ&lt;sub&gt;t&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(b)</td>
<td>43</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>8 Ω&lt;sub&gt;t&lt;/sub&gt;</td>
<td>(b),(i)</td>
<td>43</td>
<td>0.00</td>
<td>0.16</td>
<td>-0.35</td>
<td>0.47</td>
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<td>9 (Ω&lt;sub&gt;t&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(b)</td>
<td>43</td>
<td>0.03</td>
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<td>17.88</td>
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<td>11 (i&gt;de novo Producers&lt;sub&gt;t&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(a)</td>
<td>43</td>
<td>312.35</td>
<td>219.42</td>
<td>0.09</td>
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<td>12 &lt;i&gt;de novo&lt;/i&gt; Producers&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>(c)</td>
<td>43</td>
<td>0.00</td>
<td>5.23</td>
<td>-8.32</td>
<td>9.33</td>
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<td>13 (i&gt;de novo Producers&lt;sub&gt;t-1&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(c)</td>
<td>43</td>
<td>26.76</td>
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<td>14 Δ&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>(c)</td>
<td>43</td>
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<td>0.05</td>
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<tr>
<td>15 (Δ&lt;sub&gt;t-1&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(c)</td>
<td>43</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>16 Ω&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>(c)</td>
<td>43</td>
<td>0.00</td>
<td>0.12</td>
<td>-0.26</td>
<td>0.39</td>
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<tr>
<td>17 (Ω&lt;sub&gt;t-1&lt;/sub&gt;)&lt;sup&gt;2&lt;/sup&gt;</td>
<td>(c)</td>
<td>43</td>
<td>0.01</td>
<td>0.03</td>
<td>0.00</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Note:
(a) Mean-centered.
(b) Residualized on Factor 4.
(c) Residualized on Factor 10.
(i) Δ is the (network) density of a market network.
(ii) Ω is the ‘saturation’ density of a market network.

<table>
<thead>
<tr>
<th>Model Factors</th>
<th>H1</th>
<th>Replication Test †</th>
<th>H2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Market Rev. (_{t-1}) ($B))</td>
<td>-0.205</td>
<td>-0.310</td>
<td>-0.336</td>
</tr>
<tr>
<td></td>
<td>(0.060)**</td>
<td>(0.124)**</td>
<td>(0.107)**</td>
</tr>
<tr>
<td>4-Firm Concentration Ratio (_{t-1})</td>
<td>0.674</td>
<td>0.529</td>
<td>0.662</td>
</tr>
<tr>
<td></td>
<td>(0.664)</td>
<td>(0.745)</td>
<td>(0.753)</td>
</tr>
<tr>
<td>(^{(a)}) Producers (_{t-1})</td>
<td>-0.003</td>
<td>-0.001</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>(^{(a)}) (Producers (_{t-1}))^2 / 100</td>
<td>-0.094</td>
<td>-0.145</td>
<td>-0.165</td>
</tr>
<tr>
<td></td>
<td>(0.028)**</td>
<td>(0.035)**</td>
<td>(0.036)**</td>
</tr>
<tr>
<td>(^{(a)}) δ(_{t-1})</td>
<td>8.546</td>
<td>(6.117)+</td>
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</tr>
<tr>
<td>(^{(b)}) (Δ(_{t-1}))^2/100</td>
<td>-1.565</td>
<td>(.490)**</td>
<td></td>
</tr>
<tr>
<td>(^{(b)}) Ω</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(^{(d)}) de novo Producers</td>
<td>-0.012</td>
<td>-0.031</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.122)</td>
<td>(0.014)*</td>
<td>(0.017)</td>
</tr>
<tr>
<td>(^{(d)}) (de novo Producers (_{t-1}))^2</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.001)**</td>
<td>(0.001)</td>
<td>(0.002)+</td>
</tr>
<tr>
<td>(^{(d)}) Δ(_{t-1})</td>
<td>0.135</td>
<td>0.010</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.072)*</td>
<td>(0.082)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>(^{(d)}) (Δ(_{t-1}))^2</td>
<td>-0.012</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.006)*</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.650</td>
<td>(1.610)*</td>
<td>-17.987</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>d.f.</td>
<td>4</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>LL</td>
<td>-74.60</td>
<td>-67.43</td>
<td>-66.695</td>
</tr>
<tr>
<td>Model Imp. (Chi2)</td>
<td>14.62**</td>
<td>14.34**</td>
<td>15.80***</td>
</tr>
</tbody>
</table>

N = 43. Standard errors in parentheses; significance levels are 1-tailed tests for hypotheses and replication tests:

- \( + = p < .10 \);
- \( * = p < .05 \);
- \( ** = p < .01 \);
- \( *** = p < .001 \)

Note: \(^{(a)}\) Mean-centering is \( (P - \bar{P}) \). \(^{(b)}\) Residualized on (a). \(^{(c)}\) Mean-centered. \(^{(d)}\) Residualized on (c).

† Models 5 and 6 replicate \( de novo \) density dependence tests from McKendrick et al. (2003).

<table>
<thead>
<tr>
<th>Model Factors</th>
<th>Controls</th>
<th>H3</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Period</td>
<td>0.009</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.014)•</td>
</tr>
<tr>
<td>ln Total Mkt. Size (employees)</td>
<td>0.455</td>
<td>0.430</td>
</tr>
<tr>
<td></td>
<td>(0.076)•••</td>
<td>(0.081)•••</td>
</tr>
<tr>
<td>Δt-1</td>
<td>-2.550</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.106)</td>
<td></td>
</tr>
<tr>
<td>(Δt-1)^2</td>
<td>-3.586</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.869)</td>
<td></td>
</tr>
<tr>
<td>Ωt-1</td>
<td></td>
<td>2.673</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.815)••</td>
</tr>
<tr>
<td>(Ωt-1)^2</td>
<td></td>
<td>-2.177</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.601)••</td>
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<tr>
<td>Constant</td>
<td>-2.398</td>
<td>-2.347</td>
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<tr>
<td></td>
<td>(0.867)••</td>
<td>(0.898)••</td>
</tr>
<tr>
<td>Observations</td>
<td>36</td>
<td>36</td>
</tr>
<tr>
<td>d.f.</td>
<td>2</td>
<td>4</td>
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<tr>
<td>LL</td>
<td>-140.82</td>
<td>-139.63</td>
</tr>
<tr>
<td>Model Improvement (χ^2)</td>
<td>2.37</td>
<td></td>
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</table>

Standard errors in parentheses; directional hypothesis tests are 1-tailed
Significance levels: • p < .05,  •• p < .01,  ••• p < .001
Table 4: Descriptive Statistics for Variables in Analysis of Population Density

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer Population</td>
<td>44</td>
<td>43.55</td>
<td>26.42</td>
<td>0</td>
<td>74</td>
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<tr>
<td>$\Omega_{t-1}$</td>
<td>43</td>
<td>.37</td>
<td>.31</td>
<td>0</td>
<td>1.07</td>
</tr>
<tr>
<td>$\Omega_{t-2}$</td>
<td>42</td>
<td>.36</td>
<td>.31</td>
<td>0</td>
<td>1.07</td>
</tr>
<tr>
<td>$\Omega_{t-4}$</td>
<td>40</td>
<td>.34</td>
<td>.31</td>
<td>0</td>
<td>1.07</td>
</tr>
<tr>
<td>$\Omega_{t-8}$</td>
<td>36</td>
<td>.29</td>
<td>.28</td>
<td>0</td>
<td>.80</td>
</tr>
</tbody>
</table>

Table 5: Non-Linear Regression Estimates of Producer Population as a Cubic Function of $\Omega$, the Saturation Density of Computer Workstation Market Networks, Market for Computer Workstations (1980-1990)

<table>
<thead>
<tr>
<th>Saturation Density $(\Omega)$</th>
<th>(Model 1)</th>
<th>(Model 2)</th>
<th>(Model 3)</th>
<th>(Model 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega_{t-lag}$</td>
<td>351.767</td>
<td>381.335</td>
<td>429.784</td>
<td>653.583</td>
</tr>
<tr>
<td>$(\Omega_{t-lag})^2$</td>
<td>(19.896)***</td>
<td>(23.147)***</td>
<td>(33.243)***</td>
<td>(72.457)***</td>
</tr>
<tr>
<td>$(\Omega_{t-lag})^3$</td>
<td>-568.655</td>
<td>-642.409</td>
<td>-764.573</td>
<td>-1,608.635</td>
</tr>
<tr>
<td>$(\Omega_{t-lag})^4$</td>
<td>(56.113)***</td>
<td>(65.511)***</td>
<td>(94.660)***</td>
<td>(275.512)***</td>
</tr>
<tr>
<td>d.f.</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>F</td>
<td>729.322</td>
<td>536.825</td>
<td>262.923</td>
<td>107.274</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.981</td>
<td>0.975</td>
<td>0.952</td>
<td>0.899</td>
</tr>
</tbody>
</table>

N = 43. Standard errors in parentheses; hypothesis tests are 1-tailed. Significance levels: + $p<.10$, * $p<.05$, ** $p<.01$, *** $p<.001$
APPENDIX A

Saturation Density

In graph theory, density is the fraction of possible edges that exist. In graphs that model social networks, the standard density ($\Delta$) measure is defined analogously. It is the ratio of existing links ($l$) among entities whose relations are being modeled to a an upper limit ($L$) based on full connectivity, computed for asymmetric relations as follows (Wasserman and Faust, 1994: 101):

$$L = \frac{n \cdot (n - 1)}{2}$$  \hspace{1cm} (1)

$$\Delta = \frac{l}{L} = \frac{2}{n \cdot (n - 1)}$$ \hspace{1cm} (2)

When modeling social relations, assessing a network’s fullness or emptiness should be based on social theory for the relations being modeled, not graph theory. Because upper limits for network connectivity reflect how close a network is to saturation of its capacity for connectedness, I use the term “saturation density” to refer to density based on theory-based limits for tie capacity.

To reflect utilization of a social network’s capacity for connectivity, saturation density replaces connectivity limits based on graph theory with theoretically expected ones. A simple but useful expression for expected connectivity limits ($\hat{L}$) is given by the linear product of network size ($n$) and the limits of each node’s capacity for the relations being modeled ($\omega$):

$$\hat{L} \approx n \cdot \omega$$ \hspace{1cm} (3)
Replacing (1) with (3) in (2) gives the simplest version of a saturation density measure:

\[
\Omega = l/\hat{L} = \frac{l}{n \cdot \omega}
\]  

(4)

**Example: Friendship.** When measuring the density of a network based on friendship ties among members of a particular group, connectivity limits should be based on theory about the number of friends group members can make and maintain in that setting. To illustrate, imagine there is a theory about a certain kind of friendship that suggests people make and maintain about 10 friends, on average. Also, imagine that theory applies to a 100-person group, and that this group’s members mostly socialize with each other and meet each other’s friendship needs satisfactorily. That is to say, they already have all the friends they can make and maintain, but they might be willing to drop some friends to make new ones they like better. In such context, new group members can find friends only by effectively stealing them from others. Conversely, existing members can only befriend new ones by dropping friends they already have, which will feel loss or theft to those who are dropped. If existing members sense this dynamic, self-interest might inhibit their willingness to help new members find those with whom they might be friends. Almost everyone has come across groups like this at some point. Variously described as exclusive, clubby, or cold, groups like this strike most newcomers as quite closed. These descriptors capture that fact that the group’s capacity for friendship ties is fully saturated, but the friendship network’s conventional density measure, which is just less than half its maximum value of 1 (0.495), does not reflect that. In contrast, the saturation density of this friendship network would be 1, indicating it is full up to its theory-based capacity for friendship ties.
**Application to Market Networks**

In monopolistically competitive markets where differentiation matters, it is not enough for organizations to have distinctive offerings; they must also become known for these things to customers who value them. Thus, audience reception to new entrants is loosely analogous to the friend-finding example above. In a group where everyone already has all the friendships they can manage, new members can find friends only by stealing them from others—the group’s capacity for friendship ties is already fully saturated. Similarly, in a monopolistically competitive market where audiences are already following as many competitors as they can, new producers can only find an audience that appreciates their distinctive offerings by diverting audience attention from other producers who are already meeting audience needs, even if imperfectly. This is what practitioners call stealing mindshare, and it requires a compelling story about why the new entrant deserves attention.

This analogy only applies, however, if there are limits to market audience capacity to track how competitors’ differentiated positions relate to each other.

*Limits to market audience capacity for tracking competitor relations*

Empirically, density falls well short of the maximum for a fully connected graph in this study’s market networks based on media coverage of who competes with whom. Compared to the maximum for a fully connectivity network ($\Delta=1$), it peaks at 0.31. While one might expect a sufficiently large and diverse market audience to generate demand for media coverage that
considers how each differentiated position relates to the others, that appears not to be the case. There are two reasons for this.

The first is obvious: no matter how large a market audience becomes, the number of ties in network models of relations among differentiated positions cannot exceed the total number of pair-wise interactions. As defined in (1), the absolute limit $L$ for market network ties is related to producer population size, or $n$, on the order of $n^2$. While there are no obvious limits to the amount that larger audiences could learn about competitors’ differences, the number of pair-wise comparisons among competitors is clearly subject to absolute limits.

The second reason follows from two key findings from the literature on categorization and cognition. Specifically, the logic and limits of human categorization and cognition provide a deeper explanation for why a market audience’s capacity to track interactions among differentiated positions does not scale with audience size; in turn, this explains why market network density peaks well below full connectivity. Categorization theory shows that people model category meaning in terms of prototypes, or common reference points (Rosch, et al., 1976; Mervis and Rosch, 1981; Barsalou, 1985; Barsalou, 1999). This suggests the process of categorization will focus audience attention on the handful of producers that best match shared category prototypes. The implications of this can be seen by contrasting two extreme cases for the homogeneity of market audience tastes.

*Complete homogeneity.* In an audience with completely homogenous tastes, its entire membership would define the category in terms of the same producer and a common
consideration set—that is, the set of producers considered as competitors and potential substitutes. In markets sustained by audiences whose members all think alike, the pair-wise competitor interactions followed by the market audience collectively would be exactly the same as those followed by any individual audience member. Specifically, the number of producers should not exceed the size of audience members’ common consideration set.

*Complete heterogeneity.* In general, however, market audience tastes are more heterogeneous. In a model of the number of pair-wise comparisons between competitors a market audience can be aware of, therefore, one would have to account not only for producer population size \( n \) and a function that describes the distribution of producers’ category typicality scores, but also audience size \( N \), average size of a member’s consideration set \( \omega \), a function that describes the dispersion of audience tastes’ on some simplified measure of their heterogeneity across several dimensions of taste, and a function that maps taste dispersion to producer atypicality. Rather than building a rich model to estimate expected market network connectivity limits \( \hat{L} \), I develop a simpler approach based on a satisficing assumption.

Specifically, I simplify the complexities of modeling audience size and heterogeneity and their effects on awareness of interactions among competitors of varying category typicality by assuming audience heterogeneity is so high that divergent tastes and category ambiguity lead audience members to select producers as category prototypes apparently at random—that is, without the focusing influence of a shared prototype. As the audience grows, every producer should eventually be selected as a prototype by at least some audience member. I further assume that the logic for relating producers to prototypes will be similar enough from member to
member that consideration sets will overlap considerably. These overlaps should reduce the number of unique competitor interactions a market audience follows so it is less than the product of producer population \((n)\) size and the formula for the number of pair-wise competitor relations in each members’ consideration set, which is \(\frac{1}{2} \omega(\omega-1)\). If audience members who select the same producer as category prototype also select the same consideration set, the number of unique comparisons simplifies to a function of the number of producers \((n)\) and the size of audience members’ consideration sets \((\omega)\), and audience size can be dropped from the expression for expected limits for market network connectivity.

Under these simplifying assumptions, even an arbitrarily large audience’s capacity to follow competitor relations is a function of the number of producers and the size of audience members’ consideration sets. More generally, the expected limits of market network connectivity \((\hat{L})\) are roughly a product of producer population size \((n)\) and the maximum size of the typical individual comparison set \((\omega)\).

As this argument leads to the same simple expressions used in (3) and (4) above, I use these equations to calculate the saturation density of market networks based on who is mentioned with whom in media coverage. For consideration set size, I follow studies of competitor analysis that suggest it is roughly equivalent to individual cognitive limits (Simon, 1947; Simon, 1974), especially those observed in studies of short memory (Miller, 1956). In a study of Scottish knitwear manufacturers, for example, Porac et al. (1995) found participants selected an average of 7 firms from a list of more than 200. Similarly, Clark and Montgomery (1999) found that participants in a study of competitor identification reported an average of 6.5 competitors. These
figures echo Miller’s (1956) seminal findings: in short-term recall tasks, people remember about seven discrete items, plus or minus two. As a starting point for sensitivity analysis, therefore, it makes sense to set $\omega = 7$.

Empirically, the structure of the market networks developed for this study is consistent with theory that suggests categories focus attention around prototypes. As Figure 6 shows, nearly two-thirds of the producer mentions for Q2 1988 go to the 4 most frequently covered producers, and over 90% of mentions go to the top quartile of producers ranked by media mentions.

**Advantages of Saturation Density**

$\Omega$ dampens the interaction between network size and $\Delta$ (Anderson, et al., 1999), thus making it a more sensible as a measure of progress toward saturation of a market network. In a panel of graphs that model longitudinal change in cognitive networks, typical patterns of graph densification produce a non-monotonic series of $\Delta$ values—that is, they rise quickly before falling steeply and then rising again. In contrast, plotting $\Omega$ over time produces a smoother curve. Figures 3 and 4 illustrate these differences. In Values of $\Delta$ and $\Omega$ are plotted over time in Figure 3. While the line for $\Delta$ clearly shows the expected early peak, the line for $\Omega$ dampens this considerably. Figure 4 shows overlaid values of producer population ($n$, on the left vertical axis) and $\Omega$ (right vertical axis) plotted over time. The line for $\Omega$ is given both raw and smoothed using an unweighted 2-year moving average. By visual inspection, changes in $\Omega$ closely approximate trends in $n$. 

As a predictor of market dynamics, the tunability of $\omega$ offers the promise of defining $\Omega$ so that 1 is the value at which adding new connections tends to displace existing ones. Thus defined, $\Omega$ is effectively an index of progress toward levels of market network density where (a) a market audience’s capacity for following competitor relations becomes saturated and (b) competition for attention is therefore likely to lead to consolidation. This is an obvious advantage over using either conventional network density or population density for similar purposes. Since different niches become crowded at different population levels (Freeman and Audia, 2006), specific values of $\Delta$ do not provide a reliable indication that a market network has reached density levels at which consolidation has become likely.
### APPENDIX B

**Table B1: Descriptive Statistics for Variables in Analysis of Market Entry (Untransformed IVs)**

<table>
<thead>
<tr>
<th>Variable (N = 43)</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
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</thead>
<tbody>
<tr>
<td>Entries (a)</td>
<td>2.49</td>
<td>2.38</td>
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<td>9</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Mkt. Sales ($B)</td>
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<td>Entrants</td>
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<td>Entrants$^2$ / 100</td>
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<td>0.59</td>
<td>0.41</td>
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<tr>
<td>de alio Producers</td>
<td>26.70</td>
<td>17.88</td>
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</tr>
<tr>
<td>De alio Producers$^2$ / 100</td>
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<td>8.71</td>
<td>0</td>
<td>25</td>
<td>-0.25</td>
<td>0.76</td>
<td>0.34</td>
<td>0.92</td>
<td>0.96</td>
<td>0.98</td>
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</tr>
<tr>
<td>De novo Producers</td>
<td>16.67</td>
<td>9.82</td>
<td>0</td>
<td>28</td>
<td>0.21</td>
<td>0.32</td>
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<td>0.88</td>
<td>0.85</td>
<td>0.74</td>
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</tr>
<tr>
<td>De novo Producers$^2$ / 100</td>
<td>3.72</td>
<td>2.80</td>
<td>0</td>
<td>7.84</td>
<td>0.17</td>
<td>0.19</td>
<td>0.46</td>
<td>0.88</td>
<td>0.86</td>
<td>0.78</td>
<td>0.69</td>
<td>0.97</td>
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</tr>
<tr>
<td>Mkt. Network Density</td>
<td>0.10</td>
<td>0.08</td>
<td>0</td>
<td>0.31</td>
<td>-0.35</td>
<td>0.84</td>
<td>0.26</td>
<td>0.69</td>
<td>0.71</td>
<td>0.78</td>
<td>0.83</td>
<td>0.45</td>
<td>0.37</td>
<td></td>
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</tr>
<tr>
<td>Mkt. Network Density$^2$</td>
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<td>0.02</td>
<td>0</td>
<td>0.10</td>
<td>-0.41</td>
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<td>0.15</td>
<td>0.53</td>
<td>0.56</td>
<td>0.65</td>
<td>0.71</td>
<td>0.27</td>
<td>0.18</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega$</td>
<td>0.37</td>
<td>0.31</td>
<td>0</td>
<td>1.07</td>
<td>-0.24</td>
<td>0.83</td>
<td>0.33</td>
<td>0.86</td>
<td>0.87</td>
<td>0.92</td>
<td>0.94</td>
<td>0.65</td>
<td>0.58</td>
<td>0.92</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>$\Omega^2$</td>
<td>0.23</td>
<td>0.27</td>
<td>0</td>
<td>1.14</td>
<td>-0.32</td>
<td>0.81</td>
<td>0.22</td>
<td>0.70</td>
<td>0.73</td>
<td>0.79</td>
<td>0.83</td>
<td>0.46</td>
<td>0.38</td>
<td>0.91</td>
<td>0.93</td>
<td>0.96</td>
</tr>
</tbody>
</table>

(a) All variables except Entries are lagged by 1 period

| Model Factors                                      | Controls (All Lagged 1 Period) | H1 Model 1 | H1 Model 2 | H1 Model 3 | H1 Model 4 | H1 Model 5 | H1 Model 6 | H1 Model 7 | H2 Model 1 | H2 Model 2 | H2 Model 3 | H2 Model 4 | H2 Model 5 | H2 Model 6 | H2 Model 7 |
|----------------------------------------------------|--------------------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| Mkt. Sales (SB)                                    | -0.205                        | -0.057     | -0.393     | -0.133     | -0.216     | -0.127     | -0.475     |            |            |            |            |            |            |            |            |
|                                                    | (0.060)**                      | (0.121)    | (0.109)**  | (0.075)+   | (0.136)    | (0.161)    | (0.175)**  |            |            |            |            |            |            |            |            |
| 4-Firm Conc. Ratio                                 | 0.674                         | 0.428      | 0.629      | 0.838      | 0.732      | 0.314      | 0.666      |            |            |            |            |            |            |            |            |
|                                                    | (0.664)                       | (0.664)    | (0.642)    | (0.623)    | (0.737)    | (0.759)    | (0.728)    |            |            |            |            |            |            |            |            |
| Producers                                          | 0.078                         | 0.072      | 0.062      |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.022)**                     | (0.024)**  | (0.023)**  |            |            |            |            |            |            |            |            |            |            |            |            |
| Producers² / 100                                    | -0.094                        | -0.098     | -0.144     |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.028)**                     | (0.032)**  | (0.035)**  |            |            |            |            |            |            |            |            |            |            |            |            |
| Δ₄₋₁                                               | 15.368                        |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (9.386)                       |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
| Δ²₄₋₁                                              | -82.220                       |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (48.206)+                     |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
| Ω₄₋₁                                               | 11.464                        |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (4.400)**                     |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
| Ω²₄₋₁                                              | -7.678                        |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (3.463)*                      |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
| **de alio** Producers                              | 0.102                         | 0.019      | 0.047      | 0.005      |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.033)**                     | (0.094)    | (0.098)    | (0.099)    |            |            |            |            |            |            |            |            |            |            |            |
| **de alio** Producers² / 100                       | -0.213                        | -0.055     | -0.084     | -0.118     |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.072)**                     | (0.131)    | (0.141)    | (0.146)    |            |            |            |            |            |            |            |            |            |            |            |
| **de novo** Producers / 100                        | 0.176                         | 0.176      | 0.189      |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.079)*                      | (0.079)*   | (0.081)*   |            |            |            |            |            |            |            |            |            |            |            |            |
| **de novo** Producers² / 100                       | -0.476                        | -0.630     | -0.827     |            |            |            |            |            |            |            |            |            |            |            |            |
|                                                    | (0.209)*                      | (0.229)**  | (0.260)**  |            |            |            |            |            |            |            |            |            |            |            |            |
| Constant                                            | -0.312                        | -0.354     | -0.386     | -0.174     | -0.487     | -0.619     | -0.688     |            |            |            |            |            |            |            |            |
|                                                    | (0.488)                       | (0.505)    | (0.491)    | (0.464)    | (0.533)    | (0.575)    | (0.566)    |            |            |            |            |            |            |            |            |
| d.f.                                                | 4                              | 6          | 6          | 4          | 6          | 8          | 8          |            |            |            |            |            |            |            |            |
| LL                                                  | -74.597                       | -72.365    | -70.378    | -76.510    | -73.558    | -70.637    | -68.471    |            |            |            |            |            |            |            |            |
| Model Improvement (χ²)                              | 4.464                         | 8.436*     | 5.905+     | 5.841+     | 10.174**   |            |            |            |            |            |            |            |            |            |            |

† 43 observations. Standard errors in parentheses; directional hypothesis tests are 1-tailed
Significance levels: + p<.10, * p<.05, ** p<.01, *** p<.001
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