Getting Counted: Markets, Media, and Reality

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Firms that do not fit into established business categories tend to be overlooked, but new markets often form around these "misfits." Because being seen as part of a growing population makes new populations seem real, counting them is important to mainstreaming new markets. Yet, if firms outside the mainstream are overlooked, how can they be counted? Extending the embeddedness perspective to social cognition about markets, this research exposes the media's central role in market formation. Using a new method for extracting data about market networks from media coverage, this study demonstrates that early entrants benefit from inviting coverage that makes a few—but not too many—links to other entrants, thus helping audiences perceive an emerging category. As the market matures, however, references to rivals become unhelpful. These findings illustrate the value of a linguistic turn to empirical studies of meaning construction and the reification of social structure.

New markets are forces for historical social change (Collins 1990; Schumpeter 1934), but explaining how they form poses a major challenge. By definition, new markets form around things that do not fit established categories. In the business world, life outside the mainstream is harsh (DiMaggio and Powell 1983), and such firms there tend to be overlooked (Zuckerman 1999). Acquiring the legitimacy that comes with being part of a growing group helps firms survive (Carroll and Hannan 1989; Lounsbury and Rao 2004), but outside recognition depends on a firm not being overlooked. A firm must be counted to move into the mainstream, but being outside the mainstream means not getting counted. This conundrum complicates the apparently simple job of counting. How do firms doing something new ever get counted?

Getting counted in society is anything but a banal topic. It impacts social theory, shaping markets and affecting social structures more broadly. Social movements, for example, gather strength when they mobilize resources such as people and money (Edwards and McCarthy 2004). Scientific and intellectual movements gain standing as they attract scholars, articles, citations, and grants (Frickel and Gross 2005). Emerging organizational forms are legitimated by population growth (see Carroll and Hannan 2000). Counts matter because they shape what people view as a "real" job, company, or market, and the same applies to scientific disciplines, artistic communities, and social or political movements. In these settings, counts lend materiality to new social structures. Understanding how new communities get counted thus promises to shed light on how the uncounted survive obscurity and come to be seen as "for real."

To better understand how new social structures become real, this research examines how firms in an emerging market get categorized and counted. To technologists, the reality of a new product concept simply depends on building a

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working prototype. From this perspective, linking the ontological status of inventions to mere counts probably seems strange, especially as it clashes with the technocratic adaptation of Hegelian idealism: the best products win. But the truth is that superior products do not always win. Economists explain this as a function of chance and changeover costs (Arthur 1994), but a more fundamental explanation requires a study of social processes for making sense of experience.

SOCIAL CONSTRUCTION, MARKETS, AND ORGANIZATIONS

As Durkheim ([1912] 1995) argued, shared beliefs define reality. In his seminal study on religious life among Australian aborigines, he found that the totems they worshipped had real powers—not imaginary powers—because shared beliefs about the totems structured society into clans and shaped their interactions. Going further, Berger and Luckmann (1966) argue that reality itself is socially constructed. Some balk at linking reality to mere naming conventions, but it is clear that at least "social realities" are produced by processes for developing and maintaining collective agreement (see Searle 1995). From money to law to the laws of markets, a society's workings depend on shared views about what is real. In philosophy, some scholars have taken a "linguistic turn" to questions about what is real, arguing that reality is defined by ordinary language as it is used to make sense of experience (Rorty 1967 [1992]:1–39, 361–74). Often referred to as neopragmatism, this study roughly follows in that path.

In the world of organizations, shared views about what a real organization is and does promote stability and homogeneity that make it hard for organizations to change or break away from the pack (DiMaggio and Powell 1983; Zucker 1977). Still, even widely held views are subject to radical renegotiations—what Kuhn (1962) calls paradigm shifts. Thanks to Kuhn, "paradigm shift" has entered everyday language, but many technologists still prefer to see reality as above nominalist thinking (naming, counting, and meaning construction). The dominant view outside the humanities and certain social sciences is a realism in which the scientific method neutralizes social construction. Technologists simply are unlikely to take social construction seriously until empirical work shows it in action and explains why it matters.

To clarify the social construction process, I tackle the counting conundrum with a new approach to the empirical study of meaning construction. Firms offer competing definitions of market concepts, which confuses category meaning (Fligstein 1996). This study starts, therefore, by drawing on Peirce's (1992) insight that going from cases to categories requires one to draw patterns from data. The focal approach combines the social network analysis of economic sociology's embeddedness perspective (Granovetter 1985) with a linguistic turn to views about what is real. As producers in a nascent market increasingly interact, the accumulating discourse embeds them in a shared cognitive network that enables their categorization. This cognitive embeddedness (Porac and Rosa 1996; Zukin and DiMaggio 1990) helps legitimate a market by enabling a census of its entrants, thus transforming the category into something that seems real: the abstract market has become reified.

This line of reasoning suggests a basis for studying market formation: patterns of association among market entrants found in the relevant public discourse. Media coverage is ideal for extracting and analyzing these patterns because coverage—and firms' attempts to solicit coverage—is traceable through firms' press releases. The test market for this study is computer workstations, a product that emerged in the 1980s. More expensive and powerful than personal computers, yet not as powerful or as expensive as mini- or mainframe computers, the first workstations sat outside the mainstream.

Using new methods, I mine more than 60,000 single-spaced text pages of media coverage to uncover patterns of association that predict firm attention, prominence, and survival. The results show that entrants benefit from publicity efforts in a market's early days when press releases reference a rival or two, thus embedding them in an emerging category. As a category takes shape, however, these references no longer legitimate the market and they become unhelpful. Overall, I show that media discourse embeds firms in shared cognitive structures for making sense of new markets. These structures enable counts of new populations, thereby also shaping firm performance and perceptions that a market is for real.

THEORY

Market formation depends on what White calls "context" (White 2002: Ch. 2), a culturally shared approach to categorizing producers. This starting point for social comparisons is essential to White's influential model of market formation (White 1981), in which watching and reacting to competitors' visible commitments to price and volume leads a firm to create its schedule of differentiated cost-quality positions. Before a category exists to guide these social comparisons, however, it is fair to ask how firms know whom to watch. White suggests looking to culture and discourse to see how market categories are constructed (White 2002:11).

This research extends White's work by looking to media coverage for discourse that shapes culturally shared categories for making sense of markets. Media coverage helps audiences sort out the meaning of emerging market categories by facilitating a virtual dialogue about product similarities and differences (Rosa et al. 1999). In this process, firms find their rivals and watch others' moves by looking through the lens of media coverage, rather than looking directly at public positioning statements (Kennedy 2005). Much less is known about how the media creates perceptions that new populations are emerging.

MARKET SENSEMAKING THROUGH COGNITIVE EMBEDDING

The media's role in defining new markets can be conceived as market sensemaking, a macro version of Weick's approach to meaning construction in organizations. To explain how people deal with "something that does not fit," Weick (1995:3) defines sensemaking as publicized speculation that makes an unexpected or unfamiliar thing more plausible. For a nascent market, news stories do this in two ways. First, media coverage brings visibility and "cognitive legitimation" (Aldrich and Fiol 1994). Second, news stories position not-yet-legitimate firms as constituting an increasingly coherent category (Lounsbury and Glynn 2001), making firms countable and thus less odd. Weick puts it this way, "As anomalies become shared, sensibleness should become stronger" (Weick 1995:3).

Market sensemaking contributes to shared interpretations through cognitive embedding, the process of building a shared mental map of associations that make up a new category or concept. Cognitive embedding is a macro-social mechanism for a collective version of the type of inference Charles Peirce proposed to explain how people go from cases to categories. In his pioneering work on logic, Peirce recognized that the human impulse to organize experience depends on a mode of inference that is neither deductive nor inductive. As his thinking developed, Peirce distinguished a third mode of inference that he variously referred to as hypothesis, retroduction, and abduction (see Peirce 1992:141). Each of these terms helps explain the idea: categorization entails conjecture about patterns (hypothesis) developed by working from potential category instances backward to a general pattern (retroduction) that is drawn out or captured from data (abduction). As the media continue to apply a new category label to a nascent market, audiences arrive abductively at a shared interpretation of its meaning. As illustrated by the emergence of minivans, for example, media coverage can stabilize category meaning that, in turn, unlocks demand (Rosa et al. 1999). Significantly, categorization enables the counts that are needed to observe the growth of a nascent population.

Early on, however, counts are complicated by what Quine (1960) referred to as the indeterminacy of translation. By translation, Quine meant the subtle shifts of interpretation that occur as terms move from person to person. As market sensemaking embeds firms in a shared cognitive scheme, translation becomes easier, eventually producing a category coherent enough to enable consistent counts. As Rorty argued (1967 [1992]), everyday language is used in both the *translation* that spreads category claims and in the *evaluation* of whether new categories are real.

In business, the preeminent forum for abductive inferences (hypotheses) about new categories, the translation that spreads them, and evaluations of their validity arise from the media. Media-based market sensemaking thus supports and reflects an iterative process of meaning construction that cycles through abduction, translation, and evaluation (see Figure 1). As this process associates firms that are doing something new, it embeds them in categories that make it possible to count them and observe growth, which helps new markets appear real.

Media Co-mentions and Market Networks

Analyzing media co-mentions (references to more than one firm in the same news story or release) provides a way to observe the associations that are necessary to construct new market categories. Until multiple firms are discussed as having entered a defined new market, the abductive category inference may be overlooked. If used at all, translations will be messy, and evaluations of a category's meaning, validity, and usefulness are unlikely to be favorable. On the other hand, if news stories begin to combine mentions of market entrants, the cumulative effect of such co-mentions will embed firms in a network that reflects how people are defining and interpreting the market concept.

Exploring cognitive embedding through co-mentions fits with the concept of modeling markets as networks (White 2002). We can construct networks in which nodes are firms and links indicate, for example, the rivalry or similarity suggested by mentioning them together in news stories about an emerging market. Such a cognitive market network provides a model of how people conceptualize a market concept, and it can be used to observe the iterative meaning construction process shown in Figure 1.

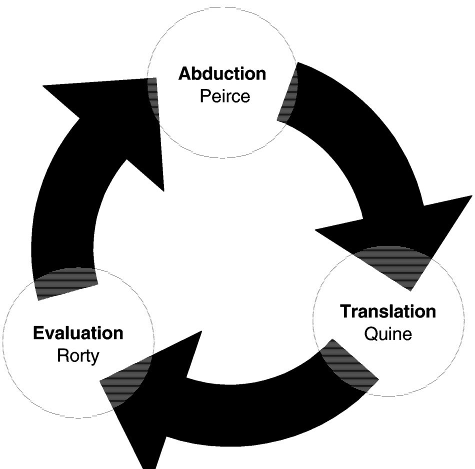

Figure 1. Iterative Meaning Construction Process

Specifically, news stories that mention firms together embed the firms in a network that, over time, shapes and reflects the market. While audiences cannot absorb and sort the information required to define a new category from details about all of its potential instances, they can abductively grasp new market concepts by reflecting on what they learn about firms mentioned together in news stories. As co-mentions accumulate, audiences weigh the resulting cognitive network to assess whether it constitutes a "real" market. When people see a term consistently applied to a population of firms, they comprehend a category, which makes it possible to count its members. Cognitive embedding through media co-mentions thus supports the development of categories, counts, and the validation they convey (Carroll and Hannan 1989).

Just as embeddedness in social relations predicts a firm's performance in a market (Granovetter 1985), embeddedness in emerging cognitive market networks should affect how a firm fares in emerging markets. In exchange networks, survival improves when firms are embedded in networks of supportive relationships with repeated exchange partners (Uzzi 1996), but being too exclusive in these relationships reduces survival by narrowing firms' bases of support (Uzzi 1997). Applying these findings to market sensemaking, news stories that consistently co-mention entrants help audiences "connect the dots" by developing a coherent picture of how category members are related and, thus, what the category means. Potential market pioneers are transformed from a "band of misfits" into a legitimate business population.

Press Releases and Producer Voice in Market Sensemaking

How do firms outside the mainstream project their presence to achieve the media-based market sensemaking that makes them countable? News stories mediate conversation about whether and how to define market categories around new products, but the two-way dialogue between producers and consumers is controlled by neither side (Rosa et al. 1999). This is reasonable because market sensemaking is mediated by third-party news reporters whose professional journalistic norms prohibit accepting payment from or developing social obligations to any source, whether producer or consumer. It is this independence that makes reporters' stories an important source of legitimation for firms outside the mainstream. High technology firms spend liberally on public relations (PR) efforts designed to woo reporters into covering what they are doing, especially when their work does not fit established market categories. In 2002, the Council of Public Relations Firms estimated global revenues for PR at US $5.4B. They estimate that high technology makes up 30 percent of U.S. revenues, which are 40 percent of the global total.

PR tactics vary widely (Jackall and Hirota 2000), but press releases are a common element of virtually all PR efforts. When an organization wants publicity for something it is doing, it issues a press release. To meet deadlines, busy reporters often rely on press releases for background facts, occasionally lifting intact phrases or even entire passages. Knowing this, firms craft press releases that tell the story they want passed on to the public. Firms looking to shape collective market sensemaking thus use press releases to provide strategic sensegiving to the media and beyond (Fiss and Zajac forthcoming; Gioia and Chittipeddi 1991; Kuperman 2003).

Despite being written in the style of regular news stories, press releases exhibit several features that distinguish them as press releases. First, they are marked as press releases near the top of the text. Sometimes they note an embargo date before which related news stories may not be released. In addition, they usually provide contact information below the body text of the story so that reporters who choose to write related stories do not have to spend time finding someone to call for questions or quotes. Figure 2 shows a sample press release from market pioneer Apollo Computer. This release includes a product announcement (Apollo mentions only itself in a discussion focused on product details), a claim that there is a new category forming around the product (anonymous competitors are "current systems on the market"), and an assertion of leadership position in the market based on that category (a field for workstations).

In high technology, press releases are a standard tool for soliciting the attention and legitimation that media coverage brings to new products. Full-text media archives capture everything that goes out over the wire services that distribute press releases, so media archives contain a remarkably rich record of how frequently firms seek media attention. In addition, the full text in these archives makes it possible to analyze whether contents of releases contribute to cognitive embedding. Releases that mention only the issuer, for example, miss the opportunity to connect a firm to an emerging market category; releases that reference rivals suggest connections that link the issuer to the emerging population.

Cognitive Embedding and Firm Performance in New Markets

Although suggesting connections to rivals should promise benefits, packing releases with too many connections could backfire by overloading audiences' cognitive capacities. Human short-term memory is limited (Miller 1956); on average, limits hover around seven discrete items. If the number of rivals co-mentioned in releases rises to the threshold of forgetting, the issuer could get lost in the throng. Firms trying to create a new market thus benefit from issuing releases that neither under- nor overembed them in the cognitive market network established by media coverage. This parallels Uzzi's (1996, 1997) finding that firm performance is undermined by both under- and overembeddedness in exchange networks. As firms seek a say in market sensemaking, the number of rivals they mention in their press releases should impact three dimensions of organizational performance: media coverage, prominence (positioning within the category), and survival (exit rate).

Media coverage. Jensen (2004) finds that alliance announcements in the computer industry increase securities analysts' coverage at a decreasing rate; a similar logic should apply to press releases more generally. When firms issue releases that suggest connections to a few (but not too many) rivals, they should receive more media attention than would firms with no releases, firms whose releases mention only themselves, and firms whose releases mention many rivals. That is, reporters are more likely to cover firms whose releases suggest that they are embedded in the network of firms seen as having entered the market. As previously mentioned, attention matters because it contributes

COPYRIGHT	1983 Business Wire, Inc. October 27, 1983, Thursday
DISTRIBUTION	Business Editors
DATELINE	BOSTON
LENGTH	350
HEADLINE	APOLLO-COMPUTER; Introduces new high performance workstations and software packages for technical professionals
BODY	Apollo Computer Inc. Wednesday announced a number of new products, broadening its product line and continuing its commitment to increase the productivity of the technical professional. The products announced are: – Two new computational nodes, the DN460 and DN660, which provide powerful, high end, 32-bit super-mini performance at a fraction of the price of current systems on the market; – A new DOMAIN Server Processor (DSP160), providing a high end, super-mini performance computational resource which can be shared throughout the Apollo network; … – The DOMAIN Software Engineering Environment (DSEE), a set of four integrated, interactive functions for software engineering teams, designed to aid in efficient project control and documentation, and – SR7, a new software release which adds new graphics, communications and program development functionality to the DOMAIN operating system. "We feel confident that these new products, combined with our history of producing high-quality, dependable workstations, will further position Apollo as a leader in its field," stated Charles P. Spector, the company's president and chief operating officer. "As well, these new computational nodes, communications gateways and software products adhere to Apollo's longstanding commitment to offer extremely powerful and capable products at a price which allows a wide range of customers the opportunity to experience the benefits of sophisticated computer power."
CONTACT	Apollo Computer Inc., Chelmsford, Mass. Nicholas C. D'Arbeloff, 617/256-6600, ext. 6695 Ronni Sarmanian, 617/256-6600, ext. 6400

Figure 2. Sample Press Release

to "cognitive legitimation" (Aldrich and Fiol 1994). While visibility does not guarantee performance benefits (Fombrun and Shanley 1990), it can increase prominence (Rindova, Williamson, and Petkova 2005), a factor that boosts market valuations (Pollock and Rindova 2003) and return on assets (Deephouse 2000). In the competition for attention, coverage is an important measure of performance, and it should be curvilinearly related to the number of rivals a firm tends to reference in its press releases. This leads to my first hypothesis:

Hypothesis 1: Firms can boost their coverage by issuing press releases that reference a few, but not too many, rivals.

If referencing rivals in releases influences actual news stories, firms that issue these releases may appear in stories that mention them with others. When the media co-mention a firm, audiences are more likely to perceive an emerging category and to see the firm as being embedded within it. As with releases, being mentioned in conjunction with too many firms should increase the risk of getting lost in the shuffle. Eventually, being mentioned with more and more others should have a negative effect, leading to the following hypothesis:

Hypothesis 2: The overall coverage a firm receives should be related to the extent to which, on average, news stories mention it neither alone nor in too large a crowd.

While releases are designed to attract news stories, it is possible that firms mention others in their releases only *after* seeing these connections in news stories. This would mean that a firm's tendency to be mentioned with others in news stories could be related to prior coverage, rather than to the firm's tendency to reference a few, but not too many, rivals in press releases. This potential mediation effect should also be tested.

PROMINENCE. Cognitive embedding also affects a firm's prominence, or position, in an emerging market category. As market sensemaking elaborates meaning, it simultaneously develops differentiated positions and an overall structure of competition. By co-mentioning firms, news stories shape how audiences see emerging rivalries. This matters because a firm's position can provide a source of lasting advantage (Lieberman and Montgomery 1988). In economics, these positions are studied as major determinants of stable differences in firm performance (McGahan and Porter 1997). In sociological terms, this follows Tilly's (1998) argument that categories establish boundaries that define societies, divide them into subgroups, and naturalize lopsided access to opportunity.

While firms spend liberally on publicity-based positioning efforts, linking PR to realized positions is difficult, but not impossible. In their analysis of the semiconductor industry, Podolny, Stuart, and Hannan (1996) suggest one way this might be done. They found that semiconductor makers benefited from having patents widely cited in the relevant patent literature, showing that status shapes competitive outcomes. Similarly, in the wine industry firms benefit from associating with prominent affiliates (Podolny 1999). Although status *orders* are more fluid in a market's early days than later on, firms that come first to consumers' minds stand the best chance of ultimately becoming high-status players, and those most often mentioned with others should be most likely to come to mind first. As nascent markets move into the mainstream, media prominence should help firms survive the rigors of intensifying competition. Rindova and colleagues (2005) show, for example, that quality rankings contribute to the price that firms can command. Within media discourse overall, considering releases and actual news stories separately leads to the following hypotheses:

Hypothesis 3: Firms can enhance their prominence in nascent market networks by issuing press releases that reference a few, but not too many, rivals.

Hypothesis 4: A firm's prominence in nascent market networks will be boosted by media coverage that references the firm neither alone nor in too large a crowd.

SURVIVAL. Positioning provides an advantage that helps a firm survive both the obscurity of doing something new and the rigors of competition that eventually come with market growth. Numerous studies find that the most prototypical items in a category are first and most frequently cited when participants are asked to list category members (Rosch, Simpson, and Miller 1976). Even in fuzzy categories, participants show remarkable levels of agreement about whether to place various cases in the category (Rosch 1975). In network terms, category typicality means centrality in cognitive market networks. Practitioners refer to this as a high "share of mind" (Christian 1959), or "mindshare," a concept defined by the Oxford English Dictionary as, "Consumer awareness of a particular product or brand, esp. compared to the profile enjoyed by competitors' products." Again, considering press releases and news stories separately, this leads to two more hypotheses:

Hypothesis 5: Firms can improve their chances of surviving in new markets by issuing press releases that reference on average a few, but not too many, rivals.

Hypothesis 6: Coverage that references a firm neither alone nor in too large a crowd should have a beneficial effect on the firm's survival chances.

CATEGORY DEVELOPMENT. As media coverage of a growing market associates entrants with one another, the resulting cognitive market network grows in size and complexity and becomes less susceptible to changes by any single participant (Powell et al. 2005). Survival struggles shift from defining the market category to competing for differentiation within it (Fligstein 1996; Lounsbury and Glynn 2001). That is, as a market is accepted as legitimate, survival depends on establishing positions within the category (Carroll 1985; Peteraf and Shanley 1997). As firms find it increasingly difficult to affect the structure of competition conveyed by media coverage, intensified competition for attention reverses the effects of calling attention to the competition. The value of referencing rivals in press releases should thus go from being positive to negative as the market unfolds:

Hypothesis 7: As a market develops, referencing a few (but not too many) rivals in press releases will negatively impact a firm's survival chances.

METHODS

BACKGROUND

SITE. In the early 1980s, workstations emerged as a distinct category of computing machines that bundled features previously available only in multiple-user machines into a single unit that could be placed in individuals' offices or cubicles. Their smaller size, more robust power, and lower cost compared to their nearest substitute—high-end minicomputers typically shared among departments—made workstations particularly attractive to technical and scientific users with high demands for computing power.

DEMOGRAPHY. An industry catalog publication, *DataSources,* provided most of the demographic data (e.g., firm size, age, entry date, and exit date); I used LexisNexis archives to fill in gaps as needed. As Figure 3 shows, the market grew to 73 firms by 1987 and dwindled to 53 by the end of the decade. This is very similar to data developed separately by Sorenson (1997) to study questions of organizational form development and adaptation in the context of the market for computer workstations.

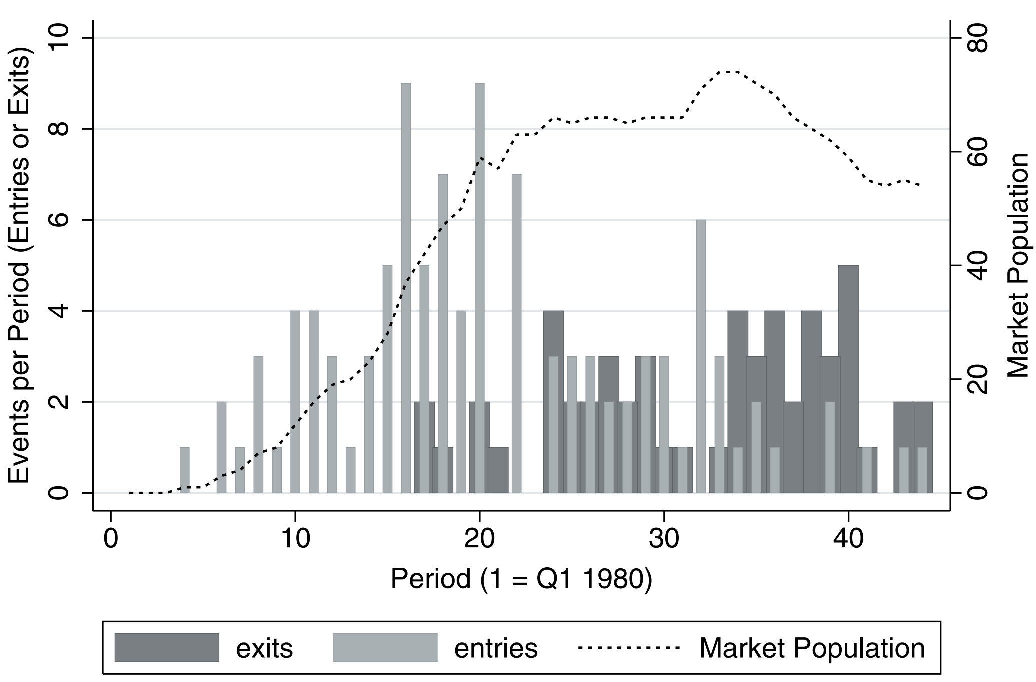

Figure 3. Market Entry, Exit, and Density: Market for Computer Workstations

PERIOD. I focus on the years 1980 to 1990 to target the formative period of the computer workstation market. This focal period also avoids niche legitimation that occurred as PC and workstation markets began to abut in the early 1990s (see Bell [1986] for an explanation of the technology evolution that led to the computer workstation category, Goldberg [1988] for a discussion of the history of the market, and Sorenson [1997] for a study of changing strategies and organizational forms in this market). During the study period, rapid product introductions roughly followed a quarterly rhythm, so I use calendar quarters as analysis periods. This has the added advantage of coinciding with the editorial planning cycles at many trade news publications, which influence the timing of product introductions and vice versa.

DATA COLLECTION. I extracted the data for this study from news stories and press releases collected from 34 media outlets, including weekly and monthly trade publications devoted to computers and information systems, wire services for press release distribution, business news magazines, local and national newspapers, and general news magazines. I retrieved more than 28,000 stories and releases that mentioned the words "computer" and "workstation" but not immediately after the words "personal computer" or "PC." In all, the data set comprises approximately 60,000 pages of single-spaced text organized into quarterly chunks for analysis.

To capture the basic association data needed to produce the study's key variables, I developed and used a software tool that takes two inputs: a collection of stories and releases, and a list of terms to be associated. In this context, the terms to be associated are names that refer to firms that entered the market. The tool parsed each release and story to capture every firm mentioned and recorded those mentions in a "mentions table" where each row recorded the article and a mentioned firm. For a more in-depth examination of this tool and the matrices produced, see the Appendix.

KEY INDEPENDENT VARIABLES

This study uses two main independent variables. The first, average release density (ARD), measures the extent to which a firm's releases mention rivals in the potential market. The second, average story density (ASD), measures the extent to which media news stories that mention a firm also mention other producers. While ARD captures how a firm tries to position itself, ASD provides a reflection of the firm's positioning in the public eye.

I produce ARD and ASD for each firm for each period by counting the number of firms mentioned in each text that mentions the focal firm, summing those counts, and dividing them by the total number of releases or stories that mention the firm. To produce a cognitive market network that models the category's meaning and structure, I transform the "mentions table" to produce a list of network edges (i.e., connections between firms) that are then combined with the list of active firms (i.e., nodes) to produce a firm-by-firm network. (For additional treatment of this method for going from stories to structure, see Figure A in the Appendix.)

AVERAGE RELEASE DENSITY (ARD). If firm i issues releases in period t, ARD_{it} is the average number of producers mentioned in all of the period t releases. If there are no releases, ARD_{it} is defined as 0. While quarterly averaging maps nicely to the seasonality of news coverage and product introductions, it gives a noisy measure of a firm's approach to positioning because many firms focus their publicity efforts only in certain quarters. To produce a less noisy yet still dynamic measure of ARD, I applied a geometric moving average, computed as follows:

$$\mathrm{GMA(ARD)} = \sum_{j=1}^{t} \mathrm{ARD}_j^{2^{\frac{1}{(t-j+1)}}} \qquad (1)$$

Because I use this version of ARD in all analyses, I refer to it throughout this article as ARD for simplicity.

One of the advantages of this measure is that it is independent of release levels, which allows for better comparisons between firms that vary in release activity. In effect, ARD reflects a firm's tendency to dignify the competition and legitimate the turf over which they compete. To test the hypothesized curvilinear effect of ARD, I also use its square (ARD^2) in all analyses. To assess whether this effect reverses as the category develops (Hypothesis 7), I explore two additional variables: an interaction product of ARD and analysis time (calendar quarter number), and time squared. Like ARD, these measures are dynamic.

AVERAGE STORY DENSITY (ASD). If stories mention firm i in period t, ASD_{it} is the average number of producers mentioned in all of period t stories that mention firm i. In periods where no stories mention a firm, ASD_{it} is 0. The measure is computed as follows:

$$\text{ASD}_{it} = \frac{\sum_{d=1}^{n} d \times C_{it}(\text{SD} = d)}{C_{it}(SD > 0)} \quad \text{if} \quad C_{it}(SD > 0) > 0\text{; otherwise } 0 \tag{2}$$

where n is population density (number of active entrants in period i), SD is story density (number of entrants mentioned in any story), and $C_{it}(exp)$ is the count of stories mentioning firm i in period t that satisfy *expression*. To test the hypothesized curvilinear impact of ASD, I entered its square in all analyses where ASD is used. In analyses of coverage and coverage centrality, it is lagged by one period. In analyses of market exit, I applied a geometric moving average to relate exit to a less-noisy but still dynamic average of ASD.

The ARD/ASD approaches for moving from stories to market structure provide a path grounded in theory for observing meaning construction and sensemaking in action. Over a sufficiently large volume, cognitive market networks based on media coverage offer three valuable views of market formation. First, they reveal category prototypes by identifying which producers are most frequently co-mentioned with others. These are the firms likely to come to mind first when producers, analysts, and customers think about the market (high mindshare). Second, the networks reveal likely losers. Producers that are discussed mostly alone will be less embedded in cognitive maps of the category, so they will be slow to come to mind as people think about the market (low mindshare). Third, the networks reveal market segmentation. Producers that are frequently co-mentioned are likely to be close competitors. These networks thus reflect the duality of structure and meaning in market categories (Mohr 1998; see also the Appendix).

Dependent Variables and Estimation Techniques

I test the cognitive embedding argument from several angles using three dependent variables for media attention, prominence, and exit rate (survival). The following sections explain measures and estimation techniques for each.

ATTENTION AND PROMINENCE. For each period that a firm was active in the market, I measure media attention as the number of stories that mention the firm; this count is called "coverage." I measure a firm's prominence in a market network as degrees centrality, the count of links to each firm for each period. Because both measures are counts, Poisson regression is the obvious choice for model estimation. Since the data violate the equidispersion assumption ($G^2 = 8144.4$, $p < .01$), though, I use negative binomial regression to avoid deflated coefficient standard errors and spurious significance (Cameron and Trivedi 1986).

The fixed-effect estimator option controls for stable characteristics of firms not included in the study variables, and robust standard errors are clustered on organizations. To the extent that product quality is a stable element of a firm's overall capabilities, fixed-effects estimation provides some control for the overall technical quality of a firm's products. This is important because the conventional engineering perspective on success in high-technology markets centers on having the best product.

MARKET EXIT. I test the survival hypotheses by estimating the hazard rate of market exit. Exit is coded as 1 for the period in which firms failed outright, were acquired, or sought bankruptcy protection; otherwise, exit is coded as 0 from entry to the exit period or the final analysis period, whichever came first. The general approach to analyzing failure or survival events is to estimate the probability that a subject will "fail" within a specific interval, given that the subject survived to the beginning of the interval. By taking the limit of the probability of failure within a time interval over the change in time that defines the interval, it is possible to estimate instantaneous hazard rates h, as follows:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t + \Delta t > T > t | T > t)}{\Delta t} \tag{3}$$

Since hazard rate estimation depends on probability distributions used to predict "arrival" of failure events, hazard models rely on assumptions about the probability distribution of failures. In many cases, however, this distribution is not known in advance, and in these situations, parametric hazard-rate modeling risks a mismatch between failure data and the probability distribution employed. Because there is not much theory on what happens in the earliest moments of new niches, it seems wise to avoid these assumptions for this study. While Cox (1972) regression is a popular method for circumventing problems of unknown probability distributions, analysis of Schoenfeld residuals[1] shows that the workstation failure data violate the underlying proportional hazards assumption ($p < .05$).

I therefore estimate hazard rates of market exit using piecewise constant hazard-rate estimation in Stata using routines developed by Sørenson (1999). Piecewise models make neither distributional nor proportionality assumptions. Instead, they estimate hazard rates in terms of the contributions made by separate hazard rates observed for predetermined time "pieces" (see Blossfeld and Rohwer 1995). The method requires that data be organized according to discrete timepieces, which fits well with a quarterly analysis of press release activity and media coverage. The quarterly analysis periods used in this study are small enough to allay concerns about baseline hazard rate change within periods.

Controls

Because large, established organizations may attract media attention more easily than would small new firms, I use size and age as controls. Size is measured as the natural log of the number of employees; age is measured as an organization's age in years at the time of market entry. For entrants active in other businesses, size and age refer to the entire organization, not just to their workstation-focused units. Media attention and prominence can also be related to market experience, so I also use them as a control in analyses of coverage and coverage centrality.

I also use lagged dependent variables as controls in analyses of coverage and coverage centrality. In market-exit models, I use both coverage and coverage centrality as controls; this is because market-exit analyses assess whether and how ARD and ASD affect exit over and above their effects on coverage and coverage centrality. In the exit analyses, ARD and ASD are geometrically smoothed. Using lagged coverage and coverage centrality yields higher levels of statistical significance for ARD and ASD, but this choice is not as faithful to the study hypotheses. They do not predict that exit rate is related to the prior period's media mentions; instead, they predict that exit is related to tendencies in (1) whether and how firms solicit media coverage, and (2) the extent to which a firm is mentioned singly versus with others. Applying the geometric moving average gives a better picture of these tendencies.

Finally, as previously noted, fixed-effects estimation provides a measure of control for product quality in analyses of coverage and coverage centrality. Quality may vary, but inasmuch as it depends on firm capabilities that are difficult to alter, changes should generally be slight.

RESULTS

Descriptive statistics. Figure 4 shows how the data break down into releases versus news stories and the number of market entrants mentioned in each. The proportion of news stories that mention only one competitor is considerably lower than the proportion of press releases that mention only one competitor. This pattern fits the prediction that mentioning competitors—or community—suggests to reporters that would-be pioneers are doing something worth seeing as "for real." This is consistent with neo-institutional theory's emphasis (DiMaggio and Powell 1983; Meyer and Rowan 1977) on the value of fitting into legitimate categories (see especially Zuckerman 1999).

Table 1 shows descriptive statistics and correlations. While correlations between explanatory variables are generally low, correlations between lagged and squared versions of some

[1] See Grambsch and Therneau (1994) and Schoenfeld (1982); details of Stata implementation are available from Cleves, Gould, and Gutierrez (2002).

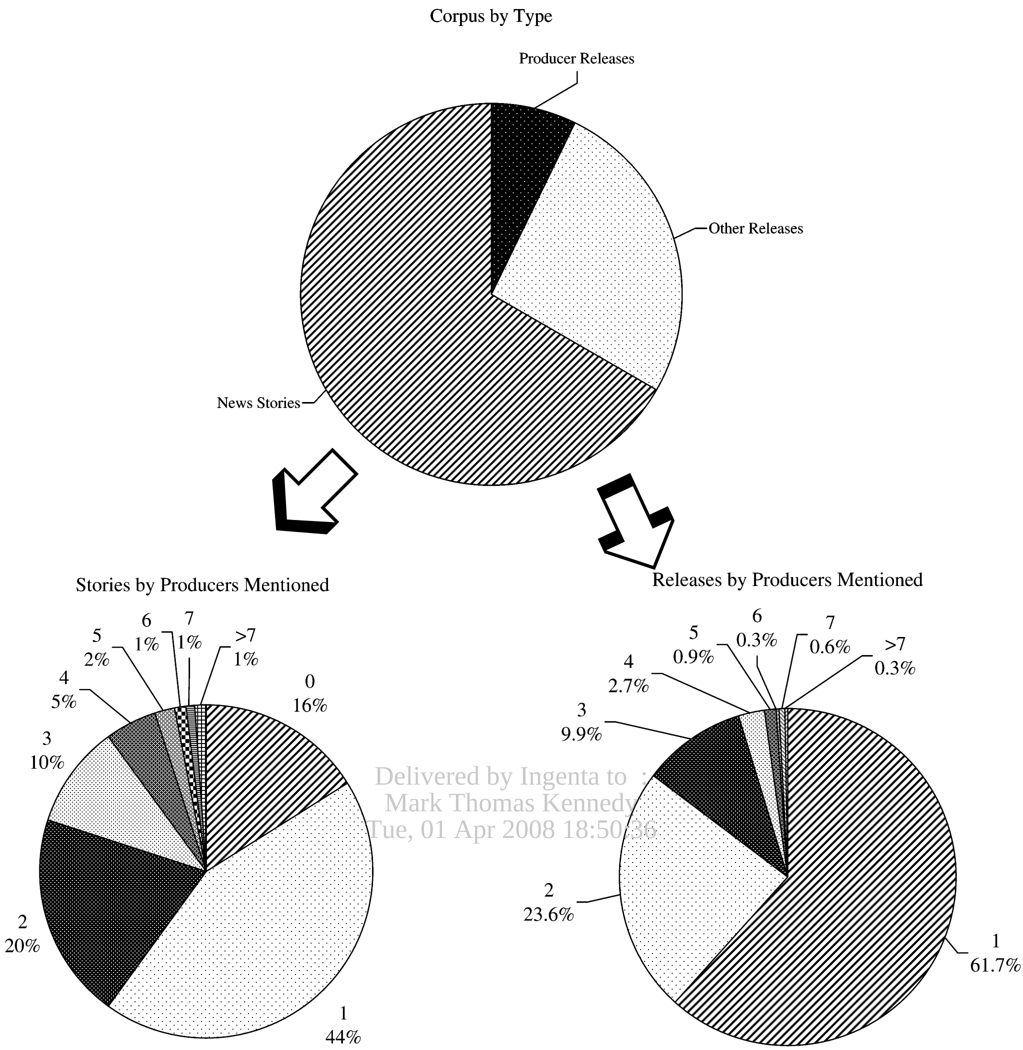

Figure 4. Corpus Breakout by Story Type, Story Density, and Release Density

Note: 1 to > 7 indicate the number of market entrants mentioned in each story or press release.

model factors are high. To investigate potential inflation of coefficient standard errors, I use OLS regressions to check variance inflation factors by period. In several periods, variance inflation factors for ASD and ASD^2 hover between 10 and 11 (10 indicates multicollinearity problems). Increasing the exponent on the quadratic term to 2.2 drops variance inflation factors comfortably below 10, and using an exponent of 3 reduces variance inflation factors to around 5. With both transformations, results patterns are unchanged in all models. To ease interpretation, I use the squared terms.

Analysis of coverage (hypotheses 1 and 2). Table 2 shows the results of maximum likelihood estimation of cross-sectional, time-series, negative-binomial models of firm-period media coverage, measured as the count of separate news stories that mention market entrants. Unless otherwise stated, hypothesis tests are one-tailed, because all hypotheses specify both a relationship and a direction. All models are estimated with firm-fixed effects. As a robustness check, I ran seemingly unrelated regression models to check for correlation between models of coverage, coverage centrality, and exit. The Breusch-Pagan test of model independ-

Table 1. Descriptive Statistics and Correlation Matrix

	Variable	Obs.	Mean	SD	Min.	Max.	Correlations															
							(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Coverage	1228	19.5	59.59	0	590																
(2)	Coverage Centrality	1228	9.63	11.05	0	50	.66															
(3)	Exit	1228	.02	.15	0	1	–.05	–.13														
(4)	Coverage $_{t-1}$	1228	18.65	57.63	0	590	.96	.64	–.03													
(5)	Coverage Centrality $_{t-1}$	1228	9.49	1.95	0	50	.66	.87	–.04	.66												
(6)	Size	1228	7.24	2.44	2.20	12.9	.44	.57	–.03	.44	.58											
(7)	Age at Entry	1228	19.00	24.30	.13	98	.27	.26	–.05	.27	.27	.67										
(8)	Experience	1228	12.70	8.02	1	37	.09	.25	.08	.09	.27	.16	.08									
(9)	Density $_{t-1}$	1228	6.44	13.02	7	74	.08	.27	.04	.07	.28	.07	.02	.29								
(10)	[a] ARD	1228	.69	.74	0	4.28	.23	.39	–.01	.23	.38	.35	.12	.24	.22							
(11)	[a] ARD^2	1228	1.02	1.68	0	18.36	.14	.26	.01	.14	.26	.21	.02	.17	.19	.91						
(12)	[a] ARD $\times$ t	1228	21.97	25.15	0	123	.28	.46	.01	.28	.46	.35	.12	.33	.26	.96	.87					
(13)	[a] ARD $\times$ t^2	1228	1114	1908	0	15334	.21	.36	.03	.22	.37	.23	.04	.27	.21	.87	.92	.93				
(14)	ASD $_{t-1}$	1228	2.04	1.60	0	5	.13	.48	–.04	.13	.57	.30	.11	.22	.28	.21	.16	.27	.23			
(15)	ASD $_{t-1}{}^2$	1228	6.72	6.87	0	25	.04	.35	–.03	.03	.46	.16	.03	.21	.30	.14	.13	.20	.19	.95		
(16)	[a] ASD	1228	2.02	1.34	0	4.71	.15	.62	–.12	.15	.59	.35	.14	.25	.32	.24	.17	.31	.25	.81	.73	
(17)	[a] ASD^2	1228	5.89	5.42	0	22.17	.09	.57	–.12	.08	.52	.26	.07	.24	.33	.20	.15	.27	.23	.78	.75	.96

Note: ARD = Average Release Density; ASD = Average Story Density.

[a] Geometric moving averages applied to time-varying covariates.

Table 2. ML Estimates of Cross-Sectional, Time-Series, Negative-Binomial Models of Coverage by Entrant, Market for Computer Workstations (1980 to 1990)

	Controls	Hypothesis 1	Hypothesis 2
Factors	Model 1	Model 2	Model 3
Coverage $_{t-1}$	.002	.002	.002
	(.000)***	(.000)***	(.000)***
Size	.254	.245	.201
	(.036)***	(.036)***	(.036)***
Age (at entry)	–.013	–.014	–.012
	(.004)***	(.004)***	(.004)***
Experience	–.018	–.015	–.021
	(.011)	(.012)*	(.012)
[a] Average Release Density		.395	.378
		(.104)***	(.102)***
[a] Average Release Density^2		–.152	–.144
		(.041)***	(.040)***
Average Story Density $_{t-1}$			.366
			(.073)***
Average Story Density $_{t-1}{}^2$			–.049
			(.014)***
Constant	–1.089	–1.048	–.694
	(.450)*	(.445)*	(.449)
Observations	1228	1228	1228
Firms	74	74	74
Periods	41	41	41
d.f.‡	39	41	43
Model Improvement (χ^2)		15.709***	35.914**

Notes: Coefficients for period dummy controls are omitted; some period dummies dropped due to collinearity. Standard errors are in parentheses.

[a] A geometric moving average is applied to these firm-period measures to get a less noisy view of tendencies on these variables.

* $p < .05$; ** $p < .01$; *** $p < .001$ (one-tailed tests for hypotheses).

ence ruled out concerns about model correlation ($\chi^2 = 94.37$, d.f. = 3, $p < .001$).

Model 1 shows results using controls for prior period coverage, size, age at entry, and experience in the market; all but experience are significant. Model 2 shows results for Hypothesis 1, which predicts that average release density (ARD) and its square should lead to coverage. The results support the predicted impact of ARD and ARD^2 on coverage ($p < .001$; $\chi^2 = 15.71$, d.f. = 2; $p < .001$). Model 3 shows results that strongly support Hypothesis 2, the prediction that coverage is also curvilinearly related to average story density, or ASD ($p < .001$; $\chi^2 = 35.91$, d.f. = 2; $p < .01$). I analyzed the full model using random effects estimation, and, as expected, the coefficients are higher but coefficient significance levels remain unchanged.

These findings are consistent with the cognitive embedding argument that firms attract more attention when their press releases reference a few, but not too many, rivals. Coverage flows to firms whose PR releases link them to other firms in cognitive structures that reflect how people interpret the meaning of nascent market categories. Firms receive more coverage when their mentions in the prior period's news stories are neither purely alone nor in crowds that are too large. These results suggest that initial increases in such embeddedness help firms operating in not-yet-legitimate markets avoid being overlooked. The fact that coefficients are lower for fixed-effects models than for random-effects ones suggests that stable characteristics of firms are part of the story here. Product quality, for example, probably accounts for at least part of the difference between random and fixed-effects results.

MEDIATION ANALYSIS. Since ARD could follow ASD (rather than the reverse, as predicted in Hypothesis 2), I test this using cross-sectional, time-series, OLS estimation to perform a simple mediation analysis. The results show that ARD predicts ASD ($p < .05$) but ASD does not predict ARD. While ARD remains significant in analyses of coverage and coverage centrality, it does not affect exit, which suggests that ARD's effect on this coarser performance measure is ultimately mediated by ASD. That is, reporters deciding what stories to write pay attention to the cognitive embedding suggested by releases, not just prior-period stories. I include both ARD and ASD as independent variables in all subsequent analyses, in that order.

ANALYSIS OF COVERAGE CENTRALITY (HYPOTHESES 3 AND 4). Employing the same techniques used to test Hypotheses 1 and 2, Table 3 shows the estimation results for the models of coverage centrality from Hypotheses 3 and 4. Model 1 shows results for the model with controls only. Size is significant, but age at entry and experience in the market are not. Model 2 shows support for Hypothesis 3, the prediction that ARD should have an inverse U-shaped relationship to coverage centrality ($p < .001$; $\chi^2 = 29.94$, d.f. = 2; $p < .001$). Model 3 shows results for Hypothesis 4, the prediction that ASD also has an inverse U-shaped relationship to coverage centrality ($p < .001$; $\chi^2 = 55.17$, d.f. = 2; $p < .001$).

Table 3. ML Estimates of Cross-Sectional, Time-Series, Negative-Binomial Models of Coverage Centrality by Entrant, Market for Computer Workstations (1980 to 1990)

	Controls	Hypothesis 3	Hypothesis 4
Factors	Model 1	Model 2	Model 3
Coverage Centrality $_{t-1}$	.029	.027	.022
	(.004)***	(.004)***	(.004)***
Size	.298	.287	.253
	(.039)***	(.039)***	(.037)***
Age (at entry)	–.000	.001	.001
	(.005)	(.004)	(.005)
Experience	–.005	–.010	–.013
	(.010)	(.011)	(.010)
[a] Average Release Density		.538	.530
		(.069)***	(.069)***
[a] Average Release Density^2		–.079	–.168
		(.013)***	(.013)***
Average Story Density $_{t-1}$			.477
			(.068)***
Average Story Density $_{t-1}{}^2$			–.075
			(.013)***
Constant	–2.453	–2.153	–2.072
	(.507)***	(.499)***	(.498)***
Observations	1228	1228	1228
Firms	74	74	74
Periods	41	41	41
d.f. ‡	39	41	43
Model Improvement (χ^2)		29.492***	55.171***

Notes: Coefficients for period dummy controls are omitted; some period dummies dropped due to collinearity. Standard errors are in parentheses.

[a] A geometric moving average is applied to these firm-period measures to get a less noisy view of tendencies on these variables.

* $p < .05$; ** $p < .01$; *** $p < .001$ (one-tailed tests for hypotheses).

These findings are consistent with the cognitive embedding argument that firms who reference a rival or two in releases position themselves such that the meaning and structure of their product market categories are understood. Conventional wisdom suggests that would-be pioneers emphasize points of differentiation to support their positioning claims; study results suggest such differentiation is most effective when firms dare to dignify one or two competitors in their PR releases. These results fit with the argument that coverage centrality—being most often mentioned with others whenever stories about the market are told—should follow from a tendency to be mentioned in stories neither singly nor with so many others as to get lost in the shuffle and be forgotten. While too-low ASD leads to obscurity, too-high ASD appears to produce crowding that increases the risk of being forgotten.

ANALYSIS OF MARKET EXIT (HYPOTHESES 5, 6, AND 7). Table 4 shows the results of maximum-likelihood estimation of piecewise constant models of exit from the market for computer workstations. I estimated models in STATA using routines supplied by Sørenson (1999). Period and year dummies are included in all models, but they are omitted from the table due to space constraints.

Model 1 shows results with controls for size, age at entry, and period. While age is significantly related to exit, size is not. Model 2 shows density and its square. Consistent with prior research, population density affects exit negatively, while density squared has a positive effect on exit. With a one-tailed test, the coefficients are significant ($p < .05$), though model improvement is only marginally significant ($\chi^2 = 4.61$, d.f. = 2, $p < .10$). Even though this study focuses on the early period in which workstation population did not decline significantly, test results replicate the familiar density dependence pattern: the beneficial legitimating effects of increasing entry are overwhelmed as continued entry leads to intensifying competition for customers.

Models 3 and 4 show results when coverage and coverage centrality, the dependent variables estimated in the previous analyses, are added to test whether ARD and ASD impact exit beyond their effects on coverage and coverage centrality. To put all of the media-based covariates on an equal footing, I applied a geometric moving average to coverage, coverage centrality, ARD and its interactions, and ASD. This provides a dynamic view of firms' current media profiles while incorporating the historical trend; it also smoothes out drops during quarters in which firms neither seek nor receive news coverage. Using moving profiles, rather than "just what happened in the past quarter," maps nicely to the ideas behind the market-exit hypotheses.

Although Model 3 shows a negative relationship between coverage and exit, this relationship is not significant, and neither is model improvement. In Model 4, however, the negative coefficient for coverage centrality is significant ($p < .01$), as is model improvement ($\chi^2 = 18.51$, d.f. = 1, $p < .001$), suggesting that exit risk declines with increasing prominence in the cognitive market network based on media co-mentions. Note that the coverage coefficient switches from negative to positive when centrality is introduced. This suggests that media coverage benefits go to those who are central in the cognitive networks it creates.

Model 5 shows the results of Hypothesis 5, which states that ARD should have a U-shaped curvilinear effect on exit rate. When ARD and its square are added to Model 4, a specification that includes coverage and coverage centrality as controls, neither is significant and the model is not improved. As expected, this is also true when ARD and ARD^2 are added individually. When added to a model that includes the controls but not coverage or coverage centrality, however, ARD and ARD^2 are both significant and the model improves. Referencing rivals thus does not affect exit directly, but it appears to affect it indirectly by its effects on attention and prominence.

Models 6 and 7 show results for Hypothesis 6, which predicts that exit should have a U-shaped relationship to ASD. While the results do not show the predicted U-shaped relationship, they do show support for the idea that being mentioned with others in news stories is more helpful to firms than being mentioned alone. Model 6 shows that ASD has a significant negative impact on exit, with marginal model improvement ($\chi^2 = 3.03$, d.f. = 1, $p < .10$). When ASD^2 is added in Model 7, its coefficient is significant ($p < .01$) and negative, not positive as predicted, and both the coefficient and the model improvement statistic are significant

Table 4. ML Estimates of Piecewise Constant Rate Models of Exit from the Market for Computer Workstations (1980 to 1990)

	Controls				H5	H6		H7
Factors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Size	–.005	–.008	.244	.398	.409	.433	.455	.428
	(.123)	(.124)	(.125)*	(.127)**	(.136)**	(.139)**	(.136)**	(.133)**
Age at Entry (years)	–.030	–.030	–.046	–.059	–.056	–.058	–.069	–.061
	(.013)*	(.012)*	(.015)**	(.020)**	(.020)**	(.020)**	(.021)**	(.018)**
Period	.017	.137	.162	.185	.168	.160	.274	.245
	(.178)	(.232)	(.224)	(.225)	(.231)	(.225)	(.237)	(.236)
Population Density $_{t-1}$		–2.431	–2.129	–2.380	–2.554	–2.450	–2.194	–2.104
		(1.323)	(1.035)*	(1.142)*	(1.274)*	(1.214)*	(.972)*	(.988)*
Population Density $_{t-1}{}^2$		.019	.017	.019	.020	.019	.017	.017
		(.010)	(.008)*	(.009)*	(.010)*	(.009)*	(.008)*	(.008)*
[a] Coverage			–.079	.017	.017	.003	–.010	–.016
			(.061)	(.005)**	(.005)**	(.010)	(.018)	(.022)
[a] Coverage Centrality				–.230	–.222	–.103	–.002	–.006
				(.041)**	(.043)**	(.061)	(.111)	(.127)
[a] ARD					–.634	–.613	–.813	–15.655
					(.526)	(.536)	(.541)	(4.461)**
[a] ARD^2					.254	.228	.278	2.276
					(.151)	(.153)	(.168)	(.592)**
[a] ASD						–.519	2.570	2.876
						(.237)*	(.641)**	(.777)**
[a] ASD^2							–1.230	–1.380
							(.276)**	(.306)**
ARD x t								.434
								(.136)**
ARD x t^2								–.002
								(.001)**
[b] Observations	1,228	1,228	1,228	1,228	1,228	1,228	1,228	1,228
d.f.	29	31	32	33	35	36	37	38
Log-likelihood	–34.530	–32.226	–26.517	–17.263	–16.608	–15.092	–5.034	–.699
LR Chi^2		4.609	7.838	18.509**	1.310	3.032	20.116**	11.505**

Notes: Coefficients for year and period dummies are omitted; robust standard errors are used. Standard errors are in parentheses. ARD = Average Release Density; ASD = Average Story Density.

[a] A geometric moving average is applied to these firm-period measures to get a less noisy view of tendencies on these variables.

[b] 1,228 firm-period observations from 74 firms over 41 possible periods containing 27 failures.

* $p < .05$; ** $p < .01$; *** $p < .001$ (one-tailed tests for Hypotheses 5, 6, and 7, density controls).

($p < .01$; $\chi^2 = 20.12$, d.f. = 1, $p < .001$). These results show that the exit rate falls with initial increases in the average number of firms mentioned with a focal firm, but they do not show the hypothesized downside of being mentioned with too many other firms. In these data, there is no such thing as being overmentioned with others—that is, even being mentioned in a crowd appears to be helpful for firms in new markets. This suggests a new version of the old "there is no such thing as bad publicity" adage, namely, "There is no such thing as being mentioned with too many competitors."

Model 8 shows the results of Hypothesis 7, the prediction that the effects of referencing rivals change as the category develops. When the interaction factor (ARD $\times$ time) and its square are added to the model, coefficients for both are significant ($p < .01$), with significant model improvement ($\chi^2 = 11.51$, d.f. = 1, $p < .01$). This result shows that suggesting connections to competitors goes from being helpful to unhelpful as the relevant community accepts a nascent niche as an established market—one that is "for real."

Figures 5 and 6 interpret this study's key findings. Holding other factors at mean levels, Figure 5 shows how average release density affects exit rate. To demonstrate ARD's interaction with time, separate lines are shown for years 3 and 6 to 9; in each case, the domain extends from zero to the maximum observed value for that year. In year 3, increases in ARD uniformly reduce exit rates, albeit at a reducing rate, and year 6 is much the same. In years 7 and 8, lower levels of ARD reduce exit rate, but higher levels of ARD increase it. Note that hazard rate minima correspond to ARD values of more than one (1.6 and 1.3, respectively). In other words, compared with firms that do no publicity (ARD = 0), the exit rate is cut roughly in half for firms that issue press releases in which they reference a rival or two at least part of the time.

Figure 6 illustrates the effects of being mentioned alone in actual news stories versus being mentioned with others. Over the analysis peri-

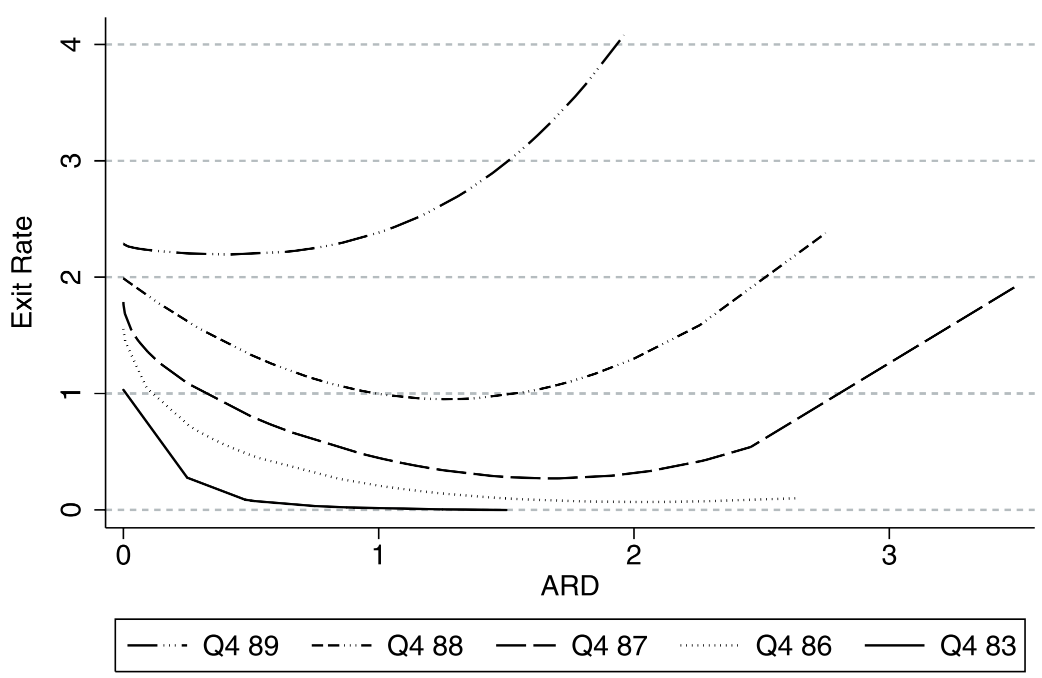

Figure 5. Interpretation of Average Release Density (ARD) Effects on Exit

Notes: Exit rate by ARD and Time. Market for computer workstations (1980 to 1990).

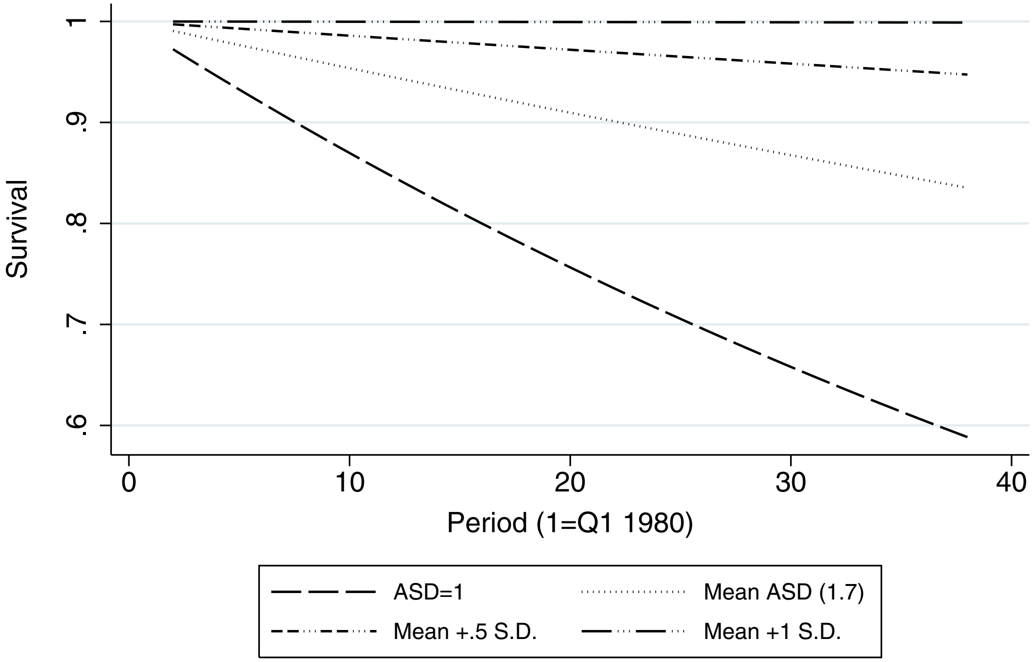

Figure 6. Interpretation of Average Story Density (ASD) Effects on Survival

Notes: Survival by ASD. Market for computer workstations (1980 to 1990).

od, the survival rate for firms always mentioned alone (ASD = 1) declines to less than 20 percent, while being mentioned with rivals bumps that up considerably. At the mean level of ASD (1.7), the survival rate rises to nearly 60 percent, a three-fold increase. For firms with ASD one-half standard deviation above the mean, the survival rate soars to nearly 90 percent, over four times the rate experienced by firms that are always mentioned alone.

DISCUSSION

The counting conundrum is at the heart of the long odds faced by would-be field pioneers. This study, in its examination of media coverage about a new market, shows that media coverage makes market entrants countable as a new population by embedding them in an emerging category. Audiences must learn to see market entrants as a distinct new population—or, to put it a little more strongly, as a population that is "for real."

Overall, the linguistic turn to meaning and structure offers new ways of studying the dynamics of social fields such as markets, organizational forms, and social movements. Integrating ideas about social structure with philosophical approaches to meaning, as well as advances in search and information processing, yields practical approaches to empirical work that relate the ontological status of new social realities to everyday language as it is used in the abduction, translation, and evaluation of claims.

Limitations and directions for future research. This study's limitations suggest directions for future research. Although I examine data from more than 60,000 pages of text spanning a 10-year period, co-mention patterns remain a blunt instrument for modeling emerging market concepts. While stripping market stories down to associations among firms claiming to have entered the market enables large-scale analyses, this comes at the price of ignoring other factors likely to be important to a linguistic approach to market formation. For example, future research could consider the effects of power and status. After all, not every mention is created equal, so to speak. Because categories are defined in terms of both cases and unifying concepts, future work should examine linking categories and counts to both types of associations. Finally, understanding language's role in meaning construction will also require exploring the rhetorical and emotional impact of stories (Green 2004; Weber, Thomas, and Rao 2006). This promising area of research can shed light on how people receive offers of the symbolic associations that construct meaning.

To keep a manageable scope, this study focuses on commercial workstations, leaving out important foundational research done at SRI in the 1960s and at Xerox PARC in the 1970s. Ruef (2000) makes a compelling case for understanding new industries as products of community interactions; Baum and Oliver (1992) demonstrate that links to legitimating institutions impact the survival of new types of organizations. Further work should explore links between commercial markets, proto-industries, and research and development communities.

For markets and other types of social fields, developing general theories of field dynamics requires analyzing both successes and failures. At best, however, single-case studies can only suggest general patterns. While formal modeling can contribute to theorizing, testing theory raises the level of analysis to multiple markets or fields. Depending on the mechanisms of interest, such a move could require increasing data collection and analysis considerably; this will demand tools and techniques for very large-scale studies of the links between cognitive and social structures. Future research should step up to this challenge.

CONTRIBUTIONS TO METHOD. As previously noted, this study offers new methods for extracting models of macro-social cognition about categories from relatively large collections of media coverage (see the Appendix). In addition to answering calls for exploration of the dual relationship between language and cognition (Carley 1994; Mohr 1998; Vygotsky 1986), these new techniques produce data suitable for large-scale analysis of quantitative structural data extracted from texts. By scaling up extraction, I show that cognitive mapping techniques can be used to build networks that track the construction of meaning as categories that define new fields evolve. This research successfully uses these techniques to analyze whether the structure of market networks is shaped by the inputs of market participants.

Looking ahead, rapid advances in tools that retrieve network analysis and information are opening new frontiers for studying social structure. No one person could hope to make sense of or even consume all of the overlapping and conflicting stories about a nascent field contained in ever-expanding text and Internet archives, but it is increasingly practical to analyze substantially all relevant media discourse to see if it is producing a coherent category. This study's theory and methods are a promising step in that direction. Further refinements should make it possible to test hypotheses about general patterns in field dynamics (e.g., Powell et al. 2005). In the case of markets, for example, it should be possible to relate patterns in market networks to consolidation and decline, not just to formation and growth.

CONTRIBUTIONS TO THEORY. This study offers three main contributions to theory. First, I show that media-based market sensemaking shapes markets, especially by embedding entrants in shared cognitive networks that audiences can use to make sense of what the firms do. This extends White's (1981, 2002) work on social comparisons in market formation by offering a discursive mechanism for directing competitor analysis and shaping what White calls context. Significantly, this mechanism enables the counts that help move new markets into the mainstream.

Second, I provide a new view of counts and their role in market formation by resolving the counting conundrum. This new view translates the linguistic turn of neopragmatist philosophers of meaning into novel methods for empirical exploration of meaning construction and its role in the assembly of new social structures. As mentioned in the introduction, I follow a neopragmatist path, but only roughly. Compared to the poetic analyses that Rorty advocated, this approach lends itself to empirical analyses of symbols, the process of constructing shared interpretations of them, and how this all relates to social realities.

Ultimately, turning to talk suggests an explanation for when and why simple counts are reasonable proxies for the legitimacy of new social realities, a much more complex construct (Baum and Powell 1995). Counts are reasonable proxies of legitimacy when they come from directories published by trade associations that exist to distinguish legitimate market categories from rejected pretensions. By controlling for these counts in analyses of market exit, my results suggest that their familiar effects are trumped by variables constructed from the talk that positions firms in a nascent market by embedding them in a shared cognitive structure. This underscores the linguistic foundations of counts and their effects on markets.

Since legitimacy is determined by many factors, however, it takes more than discursively observed connections among firms to identify a legitimate new market. Consider, for example, the markets defined around well-understood social realities that are nonetheless mostly illegitimate (e.g., "the oldest profession" or other "underground" markets). Meaning construction produces social realities that enable counts, but not all social realities are counted. Meaning construction that permits counts represents only an input to legitimation. While framing this study as pertaining to reality construction might seem ambitious, it actually embodies a conservative response to thinking carefully about the differences between legitimacy and perceptions of reality. Future research could benefit from vigilantly distinguishing between the two, and a linguistic turn to meaning construction holds the promise of breakthrough insights in that effort. Compared to conventional studies of institutional environments and their ecology, analyzing the language used to define these environments moves the level of analysis down a notch to focus on more basic mechanisms—by analogy, it is like studying a phenomenon using chemistry rather than biology.

Third, this study also shows that firms actively shape the markets they eventually inhabit. By tuning into the channels that give firms a voice in market sensemaking, I show that the inhabitants of a new organizational environment have both a material interest and a very real say in its construction. This finding joins and extends an emerging stream of research that links the dynamics of social fields to the emergence of distinct identities (Jensen 2007; McKendrick et al. 2003; Pólos, Hannan, and Carroll 2002) and network evolution (Powell et al. 2005), particularly through the linguistic turn to the landscapes of institutional and organizational environments (Green 2004; Lounsbury and Glynn 2001; Lounsbury and Ventresca 2003; Suddaby and Greenwood 2005).

CONCLUSION

Tracking firms' discursive contributions to market construction suggests the outlines of a viable alternative to the materialist, evolutionary framing that has dominated theorizing about organizational environments for the last several decades. New insights into the dynamics of social fields are likely to arise by fusing the linguistic turn of neopragmatist philosophers with a cognitive adaptation of economic sociology's embeddedness perspective and its use of network analysis. In support of this theoretical move, advances in computer science for search are enabling powerful new techniques for finding and analyzing patterns in unstructured text.

These perspectives hold the potential to show us meaning as it is constructed and to link it to the emergence of new social structures. At first, new social structures are little more than shaky symbolic scaffolds strung up to support the building of more permanent structures for reallocating resources—usually toward the builders. As communities develop shared interpretations of these symbolic frameworks, their initial flimsiness is transformed into the material solidity of reinforced steel bars, and they begin to operate as the familiar iron cage, bringing rewards for conformity and sanctions for deviation. Whatever the motivations, this transformation is wrought by language. A linguistic turn in theory and method therefore promises a practical way to advance understanding of how meaning and structure relate to the activities of those who fashion them, even as they are fashioned by them. By offering empirical analyses of meaning making and its consequences, sociologists could confirm Rorty's speculation (1967 [1992]:374) that philosophical methods for analyzing meaning and language may ultimately merge with scientific ones—social scientific ones, to be precise.

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APPENDIX

Conceptually, extracting networks that model market categories from media coverage builds on Carley's (2002) call to move beyond content analysis of text to pattern-level analyses that provide maps of social cognition. Drawing on work that links language to the structure of mental models, Carley analyzes transcripts of team interactions to develop and illustrate approaches for extracting "team" mental models of concepts (see Carley 1986, 1994). Whereas Carley's work illustrates approaches for going from concepts to categories using a fairly detailed analysis of a relatively small amount of live conversation "text," my study features an approach that moves from cases to categories by using a simpler, larger-scale approach to develop category "maps." Specifically, I develop "cognitive market networks" by extracting patterns of mere co-mentions from a corpus of tens of thousands of pages of media discourse.

METHODS FOR EXTRACTING CATEGORY MODELS FROM A CORPUS OF MEDIA COVERAGE

As previously noted, the key variables in this study were developed from a corpus of media coverage using software designed to extract within-story patterns of association of terms that refer to producers. Working from lists of active market entrants for each period, the software parses all stories to develop story profiles, period counts of stories mentioning each firm, and unfolding graphs of category structure obtained from building firm-by-firm co-mention networks for each period. Called S2S (Stories to Structure), the software operates on batches of stories organized by analysis period. From a single file containing all of the news stories for a given analysis period, the software isolates individual stories to capture a summary profile including, but not limited to, date, source, length, copyright holder, and contact information (if present). The resulting profile data is then used for a number of purposes, including distinguishing press releases from regular news stories. In addition, the body text of each story is parsed to count mentions of strings associated with firm names. I then use firm period-mention counts to produce a firm-by-firm co-mention matrix (M), in which each i,j element contains the number of times firms i and j are co-mentioned in that period's stories.

To illustrate, consider six firms (A to F) that have released products. These products are increasingly understood as similar enough that they constitute a new market: widgetrons. For the current quarter, suppose there are nine stories (1 to 9) about widgetrons. (Typically, there are many more stories than there are firms, but this keeps things manageable for purposes of illustration.) Upon reading all nine stories, say we find that Firm A is mentioned in Stories 1, 3, 7, 8, and 9; Firm B in 2, 3, and 7; Firm C in 4; D in 4, 5, and 6; Firm E in 5; and Firm F in all but 4, 7, and 8. As illustrated in Figure A, this count information can be summarized in a mentions matrix and summarized even further in a co-mention matrix. The interior cells of the mentions matrix show a 0 or 1 to indicate whether firms (in the rows) are mentioned in the stories (in the columns). The co-mention matrix M collapses this to show in its cells how many times each pair of firms is mentioned together across all stories. For example, Firms B and F are mentioned together twice; Firms C and F are never mentioned together.

These co-mention matrices capture similarity relationships in a graph (or network) structure that reveals both the emerging meaning of the product category and the social structure of the emerging product market. A longitudinally unfolding series of these co-mention matrices traces the emergence of both category meaning and market structure. The resulting category graphs ("categraphs") model networks of competitive relationships in the macro-socially constructed market space being worked out through the sensemaking of public discourse.

Social network analysis of a categraph provides quantitative measures of properties of the market network and firms' positions in it that map onto features of competition such as mindshare, the intensity of rivalry, and the emergence of market segments. In the simple hypothetical example shown in Figure A, Firm F possesses the highest degree of centrality in M. Practically speaking, this means Firm F is most often mentioned with others in stories

Firm-by-Story Incidence Matrix: A Mentions Matrix

	1	2	3	4	5	6	7	8	9
A	1	0	1	0	0	0	1	1	1
B	0	1	1	0	0	0	1	0	0
C	0	0	0	1	0	0	0	0	0
D	0	0	0	1	1	1	0	0	0
E	0	0	0	0	1	0	0	0	0
F	1	1	1	0	1	1	0	0	1

Cognitive Market Network as a Firm-by-Firm, Co-Mentions Matrix (**M**)

M	A	B	C	D	E	F
A		1	0	0	0	1
B	1		0	0	0	2
C	0	0		1	0	0
D	0	0	1		1	1
E	0	0	0	1		1
F	1	2	-	1	1	

Cognitive market network:
Shows F is most central in M (degrees of centrality).

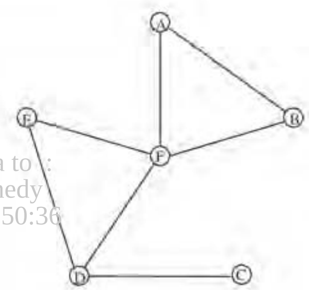

Figure A. Procedure for Going from Stories to a Cognitive Market Network

about the market. Conceptually, it means that Firm F leads in a kind of prominence marketers and practitioners refer to as "mindshare." In contrast, Firm C is peripheral. In the language of this article, stories 3 and 5 have the highest "story density" at 3; that is, these stories contain references to three of the firms we are analyzing.

It should be practical to scale up the techniques used here by several orders of magnitude and, at the same time, to go beyond co-mention analysis to identify increasingly sophisticated patterns of association among terms of interest.

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