When to Take or Forgo New Product Exclusivity: Balancing Protection from Competition Against Word-of-Mouth Spillover

Manufacturers or resellers introducing a new product often must decide whether and for how long to be its exclusive seller. Standard models of competition and conventional wisdom suggest that exclusivity boosts profits. However, using both agent-based simulations and game-theoretic modeling, the authors find that positive word of mouth (WOM) from customers of rival firms can make exclusivity unprofitable. This reversal of conventional wisdom occurs because WOM creates a positive externality, and a firm holding exclusivity cannot benefit from the WOM spillover generated by customers of other firms. The benefits of forgoing exclusivity are magnified by (1) the presence of locked-in customers who consider buying from only a single firm, (2) the extent to which opinion leaders are among a firm's own locked-in customers rather than those of competitors, and (3) customers' low price sensitivity. In addition, firms sometimes benefit from forgoing exclusivity even without WOM from rivals' customers, but only when the combination of large-scale lock-in, high price sensitivity, and strong WOM among the firm's customers exists.

Keywords: product exclusivity, new products, word of mouth, social networks, social contagion

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hen the marketing executives of Comverse Technology launched their innovative voice-based verification product in Japan in 1995, they had an intriguing interaction with NTT DoCoMo (NTT hereinafter), one of their potential distributors. Comverse offered NTT the opportunity to be the exclusive distributor of the new product in Japan. The firm agreed to represent Comverse but rejected the exclusivity offer. Moreover, NTT executives insisted that Comverse sell the product through other distributors in addition to NTT.

NTT's response was surprising because it contradicts the conventional wisdom among both practitioners and

Renana Peres is Assistant Professor of Marketing, School of Business Administration, Hebrew University of Jerusalem (e-mail: renana.peres@ mail.huji.ac.il). Christophe Van den Bulte is Professor of Marketing, The Wharton School, University of Pennsylvania (e-mail: vdbulte@wharton. upenn.edu). The authors benefited from discussions with Oded Koenigsberg and from comments by Ronald Burt, Jeffrey Cai, Anne Coughlan, Chrysanthos Dellarocas, Jacob Goldenberg, Michael Haenlein, Yogesh Joshi, Barak Libai, Gary Lilien, Eitan Muller, Raji Srinivasan, Upender Subramanian, the review team, seminar participants at the University of Pennsylvania and the University of Texas at Austin, and participants at the 2010 Workshop on Information Networks and the 2011 Marketing Science Conference. The authors thank Tal Tamir for her research assistance. This research was supported by the Kmart Fund and the Israel Internet Association. Parts of this research were conducted when Peres was Visiting Assistant Professor at the University of Pennsylvania and when Van den Bulte was Chazen Visiting Scholar at Columbia University. V. Kumar served as area editor for this article.

researchers. Manufacturers and resellers typically prefer to be exclusive for three reasons. First, they do not have to compete for customers and thus can achieve higher sales. Second, monopoly enables them to charge higher prices. Third, being the exclusive seller can increase a company's bargaining power with suppliers and generate increased economies of scale or experience, all of which may lower costs and boost margins. Lack of business stealing, monopoly pricing power, and cost improvements all typically result in higher profits.

What, then, motivated NTT to insist on nonexclusivity? As its managers told the Comverse team involved during negotiations, NTT was less concerned about protecting itself against the negative effects of competition than about capitalizing on a positive externality of competition. Specifically, NTT considered that although accepting exclusivity would protect it against rivals and boost its bargaining power with Comverse, the product's great innovativeness made it even more important to establish its credibility and legitimacy as quickly and as widely as possible. Having NTT—or any other firm—be the sole seller would have limited the number of reachable customers and thus curtailed the amount of word of mouth (WOM) and peer-based legitimation in the Japanese market. This, in NTT's estimation, outweighed the standard benefits of exclusivity.

A counterexample that illustrates the conventional wisdom is AT&T's decision to offer favorable terms to Apple in exchange for being the exclusive U.S. service provider for the early iPhone. These terms included an unprecedented revenue-sharing agreement that gave Apple approximately \$10 a month from each iPhone customer's bill (Yoffie and Kim 2010). This strategy may have been a sound course of action for AT&T. Because its number of loyal or locked-in customers had dwindled over time, having a unique and buzz-worthy product could help restore its ability to compete against other service providers.

The contrast between NTT's and AT&T's strategies suggests that WOM is not the only consideration affecting the decision to accept or forgo exclusivity. Whether the company is exposed to intense rivalry may also be a critical driver. Of course, it is difficult to draw strong conclusions from any such anecdotes, and it is possible that one or both of these companies made the wrong decision.

The examples of NTT and AT&T suggest a tension between two considerations. Standard models of competition and conventional wisdom suggest that exclusivity boosts profits because it protects against the harmful effects of competition: fewer customers and lower margins. However, as the NTT managers noted, exclusivity also precludes a firm from benefiting from the positive externality of social contagion stemming from competitors' customers. Protection against competitors favors exclusivity, but WOM across customer bases favors the opposite. How then should firms balance those two considerations? We aim to shed light on this issue in the current research.

Rivals' customers can boost a firm's own sales in various ways. Word of mouth is one such way. Customers who talk or write positively about a new product make others aware of the category and make it credible by vouching for its reliability, ease of use, and so on. In addition, rivals' customers can increase sales through visual influence. Simply using the product in public can boost awareness, increase social-normative acceptability or legitimacy, and trigger concerns about social status. These factors have long been recognized as important elements in fashion apparel, but they arguably also matter in mobile consumer electronics (e.g., smartphones, earbuds vs. large headphones). Rivals' customers can also boost another firm's sales through installed base effects or network externalities. The utility of communication and information technology hardware and software often increases with the size of the installed base either directly (because of interoperability) or indirectly (through the increased supply of complementary products and services).

The various contagion mechanisms (awareness, belief updating, social-normative pressure, competition for status, and network externalities; see Iyengar, Van den Bulte, and Choi 2011) can operate both within and across brands or vendors (Krishnan, Seetharaman, and Vakratsas 2012; Libai, Muller, and Peres 2009). For example, a consumer who bought a Samsung smartphone may influence other consumers—through WOM, visual influence, or less directly through the greater availability of accessories and apps—to buy a smartphone as well, although not necessarily one made by Samsung. Similarly, a corporate customer who bought Comverse's voice recognition software from a systems integrator other than NTT could facilitate subsequent sales of the same software by NTT. How WOM and other contagion dynamics influence the appeal of product exclusivity is important to at least three kinds of companies. The first are resellers with the opportunity to be exclusive distributors, such as NTT and AT&T. The second are manufacturers that have developed a new technology and must decide whether to market it themselves as a monopolist or to make the technology available to competitors through licensing or by selling them key components (e.g., Chen and Xie 2007; Conner 1995; John, Weiss, and Dutta 1999; Xie and Sirbu 1995).¹ The third are companies in fashion industries, in which forgoing exclusivity for one's designs can increase not only social contagion, boosting overall demand, but also competition, depressing market share and margins (e.g., Barnett 2005).

This study investigates how the decision to take exclusivity is driven by a trade-off between seeking protection against competition and leveraging social contagion (which we refer to as WOM because that narrower term is more familiar to marketers). The contrast between the NTT and AT&T examples suggests that customer lock-in may be critical to how firms should make that trade-off. Like many other systems integrators, NTT has many locked-in customers who may monitor the offerings of other suppliers but are very unlikely to buy from them (Heide and Weiss 1995; Wuyts et al. 2004). Thus, NTT could benefit from the WOM its competitors' customers generate without fear of losing much business to these rivals. In contrast, AT&T was operating in a cell phone market with limited switching costs and was not positively regarded by its customers. Without strong customer lock-in or loyalty, it was especially eager to be the exclusive service provider of the original iPhone.

We answer our research question using both agentbased simulation and game-theoretic modeling. In so doing, we leverage the strength of each method, show that our key insights are robust to whether WOM accelerates sales or expands overall demand, and ensure that our key result is not driven by some technical assumptions specific to either method. Using formal methods of theorizing provides protection against falling victim to hidden assumptions (Moorthy 1993) and avoids biases from competitive selection in empirical data (Eyuboglu and Buja 2007).

Our work makes three theoretical contributions. First, it shows how WOM (or, more broadly, contagion) and customer lock-in *jointly* affect the optimal go-to-market strategy. The level of customer lock-in critically affects the decision to take or forgo exclusivity in markets with WOM. In essence, we show that cross-brand WOM makes competitors' locked-in customers a complementary asset (Teece

¹Matsushita licensed its VHS video recorder technology, whereas Sony kept the exclusivity over its Betamax technology. Canon commercialized its laser engine printing technology in the 1980s by selling both ready-to-use desktop laser printers to end users and printer subsystems to competitors such as HP and Apple (John, Weiss, and Dutta 1999). In the current tablet computer market, Apple has kept exclusivity over its iOS operating system, whereas Google has commercialized its Android system both directly in Nexus tablets and indirectly through licenses to Asus, Dell, Lenovo, Samsung, and others. Similarly, Microsoft has commercialized its Windows RT operating system by selling its own Surface tablets and by licensing to competitors.

1986) and that forgoing exclusivity may be a price worth paying to capitalize on that asset.² Second, we show that forgoing exclusivity can be profitable even when exclusivity is only temporary, competitors offer products of equal quality, and WOM is weaker across than within brands. Third, by documenting the interplay between customer lock-in and WOM, we provide new insights into the interlock between a "vertical" network of commercial ties and a "horizontal" network of WOM ties (Van den Bulte 2010).

We first review the related literature. Next, we discuss market characteristics likely to affect the balance between seeking protection from competition and leveraging WOM externalities. We then describe the design of the agentbased simulation study and its results and complement this with the game-theoretic analysis. We conclude with a discussion of the results' implications for theory, practice, and research.

Related Literature

WOM and Other Positive Spillovers Among Competitors

Several studies have documented the existence of positive WOM spillovers across competing firms or their brands. Gatignon, Anderson, and Lajos (2007) find that sales of a new product in one channel can accelerate sales in another channel. Research on software piracy has indicated that spillovers between the legal and pirate versions of a product can promote the penetration of the new product (e.g., Givon, Mahajan, and Muller 1995). Word of mouth can also spill over across brands (Krishnan, Seetharaman, and Vakratsas 2012), enabling later entrants to experience a faster takeoff (Libai, Muller, and Peres 2009).

Similar effects may operate through contagion processes other than WOM. Research on early product life cycle dynamics has suggested that competitors benefit from one another through their investments in distribution infrastructure or through their mere presence, legitimating the new category and assuaging customers' concerns about the absence of alternative sources of supply (e.g., Agarwal and Bayus 2002; Geroski and Vlassopoulos 1991). In addition, competitors may benefit from one another's experience either directly or through the use of common suppliers (Dockner and Jørgensen 1988).

Customer Lock-In and Positive Spillovers Among Competitors

Markets in which all firms can sell to all customers are rare. More common are markets with a mixture of "switchable" or "shared" customers who are able and willing to purchase from more than one firm and "locked-in" customers buying from only a single firm. As a result, firms often have customer bases that only partially overlap.

The pattern can stem from differences in geography, vertical industry sectors, existing service contracts, or brand loyalty that makes some customers consider only a single company (e.g., Fershtman and Muller 1993; Gensch 1984; Heide and Weiss 1995; Narasimhan 1988). Some business customers, for example, use new corporate software only if it is provided and supported by the systems integrator with which they work. Some consumers have such strong attitude toward a company or its brand that they will not buy a new product from anyone else (e.g., Apple aficionados). As a result, firms often have both customers who are sheltered from competition and others for whom they compete. The more the customer bases of the firms overlap (i.e., the greater the fraction of shared customers), the more intensely they compete.

The contrast between NTT and AT&T suggests that firms with locked-in customers are more likely to benefit rather than suffer from the presence of competitors. This is supported by a recent field experiment with a catalog retailer (Anderson and Simester 2013), in which competitors' advertising had a positive effect on customers with the highest switching costs and a negative effect on those with the lowest switching costs. This finding, the authors note, suggests that competitors' advertising primed customers to think about the category and that which company the customers purchased from (competitors vs. focal retailer) depended on lock-in.

New Product Exclusivity and WOM

Prior research has shown that positive spillovers can make it profitable for a company to invite competitors into their market, but it provides no insight into how customer lock-in affects that decision. Previous research on exclusivity in markets with WOM (or contagion in general) has also left other important questions unanswered.

Customer lock-in and opinion leader lock-in. Prior analyses have assumed that all firms can attract all customers and that all customers are equally influential (Conner 1995; Sun, Xie, and Cao 2004; Xie and Sirbu 1995). Opinion leaders (OLs) and locked-in or loyal customers who consider buying from only a single company are ignored, even though such lock-in is common and tempers the need for protection against rivals. In addition, one would expect that a firm that has most OLs locked in as loyal customers has less to gain from cross-brand WOM and from forgoing exclusivity than companies that do not have such support. To what extent does OL lock-in or lockout affect the profitability of exclusivity?

Product quality. Studies by Conner (1995) and Sun, Xie, and Cao (2004) and an essay by Barnett (2005) conclude that forgoing exclusivity can boost profits but only when other entrants provide products of inferior quality (e.g., PC clones, knockoff apparel items). In such cases, being the higher-quality vendor softens the blow from giv-

²We use the term "within-brand (cross-brand) WOM" rather than the more cumbersome "WOM affecting the sales of the product sold by the same firm (different firms)." When the focal firm making the exclusivity decision is a manufacturer, the brand refers to the manufacturer rather than the supplier of the technology (e.g., Samsung vs. HTC rather than Android). Similarly, when the focal firm is a distributor, the brand refers to the distributor rather than the supplier of the product or technology (e.g., AT&T vs. Sprint rather than Apple iPhone, NTT vs. Accenture rather than Comverse).

ing up exclusivity. Can forgoing exclusivity be optimal even without superior quality?

Exclusivity duration. Conner (1995) and Sun, Xie, and Cao (2004) further assume that exclusivity never expires. However, this assumption is not realistic: patents expire, exclusive distribution rights in perpetuity are exceedingly rare, and other sources of exclusivity erode over time as well (e.g., the novelty of product designs). More importantly, assuming perpetuity precludes firms from identifying whether the duration of exclusivity should affect the decision to take or forgo it. Firms with a limited window before their patent expires or their designs become commonplace gain only limited guidance from extant research. Are there market conditions under which long exclusivity is better but short exclusivity is worse than no exclusivity at all?

Strength of WOM within and across brands. Xie and Sirbu (1995) do not make restrictive assumptions about quality and perpetuity and show that positive demand externalities can lead a company marketing a new product to prefer competing immediately over a temporary monopoly. However, they do so under the assumption that WOM is as strong across as within brands. For example, their analysis assumes that the odds of someone buying a Google Nexus smartphone increase by the same amount when ten of his friends bought that very same phone as when they bought another Android smartphone (e.g., Samsung Galaxy, HTC One). This assumption is inconsistent with evidence on the effects of WOM within and across brands (Krishnan, Seetharaman, and Vakratsas 2012; Libai, Muller, and Peres 2009; Parker and Gatignon 1994). More importantly, the assumption is bound to drive the results against exclusivity. Can forgoing exclusivity be optimal even when WOM is weaker across than within brands?

Drivers of the Trade-Off Between Protection from Competition and WOM

Several market characteristics are likely to affect the balance between seeking protection from competition and leveraging WOM spillovers. As our discussion of prior research implies, three stand out: the strength of crossbrand WOM, the vulnerability to competition, and the lockin or lock-out of OLs. In addition to these drivers of main substantive interest, we also investigate three market characteristics that may affect their importance: whether WOM accelerates or expands sales, the speed of diffusion, and the level of homophily and clustering in the WOM network. We discuss each in the subsections that follow.

Strength of Cross-Brand WOM

The more customers buy from one firm in response to WOM from customers who have bought from another firm, the greater the benefit of competitors in the market. The stronger the cross-brand WOM, the greater the externality it generates, and thus the greater the benefits of forgoing exclusivity.

Vulnerability to Competition

Competitors can depress profits both by stealing a firm's customers and by forcing it to cut prices. We investigate both types of vulnerability to competition.

Customer lock-in. The more firms cater to the same pool of shared customers, the greater the potential for business stealing. Conversely, the greater the fraction of locked-in customers, the lower the chance of significant business stealing.

Customer cross-price sensitivity. Competing for customers who are able and willing to buy from more than one firm depresses profits even more when those customers can be swayed by small price differences. The more price sensitive customers are, the more exclusivity can help boost profits. Firms operating in industries in which customers observe a great deal of value added to the naked product (e.g., systems integration for complex corporate information technology solutions) experience less price pressure and thus benefit less from exclusivity than firms operating in commodity-like businesses (e.g., telephone and Internet access service). This distinction may also have contributed to the different decisions made by NTT and AT&T.

OL Lock-In

Not all customers are equally effective in spreading WOM. Those who are more central in the network or who are more persuasive have a disproportional impact on others' behavior. Consequently, if these OLs have such a strong preference for a brand that they would never consider buying from another source, the firm will benefit greatly from within-brand WOM and little from cross-brand WOM. Conversely, a company stands to benefit less from withinbrand WOM and more from cross-brand WOM when the OLs are locked in with its rivals.

Other Market Characteristics

WOM effects: Sales acceleration versus demand expansion. Firms can create value for their shareholders by accelerating or enhancing cash flows (e.g., Srivastava, Shervani, and Fahey 1998), and WOM can affect both the timing and the volume of sales (e.g., Libai, Muller, and Peres 2013). Therefore, to establish the generalizability of our key insight, we study the exclusivity decision in markets of fixed size in which WOM accelerates the sales of a new product as well as in markets in which WOM increases the overall level of demand.

Diffusion speed. The value of a temporary exclusivity for a new product typically depends on how quickly customers are likely to adopt. Little can be gained from being the monopolist of an underdeveloped market. If consumers are likely to adopt slowly such that most of the adoptions take place after the exclusivity expires, the value of protection against competition is low. Conversely, if the market is likely to develop quickly, it is worth more to have a temporary monopoly during that early period. Thus, the value of temporary exclusivity should increase with the tendency to adopt early regardless of cross-brand WOM.

Homophily and clustering. Social networks often exhibit homophily and clustering (e.g., Ansari, Koenigs-

berg, and Stahl 2011; McPherson, Smith-Lovin, and Cook 2001; Rivera, Soderstrom, and Uzzi 2010). Homophily is the "birds of a feather flock together" phenomenon such that nodes in a network are more likely to be connected to others who are like them than to those who are unlike them. Clustering is the "common friends are friends" tendency for closed triads to occur: if node a is connected to nodes b and c, there is a higher-than-average chance that b and c are connected as well. Clustering can affect contagion in various ways. On the one hand, it slows down the transfer of information over long distances in the network, at least when clustering comes at the detriment of bridges between remote parts of the network. On the other hand, it boosts contagion when more than a single exposure is necessary to trigger adoption (Centola 2010; Centola and Macy 2007). We do not expect these bridging and multiple exposure mechanisms to be important, because (1) contagion and information transfer rarely operate over many "hops" in the network (Dodds, Muhamad, and Watts 2003; Goel, Watts, and Goldstein 2012) and (2) our models allow for contagion with even a single exposure, consistent with empirical research in marketing (e.g., Iyengar, Van den Bulte, and Valente 2011). Even though we do not expect homophilyinduced clustering to affect the profitability of exclusivity, we manipulate homophily and clustering to establish rather than assume the generalizability of our key insight.

Methodology

We use both a simulation analysis with an agent-based model and a mathematical analysis with a game-theoretic model. Each approach has its advantages and disadvantages. Agent-based modeling is a flexible method with which to study contagion dynamics in nonregular networks and has become increasingly common in marketing (e.g., Haenlein and Libai 2013; Libai, Muller, and Peres 2013). In contrast, incorporating contagion in continuous-time mathematical models quickly becomes unwieldy even in monopolistic markets with very simple network structures (e.g., Ho et al. 2012; Van den Bulte and Joshi 2007), and identifying optimal strategies requires the researcher to remain at a high level of abstraction (e.g., Fruchter and Van den Bulte 2011; Joshi, Reibstein, and Zhang 2009; Xie and Sirbu 1995). Game-theoretic modeling offers two advantages over agent-based modeling for our research purposes. It enables us to study (1) the entire range of the theory parameter space rather than only discrete points and (2) the forward-looking behavior of profit-maximizing firms as they set prices or make other marketing decisions.

By using both approaches, we leverage the strengths of each and answer our research questions more comprehensively and robustly than by using only one or the other (see Table 1). We use the simulation as the main study, presenting its design and results in detail, and complement this work with a shorter report on the game-theoretic analysis.

Using formal methods of theorizing provides protection against hidden assumptions (Moorthy 1993) and avoids biases from competitive selection in empirical data (Eyuboglu and Buja 2007). As with any deductive reasoning, the results are already contained in the model setup

TABLE 1	
Key Market Characteristics in the Simulation an	d
Game-Theoretic Analyses	

	Simulation Analysis	Game- Theoretic Analysis
Of Primary Interest		
Strength of cross-brand WOM	Yes	Yes
Customer base overlap	Yes	Yes
OL lock-in	Yes	No
Price competition	No	Yes
Of Secondary Interest, Showing Robustness		
Effect of WOM	Sales	Demand
	acceleration	expansion
Repeat purchases	No	Yes
Number of periods	30	2
Network clustering	Low to moderate	Maximum
Number of firms	2 and 5	2

because "no process of logical reasoning ... can enlarge the information content of the axioms and premises or observation statements from which it proceeds" (Medawar 1984, p. 79). For example, the theorems of Euclid's geometry "are merely a spelling out, a bringing into the open, of information already contained in the axioms and postulates. Given the axioms and postulates, to a perfect mind (as A.J. Ayer remarked), the theorems of Euclid would be instantly obvious, without the necessity for making the information they contained explicit by a complicated deductive reasoning" (Medawar 1984, pp. 79–80).

To focus on the issues of central interest, our models assume that the exclusivity holder does not face any active competition, although they incorporate untapped market potential and thus the presence of a passive alternative available to customers. The absence of active competition is obviously a simplification; for example, Sony had exclusivity over the Betamax system but still faced competition from the VHS and Video 2000 systems, and Apple has exclusivity over its iOS operating system but still competes with Android and Windows devices.

Design of Simulation Study with Agent-Based Model

A new product is introduced into a market with 900 customers who can buy only a single unit but can vary in when they do so. We focus on a market with two firms. The customers are connected through social ties and are part of the customer base of one or both firms. Thus, as Figure 1 illustrates, the market features a horizontal network of WOM ties and a vertical network of commercial ties.

Given this new product diffusion setting, we use the present value of the cash flows as profitability metric. We consider only positive contagion because, setting aside price competition, it is intuitive that negative contagion across brands acts as an incentive to take rather than forgo exclusivity.



We first present the network characteristics manipulated in the simulation study: the overlap in customer bases, the structure of the WOM network (degree, homophily, and clustering), and the OL lock-in. Next, we discuss how exclusivity is operationalized. We then present the agentbased model of adoption and conclude with a brief discussion on the choice of parameter values. We combine all factors in a full-factorial design with 45,000 cells, with ten simulated markets in each cell of the design.

Overlap in Customer Bases

We manipulate the level of competition by varying the fraction of shared customers from 0% to 100% in increments of 20%. We equally split the remainder as locked in to either firm, so firms are always symmetric with respect to the size of their customer base.

Customer WOM Network

Number of ties (degree). The WOM networks we create have the same degree distribution as that documented by the Keller Fay Group's *TalkTrack* survey (Keller 2007) in which people are asked about the average number of people with whom they communicate regularly regarding brands and products. The average degree (i.e., the average number of WOM ties per customer) is approximately six. For simplicity, WOM ties are symmetric: if customer a is connected to b, then b is also connected to a. Consistent with recent research, we assume that the contagiousness of an adopter within each of her ties increases with her degree (Iyengar, Van den Bulte, and Valente 2011). Thus, even though ties are symmetric, the strength of influence of a on b need not be the same as that of b on a.

Homophily and clustering. We create WOM networks with different levels of homophily and clustering by means of random graphs with a planted partition (e.g., Condon and Karp 2001; Fortunato 2010). The 900 customers are organized into three separate bins of equal size, which can be based on a customer characteristic related to homophily such as gender, race, lifestyle, location, or industry. The probability that two customers, one from bin i and one from bin j, are connected is p_{ij}. For three bins, there are six probabilities: p_{11} , p_{22} , p_{33} , p_{12} , p_{13} , and p_{23} . If all these probabilities are the same, the network is a standard random or Erdös-Renyi graph without any homophily. Tuning the probabilities allows the level of homophily to increase. We create three WOM networks (Table 2). The first is a standard random network, whereas the other two exhibit "low" and "moderate" homophily because we take $p_{ii} > p_{ii}$ ($i \neq j$).

Homophily induces clustering. The global clustering coefficient (i.e., the mean probability that two nodes are connected given that they are connected to a common node) ranges from .7% to 2%. Because the three networks have the same number of nodes and the same average degree, networks with higher homophily and clustering also have a higher maximum degree, a greater fraction of high-degree nodes, and a higher probability that the high-degree nodes are connected to one another (Serrano and Boguna 2005; Volz 2004).

OL Lock-In and Lock-Out

The extent to which cross-brand WOM generates an externality is likely to depend on whether OLs are shared, locked in with the firm that can claim exclusivity, or locked in with its rival. We define OLs as the customers with the highest degree (see, e.g., Iyengar, Van den Bulte, and Valente 2011). We interlock the horizontal network of WOM ties and the vertical network of commercial ties in four ways, varying the extent to which the most influential customers are locked in with the focal firm or its competitors:

- •*Equal access*. Customers are shared or locked in with either firm independent of their number of WOM ties (degree). Thus, OLs are spread proportionally across locked-in and shared customer bases, and no firm has an advantage.
- •*Strong OL lock-in.* Customers with the highest degree are locked in with the focal firm, which can take or forgo exclusivity; customers with midrange degrees are shared customers; and the customers with the lowest degree are locked in with the rival.
- •*Moderate OL lock-in*. Moderate OL lock-in is a less extreme variation of the preceding scenario: the customers with the highest degree are shared customers. Then, by decreasing degree, customers are locked in first with the focal firm and

		TA	ABLE 2					
Homophily Parameters,	Clustering,	and	Average	Degree	in the	Three	WOM	Networks

Homophily	p ₁₁	P ₂₂	P ₃₃	p ₁₂	р ₁₃	p ₂₃	Clustering Coefficient	Average Degree	Ratio of the Top 33% to Average Degree
None	.007	.007	.007	.007	.007	.007	.007	6.42	1.45
Low	.018	.009	.009	.006	.006	.001	.01	6.37	1.59
Moderate	.035	.008	.008	.003	.003	0	.02	6.43	2

then with its rival. Thus, the focal firm again has customers with a higher average degree than its rival, but by a smaller margin.

•Strong OL lock-out. Strong OL lock-out is the reverse of the second scenario: customers with the lowest degree are locked in with the focal firm, and those with the highest degree are locked in with its rival.

Exclusivity

Exclusivity is the availability of the product through only a single firm, which is temporary, varying from zero to eight periods. For example, if a firm has exclusivity for four periods, it is the only seller for the first four periods that the product is in the market, and only its locked-in and shared customers can adopt. When the exclusivity expires in the fifth period, the product becomes available from all firms, and all customers can adopt.

Adoption Dynamics of Customers

We extend the agent-based model used by Libai, Muller, and Peres (2013). The market begins with zero adoptions and runs for 30 consecutive discrete time periods. For a market with only two firms, customers are in one of three states: 0 for not having adopted, 1 for having adopted from Firm 1, and 2 for having adopted from Firm 2. In each period, customers who have not yet adopted decide whether to buy the product from one of the firms offering it and to which they are connected. If, for example, customer i has not adopted yet and is a shared customer of Firms 1 and 2, but 1 is the exclusive seller, i's choice set for that time period is only $\{0, 1\}$: he can either remain a nonadopter or buy from 1. If he does not adopt, and the exclusivity terminates in a subsequent period, he will begin choosing from states 0, 1, and 2.

As in traditional diffusion modeling, adoption depends on two factors: (1) time-invariant external influence driven by the product's appeal and the customers' innovativeness and (2) internal influence by WOM or other forms of contagion from prior adopters. Internal influence can operate within or across brands and can do so simultaneously. For example, if a potential adopter connected only to Firm 1 has WOM ties with an adopter of Firm 1 and an adopter of Firm 2, then her decision whether to buy from Firm 1 will be affected by within-brand WOM from the first contact as well as cross-brand WOM from the second.

Adoption Probabilities

Agent-based models of new product adoption typically use a competing risk approach in which each prior adopter connected to a customer i can independently trigger i to adopt. The discrete-time hazard of i adopting is one minus the probability that both external influence and internal influence from prior adopters fail to convert him; that is, $p_i(t) = 1 - 1$ $(1 - d) (1 - q)^{N_i(t)}$, where N_i(t) is the number of customers connected to i who adopted the product before time t, d is the parameter of external influence, and q is the parameter of internal influence. This discrete-time competing-risk formulation converges to the continuous-time Bass model as the time interval shrinks to zero, provided that the network is fully connected (Goldenberg, Lowengart, and Shapira 2009). Libai, Muller, and Peres (2013) extend this framework to a competitive scenario for two firms. Here, to address our substantive questions, we extend the formulation to allow for cross-brand WOM and more than two firms

In each period, every potential adopter i considers adopting from any firm that she is connected to and that sells the product. The choice set can include zero, one, or more firms. Intuitively, if the choice set does not include any firm, the customer cannot adopt. If the choice set includes only one firm-say, Firm 1-because of exclusivity or lock-in, the probability that the customer is convinced to consider buying from Firm 1 at time t, $p_i^{l}(t)$, is also the probability of adopting from Firm 1 at time t, P_{it} (adopt from 1):

(1a)
$$P_{it}(adopt \text{ from } 1) = p_i^1(t)$$
, where

(1b)
$$p_i^l(t) = 1 - (1 - d) \times \prod_{j \in N_i^l(t)} (1 - qw_j) \times \prod_{\substack{j \in N_i^k(t), \\ k = 2...K}} (1 - qc_j),$$

where d is the external influence parameter, qw_i is the within-brand WOM parameter of a customer j, qc_i is the cross-brand WOM parameter of a customer j, and $N_i^k(t)$ is the number of customers connected to i who have adopted the product from firm k before time t.

If the customer is not locked in and there is no exclusivity, he has multiple firms from which to choose. The probability of being convinced to consider adopting from Firm 1 remains as given in Equation 1b. Similarly, the probability of considering adopting from another firm k is as follows:

(2)
$$p_i^k(t) = 1 - (1 - d) \times \prod_{j \in N_i^k(t)} (1 - qw_j) \times \prod_{\substack{j \in N_j^m(t), \\ m \neq k}} (1 - qc_j).$$

Market with two firms. There are now several possible paths to adoption, even with only two firms. The first path is that customer i considers adopting from Firm 1 but not Firm 2, the probability of which is $p_i^1(1 - p_i^2)$. The second is that customer i considers adopting from Firm 2 only, the probability of which is $p_i^2(1 - p_i^1)$. The third is that the customer is persuaded to adopt by both firms but buys from only one of the two. The probability of such an adoption is $p_1^1 p_1^2$, and the customer adopts from Firm 1 rather than from 2 according to the ratio of the probabilities, $\lambda_{i1} = p_i^1/(p_i^1 + p_i^2)$. The probabilities of adoption are (Libai, Muller, and Peres 2013):

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(3)
$$P_{i}(adopt \text{ from } 1) = p_{i}^{1}(1 - p_{i}^{2}) + \lambda_{i1}p_{i}^{1}p_{i}^{2},$$
$$P_{i}(adopt \text{ from } 2) = p_{i}^{2}(1 - p_{i}^{1}) + \lambda_{i2}p_{i}^{2}p_{i}^{1}, \text{ and}$$
$$P_{i}(do \text{ not } adopt) = (1 - p_{i}^{1})(1 - p_{i}^{2}),$$

where
$$\lambda_{i1} = \frac{p_i^1}{p_i^1 + p_i^2}$$
, $\lambda_{i2} = 1 - \lambda_{i1}$.

To create adoption events, we use the same procedure as Libai, Muller, and Peres (2013). For each customer in each period, we draw a random number from a uniform distribution between 0 and 1. If the number is smaller than the probability of adopting from Firm 1, the customer adopts from 1. If, however, the probability is smaller than the sum of the probabilities of adopting from Firm 1 or Firm 2, the customer adopts from 2. Otherwise, the customer does not adopt.

Market with more than two firms. This logic can be extended to markets with more than two firms. In a market with K firms, customers are in one of the following K + 1 states: 0 for not having adopted, 1 for having adopted from Firm 1, 2 for having adopted from Firm 2, and so on. Any combination of firms may persuade a customer to adopt. For example, in a market with three firms, one must consider the possibility that all three firms persuade the customers, that Firms 1 and 2 do but Firm 3 does not, that Firms 1 and 3 do but Firm 2 does not, and so on. Equation 3 can be generalized to any number of firms, with the probability to adopt from Firm 1 being

$$(4)P_{i}(adopt from 1) = p_{i}^{l} \sum_{S \subseteq \{2,...K\}} \prod_{s \in S} p_{i}^{s} \times \frac{p_{i}^{l}}{p_{i}^{l} \sum_{s \in S} p_{i}^{s}} \prod_{\nu \notin S} (1 - p_{i}^{\nu}).$$

The sum goes over all possible subsets S of the set of competitors (including the empty set), to cover all possible ways in which a customer can be persuaded to consider buying from Firm 1. For example, for three firms, the subsets S of competitors who can affect adoption from Firm 1 are (\emptyset , {2}, {3}, {2, 3}).

Parametrization

Table 3 provides the values of the parameters we manipulate. The parameter space in a model or experiment need not be restricted to values reported in prior empirical research (Hacking 1983); indeed, doing so actually limits the ability to generate new insights (Medawar 1979). Yet we acknowledge that some believe a model or experiment is more persuasive and valuable when its parameters or manipulations include levels consistent with quantities reported in empirical work.

Adoption parameters. The values of d, qw, and qc are identical across firms for simplicity. Comparing values of d and total WOM (qw + qc) with estimates of p and q in the Bass model is moot because the scaling of Bass model parameters is determined solely by the scaling of time (e.g., Van den Bulte 2011). Note, however, that the scaling of our parameters is consistent with annual p and q values for

many consumer durables. In addition, values of (qw + qc)/dinclude typical values of the q/p shape parameter in the Bass model, especially after considering that the q/p estimates exhibit an upward bias (Van den Bulte and Lilien 1997). We impose that qc \leq qw, consistent with Parker and Gatignon (1994), Libai, Muller, and Peres (2009), and Krishnan, Seetharaman, and Vakratsas (2012). In line with recent evidence that influentials tend not only to have more ties but also to be more contagious within each of those ties (Hu and Van den Bulte 2012; Iyengar, Van den Bulte, and Valente 2011), the value of qw_j for each customer increases with his or her number of ties: qw_j = $\alpha + \beta \times \log(\text{degree}_j)$, with $\beta > 0$ (qw_j = 0 when degree_j = 0). The parameters α and β are set such that qw_j ranges between 50% and 150% of the average. We apply the same procedure to qc_j.

Customer network structure. The degree distribution is consistent with research on WOM (Keller 2007). The global clustering coefficient ranges between .7% and 2%, but the amount of clustering is not uniform throughout the networks. For example, clustering is approximately 7.5% among the locked-in customers of the focal firm when homophily is high, overlap in customer bases is high (80%), and all influentials are locked in with the focal firm. This range is consistent with clustering of ties in prior diffusion research (e.g., Christakis and Fowler 2007; Moody 2009).

Length of exclusivity. We analyze several durations of exclusivity, ranging up to eight periods. Given the scaling of our adoption parameter, these periods can (but need not) be interpreted as years, so exclusivity durations of zero, two, four, six, and eight periods cover a realistic range.

Discount rate. We measure a firm's profitability as the present value of the cash flows from all its adoptions, each contributing a margin of \$1, over all 30 time periods with a discount rate of 10%. The margin can stem from a one-time purchase of a durable good or be the lifetime value at the time of adoption of a cash flow stream, including follow-up sales. The discount rate is similar to the annual rate computed by Schmitt, Skiera, and Van den Bulte (2001). We can safely ignore any residual value in the cash flows. We track the diffusion over 30 periods, and the adoption parameters are high enough to achieve close to complete diffusion in the great majority of runs. Such near-complete diffusion and the 10% discount rate preclude truncation artifacts in present value calculations without residual value (Fruchter and Van den Bulte 2011).

Parameter	Range
d (external influence)	.001, .005, .01, .015, .02
qw (within-brand WOM)	.04, .08, .1, .12, .16
qc (cross-brand WOM)	0, .02, .04, .08, .1, .12, .16, with qc ≤ qw
Óverlap	0%, 20%, 40%, 60%, 80%, 100%
Homophily (and induced clustering)	None, low, moderate
OL lock-in	Equal access, strong lock-in, moderate lock-in, strong lock-out
Time length of exclusivity (periods)	0, 2, 4, 6, 8

TABLE 3 Parameter Values in Simulation

Results of Simulation Study

We first present results for two firms and 10% discounting. Then, we briefly note the extent to which the results differ in scenarios with five firms or without discounting.

Profit Impact of Exclusivity by Level of Competition

Figure 2 shows how discounted profits vary by the level of competition and the length of exclusivity, averaged across all other parameters.³ Each line corresponds to a different level of customer overlap. As we expected, the lines fan out. As the duration of exclusivity increases, profits increase in markets with moderate to high levels of overlap but decrease in markets with low levels of overlap. Thus, unless exclusivity provides protection from competition, it harms rather than boosts profitability.

The order of the lines in Figure 2 shows that at the average level of within- and cross-brand WOM, greater overlap is associated with greater profits. This happens because overlap boosts not only competition but also the level of within-brand WOM. Imagine that the market features two manufacturers selling directly (A and B), a WOM network without homophily (pure random graph), equal access to OLs, and no cross-brand WOM. With 0% overlap, half the ties of A's customers are with people who are locked in with B and will never buy from A. As a result, A cannot benefit

³Profitability levels and ratios reported in Figure 2, Table 4, and all subsequent exhibits are based on geometric means such that the mean of a ratio equals the ratio of the means: GM(X/Y) = GM(X)/GM(Y). The traditional average or arithmetic mean does not have this property. Although using the arithmetic or geometric mean does not affect our key insights, only the latter provides an exact mapping of descriptive percentage gains into regression results.





Notes: We averaged discounted profits (10% discounting) across all values of adoption parameters, customer network structures, and OL lock-in structures.

fully from within-brand WOM. The greater the overlap, the more a firm has access to customers (locked + shared) who are connected to other customers to whom the firm has access, and thus the more the firm benefits from within-brand WOM.

Table 4 conveys the same information but in a different format. It shows, for each level of customer base overlap and each length of exclusivity, by what percentage discounted profits differ from those of the no-exclusivity strategy. Whereas long-term exclusivity boosts discount profits by 7%–43% when the amount of customer overlap is 40% or higher, it actually lowers them by 3%–13% when customer overlap is 20% or lower.

The Moderating Effect of Cross-Brand WOM

The results in Figure 2 and Table 4 pertain to the average market setting, which features only moderate within-brand WOM ($\overline{qw} \approx .11$) and even weaker cross-brand WOM ($\overline{qc} \approx .05$). Because the value of exclusivity is likely to vary with the strength of cross-brand WOM, the grand averages reported in Figure 2 and Table 4 provide only a coarse-grained picture.

Table 5 presents the percentage profit impact of using exclusivity at different levels of customer base overlap and specific levels of within- and cross-brand WOM. We use a low, intermediate, and high value of each contagion parameter to span the parameter space. Three of the nine possible combinations violate the condition that WOM cannot be higher across than within brands, so we excluded them from the study.

Careful reading of the results in Table 5 conveys many insights. First, we focus on conditions without cross-brand contagion (qc = 0), shown in the left-hand block of columns. As we expected, exclusivity has no impact on profitability in the absence of competition (0% overlap), but it boosts profitability even at very moderate levels of competition. The positive impact increases as the level of customer overlap increases from 0% to 100%.

Second, exclusivity can depress profits even at high levels of competition when qc > 0. This is shown by the presence of several sizable negative values in the middle and right-hand columns. For example, when customer overlap is 60%-100% and qw = qc = .08, an exclusivity period of

TABLE 4Difference in Discounted Profits Compared toNo Exclusivity, by Length of Exclusivity and Levelof Competition

Length of Exclusivit	y y	Level of Competition (Customer Overlap)											
т	0%	20%	40%	60%	80%	100%							
2	-4.3%	-1.8%	.8%	3.7%	7.1%	10.9%							
4	-7.6%	-3.0%	2.3%	8.2%	14.9%	21.4%							
6	-10.4%	-3.3%	4.9%	13.6%	23.6%	33.5%							
8	-13.1%	-3.4%	7.2%	18.5%	31.1%	43.2%							

Notes: We averaged discounted profits (10% discounting) across all values of adoption parameters, customer network structures, and OL lock-in structures.

 TABLE 5

 Difference in Discounted Profits Compared to No Exclusivity, by Level of WOM, Length of Exclusivity (T), and Level of Competition

		qc = .00 Customer Overlap					qc = .08 Customer Overlap					qc = .16 Customer Overlap							
qw	т	0%	20%	40%	60%	80%	100%	0%	20%	40%	60%	80%	100%	0%	20%	40%	60%	80%	100%
.04	2 4 6 8	-1.2% .0% 2.6% .6%	5.4% 7.3% 8.7% 10.4%	7.1% 9.2% 14.9% 18.5%	10.8% 16.6% 21.7% 26.5%	16.3% 27.6% 34.6% 40.7%	18.5% 32.0% 40.6% 46.7%												
.08	2 4 6 8	8% 8% -2.0% 9%	6.4% 10.0% 11.5% 14.1%	10.4% 19.4% 21.8% 26.2%	18.2% 30.7% 38.2% 43.5%	24.0% 41.0% 50.8% 57.6%	33.8% 52.8% 63.2% 67.8%	-6.3% -11.7% -15.1% -18.8%	-5.4% -9.8% -12.3% -13.8%	-5.2% -8.5% -9.0% -8.4%	-4.7% -7.2% -5.7% -3.3%	-4.5% -5.8% -1.9% 3.6%	-3.3% -2.1% 4.4% 12.7%						
.16	2 4 6 8	9% .0% 1.4% .0%	7.1% 14.4% 17.0% 18.7%	19.1% 30.2% 36.5% 40.7%	31.0% 49.8% 57.2% 62.5%	42.5% 63.5% 72.7% 74.5%	56.0% 77.9% 83.0% 84.9%	-4.9% -9.1% -12.4% -15.4%	-3.2% -4.9% -4.9% -4.8%	-1.9% .3% 4.7% 7.3%	1% 5.5% 13.3% 21.5%	2.3% 12.8% 26.1% 37.8%	6.1% 21.3% 40.5% 55.0%	-5.9% -11.3% -15.1% -18.5%	-5.5% -8.5% -9.0% -9.6%	-5.3% -6.3% -2.0% .8%	-4.3% -3.0% 5.8% 12.4%	-3.8% 1.1% 13.6% 25.7%	-2.7% 4.8% 24.3% 42.1%

Notes: Values are percentage changes in discounted profits (10% discounting) averaged across all levels of the external influence adoption parameter, all customer network structures, and all OL lock-in structures.

length 2 or 4 is less profitable than having no exclusivity at all. Negative values also occur when WOM is weaker across than within brands.

Third, the extent to which exclusivity hurts profits compared with the no-exclusivity baseline increases with the strength of cross-brand WOM, holding constant the level of within-brand WOM, the length of exclusivity, and the intensity of competition. This can be observed by taking any cell in one of the duration-by-overlap blocks at one level of qc and comparing it with the corresponding cell in the durationby-overlap blocks at a higher level of qc.

Fourth, a longer exclusivity period is not always better or always worse than a shorter exclusivity period. When there is cross-brand WOM, the effect depends on the intensity of competition in the market. Take, for example, the central block of entries in which qw = qc = .08. Beginning on the top row and going down the column demonstrates what happens when exclusivity lengthens. Increasing exclusivity results in lower profits at low levels of competition (0%-20% overlap), but the opposite holds at high levels of competition (80%-100% overlap). The same pattern is present in the other two blocks with positive cross-brand contagion (qw = .16 and qc = .08; qw = qc = .16).

Fifth, it is possible for a short exclusivity period to be worse than both no exclusivity and long exclusivity. That is, there are market situations in which companies should either command a long exclusivity period or forgo exclusivity entirely. For example, when qw = qc = .08 and customer overlap = 80%-100%, exclusivity that lasts only two or four periods does worse than no exclusivity, but exclusivity that lasts eight periods does better.

The sixth and final insight comes from comparing the top and bottom halves of the middle block of columns. When cross-brand WOM is moderate (qc = .08), exclusivity is less beneficial and more harmful when within-brand WOM is moderate (qw = .08) than when it is high (qw = .16). In other words, forgoing exclusivity to capitalize on cross-brand WOM has a greater impact when within-brand WOM is only moderate. Conversely, when within-brand WOM is high, there is less to be gained from cross-brand WOM. This is consistent with the notion that declining exclusivity and free riding cross-brand WOM affects discounted profits by accelerating the diffusion process—which is important especially when within-brand WOM alone cannot generate speedy diffusion.

We gain the same insight from comparing the entries when both within- and cross-brand WOM are moderate (qw = qc = .08) versus when both are high (qw = qc = .16). Exclusivity is less beneficial and more harmful when both forms of WOM are moderate rather than high. This further supports the notion that the benefits of forgoing exclusivity stem from allowing cross-brand WOM to accelerate the diffusion process.

The Moderating Effects of OL Lock-In and Diffusion Speed

The discussion thus far has focused on how advantages and disadvantages of exclusivity vary by the level of competition and the strength of WOM, especially that operating across brands. In this section, we use regression analysis to corroborate those insights and investigate to what extent the effect of exclusivity on discounted profits is moderated by OLs' lock-in, diffusion speed, and homophily.

We regress the natural logarithm of discounted profits on (1) 0/1 indicator variables for each duration of exclusivity, (2) indicator variables for each level of homophily and clustering, (3) indicator variables for each type of OL lockin, (4) the values of all three adoption parameters (divided by 10 to avoid cluttering the results with very small coefficients) as well as the interaction between the two WOM parameters, and (5) the interaction of the duration of exclusivity (DUR) with all regressors (2–5). Thus, we allow the "main" effect of duration to be nonlinear through the dummies but limit the moderator effects to be linear in duration. The latter restriction provides a better high-level view of moderator effects than reporting a very large number of coefficients of interaction between each regressor and each duration dummy.

Taking the natural logarithm of profitability as the dependent variable in a linear regression model generates regression coefficients (b) with a clear managerial meaning. Specifically, $[\exp(b) - 1] \times 100\%$ is the percentage change in profitability to be expected when the regressor increases by one unit. To ensure that the regression coefficients map in this fashion into the results in Table 4, we mean-center all variables apart from the exclusivity dummies and the DUR variable used to construct the interaction terms. We estimate the models with ordinary least squares and, given the presence of significant heteroskedasticity (White test p < .001), compute t-statistics using White–Huber heteroskedasticity-consistent standard errors.

Table 6 shows the results of these regressions for each level of customer overlap separately. After transformation, the coefficients of the DUR = x dummies map perfectly into the mean values reported in Table 4.

We next focus on the linear effects of the other variables. As we expected, the homophily and clustering variable has only a small effect. Even when significant, it is never larger than 5%. Opinion leader lock-in has a much larger effect, sometimes reaching between 30% and 40%. Compared with equal access, having the OLs locked in is associated with higher profitability, whereas the reverse holds for having them locked out. The effects become smaller as the overlap in customer base increases, and they become virtually zero when the overlap reaches 100% and firms have equal access to all customers, including OLs. Finally, higher values of the adoption parameters are associated with higher profitability. The faster the diffusion, the greater the number of sales realized earlier rather than later; thus, the more valuable a temporary monopoly is. The negative interactions between the parameters of within- and cross-brand WOM indicate that the latter is especially valuable when the former is low, consistent with our discussion of Table 5.

All these linear effects are as we predicted, and they provide face validity to our simulation design. We next address the main purpose of the regression analysis: under-

TABLE 6 **Regression Analysis by Level of Competition**

	Customer Overlap									
	0%	20%	40%	60%	80%	100%				
Linear Effects										
Intercept	5.077***	5.169***	5.245***	5.311***	5.380***	5.451***				
DUR = 2	044***	018	.008	.036***	.069***	.104***				
DUR = 4	079***	031**	.023**	.079***	.139***	.194***				
DUR = 6	110***	034***	.048***	.128***	.212***	.289***				
DUR = 8	140***	035***	.069***	.170***	.271***	.359***				
Low homophily	.032*	.015	.006	003	001	.005				
Moderate homophily	.032*	001	021	044***	044***	029***				
Strong OL lock-in	.286***	.269***	.235***	.203***	.142***	004				
Moderate OL lock-in	.284***	.233***	.149***	.096***	.044***	002				
Strong OL lock-out	375***	398***	384***	337***	226***	.002				
d	3.777***	3.403***	3.090***	2.884***	2.647***	2.411***				
qw	.293***	.264***	.251***	.241***	.259***	.284***				
qc	.453***	.388***	.315***	.250***	.159***	.048***				
qw × qc	534***	489***	442***	407***	380***	311***				
Interactions with DUR (0-8)										
Low homophily × DUR	.001	.002	.001	.001	.001	.001				
Moderate homophily × DUR	.003	.004	.005*	.003	.005**	.004**				
Strong OL lock-in × DUR	.015***	.007***	.002	005**	007***	.001				
Moderate OL lock-in × DUR	.015***	.013***	.015***	.011***	.007***	.000				
Strong OL lock-out × DUR	020***	017***	011***	007*	.001	.000				
d × DŪR	.066**	.107***	.147***	.168***	.177***	.181***				
qw × DUR	.009**	.019***	.030***	.041***	.047***	.048***				
qc × DUR	022***	029***	034***	039***	041***	034***				
qw × qc × DUR	.018*	.023**	.025***	.028***	.035***	.035***				
R-square	74.7%	76.3%	77.8%	78.9%	81.2%	83.3%				

^{*}p < .05.

Notes: The dependent variable is the natural logarithm of discounted profits. All regressors interacting with DUR are mean-centered. Each model is estimated on N = 7,500 observations, where each observation is the geometric mean of 10 random replicates in each cell of the simulation design: 5 levels of duration, 3 homophily structures, 4 OL lock-in structures, 5 levels of external influence adoption, and 25 combinations of within- and cross-brand WOM propensities.

standing how the market characteristics affect the profitability of exclusivity.

Homophily. The coefficients of the interaction terms between DUR and homophily are rarely statistically significant and always small. Homophily and the clustering it induces do not affect the profitability of exclusivity.

OL lock-in and lock-out. Opinion leader lock-in has a larger and more intricate effect. The pattern of interactions indicates that forgoing exclusivity to free ride cross-brand WOM is more effective when competition is weak and the OLs are locked in. The effect sizes in Table 6 provide rich insights. Taking into account that the DUR variable is scaled from 0 to 8 and that the lock-in variables are meancentered dummies, and interpreting the periods as years, the results in Table 6 imply that at average values of the adoption parameters (d, qw, and qc) and 0% overlap, the average company loses approximately 13% of profitability by taking an eight-year exclusivity, a company with strong or moderate lock-in experiences virtually no loss, and a company facing strong lock-out experiences approximately twice the average loss. In addition, whereas taking exclusivity in a market with 20% overlap lowers the profitability of the average firm by approximately 3%, it does not do so at all for a firm with strong or moderate interlock. Firms facing strong lock-out, in contrast, lose an additional 1%-2% per year of exclusivity. In markets with 40% overlap, exclusivity remains unprofitable for firms facing lock-out, whereas it is profitable for others. Even with 60% overlap, firms facing lock-out gain only approximately two-thirds of the benefits the average firm reaps from each year of exclusivity. Clearly, the lock-in and lock-out of OLs has a significant impact on the decision to forgo exclusivity.

Diffusion speed. Table 6 also provides insights into how the adoption parameters moderate the effect of exclusivity on profitability. The positive effect of d × DUR implies that forgoing exclusivity is especially attractive when customers are slow to adopt without WOM. The interactions of DUR with the WOM parameters corroborate the insights from Table 5. The negative effect of $qc \times DUR$ suggests that having a short exclusivity period or forgoing exclusivity altogether is more attractive when cross-brand WOM is strong. The positive effect of $qw \times qc \times DUR$ implies that the attractiveness of doing so is even higher when own-firm WOM is low. Forgoing exclusivity is especially attractive when within-brand WOM alone cannot generate sales quickly.

^{**}*p* < .01. ^{***}*p* < .001.

Robustness Checks

Zero discount rate. If forgoing exclusivity boosts profits because cross-brand WOM accelerates sales and cash flows, as we claim, it should not have a positive financial impact when the discount rate is zero. This is indeed the case. Ignoring the time value of money, the line corresponding to zero overlap in Figure 2 becomes flat, and all the negative values observed for nonzero overlap in Tables 4 and 5 become positive. Of course, zero discounting and infinite patience run counter to both human nature and sound financial management.

More than two firms. One would expect the profit impact of exclusivity to increase if there are more firms in the market. Suppose there are only two firms. With 0% overlap, exclusivity increases the market access from 50% to 100% but decreases the fraction of the market that can spread cross-brand WOM from 100% to 50%. If there are five (or, more generally, N > 2) firms, the protection from competition increases from 20% (1/N) to 100%, but the base for cross-brand WOM decreases from 100% to 20% (1/N). Therefore, a larger number of firms provides protection from competition and enlarges the WOM externality to the same extent, and there is no reason to expect significant changes in when to take or forgo exclusivity. Repeating the simulation for N = 5 confirms this finding: the percentage gains and losses that result from exclusivity are markedly larger (e.g., ranging from -24% to +155% in the equivalent of Table 4), but gains versus losses are realized in much the same market conditions as in the main analysis with two firms.

Additional Insights from a Game-Theoretic Model

Motivation

The design of the simulation study raises two questions about the generalizability of its results. First, can forgoing exclusivity be attractive when competition lowers the prices and profit margins? A primary reason for using patent protection or exclusive distribution is that exclusivity enables sellers to charge higher prices. Our simulation ignores this margin-boosting impact of exclusivity and so may overestimate the benefits of forgoing exclusivity in markets in which exclusivity affects not only access to customers but also the prices and profit margins realized when selling to these customers. The second question pertains to how WOM affects sales. The market size in the simulation is fixed, and cross-brand WOM boosts discounted profits by accelerating rather than expanding sales. Firms can create value for their shareholders by both accelerating and enhancing cash flows (Srivastava, Shervani, and Fahey 1998), and WOM can affect both the timing and the volume of sales (Libai, Muller, and Peres 2013); however, our simulation involves only the first of these two routes. Thus, the second question arises: Can forgoing exclusivity also boost profitability in markets in which cross-brand WOM increases rather than accelerates overall sales?

We investigate these two questions through a gametheoretic model. It features simpler network structure and contagion dynamics than the simulation study but has the advantages of (1) identifying the profit-maximizing behavior of firms competing through prices and (2) doing so mathematically in a continuous parameter space rather than through simulation at discrete points in the space.

Model Assumptions and Structure

The market features two firms, A and B, that compete in prices over two periods and are symmetric in all regards except that A has the option of being a temporary monopolist in period 1 and then competing against B only in period 2. The firms have a common and constant marginal cost c.

The market consists of customers who consider buying from either firm and customers who are locked in to a single firm and consider buying only from that one source (e.g., Fershtman and Muller 1993). The fraction of lockedin potential customers is α , split equally between the two firms. The remaining $(1 - \alpha)$ fraction consists of "shared" customers who might buy from either firm. We denote Segment 1 as those locked in to A, Segment 2 as those shared by A and B, and Segment 3 as those locked in to B. For simplicity, we assume the unweighted base level of demand for the product to be common across segments. That base level can be interpreted as the potential demand within each segment from those who are aware of the product and consider buying it and actually would do so if it were available at no cost. Firms cannot price discriminate between their lockedin and shared segments, nor can they credibly commit in period 1 to the prices they will charge in period 2.

Without exclusivity, the demand q_{ij1} of firm i in segment j in period 1 equals

(5)
$$q_{A11} = \frac{1}{2}\alpha(m - \beta p_{A1}),$$
$$q_{A21} = \frac{1}{2}(1 - \alpha)[m - \beta p_{A1} + \theta(p_{B1} - p_{A1})],$$
$$q_{B21} = \frac{1}{2}(1 - \alpha)[m - \beta p_{B1} + \theta(p_{A1} - p_{B1})], \text{ and}$$
$$q_{B31} = \frac{1}{2}\alpha(m - \beta p_{B1}).$$

where p_{i1} is the price of firm i in period 1 and θ represents the intensity of price competition between the two firms in Segment 2. The demand equations in Segments 1 and 3 are standard linear specifications for monopoly, and those in Segment 2 correspond to A and B being horizontally differentiated from each other in that segment (e.g., Desai, Koenigsberg, and Purohit 2010). When $\alpha = 1$, the demand system reduces to two disjoint monopolies. When $\alpha = 0$, it reduces to the duopoly specification used by Desai, Koenigsberg, and Purohit (2010). The "full" own-price sensitivity of demand equals ($\beta + \theta$) in the duopolistically shared segment, where $\beta > 0$ and $\theta \ge 0$. Thus, we do not require $\theta < \beta$. The price sensitivity under monopoly is only β .

If Firm A chooses to be exclusive in period 1, it is the monopolist not only in its locked-in Segment 1 but also in Segment 2. The demand q_{ij1} then equals

(6)
$$q_{A11} = \frac{1}{2}\alpha(m - \beta p_{A1}),$$

 $q_{A21} = (1 - \alpha)(m - \beta p_{A1}),$ where
 $q_{B21} = 0,$ and
 $q_{B31} = 0.$

We do not distinguish between trial and repeat sales in period 2 and assume that all demand in period 2 is lifted by the sales in period 1. The WOM triggered by prior sales volume boosts the product's awareness and legitimacy and so boosts the base level of demand in each segment. This contagion process operates both within and across brands. Within-brand WOM influence, the effect of which is denoted by γ , occurs when a firm's prior sales increase its base-level demand. Cross-brand WOM influence, the effect of which is denoted by δ , occurs when a firm's prior sales increase the competing firm's base-level demand. We analyze the effect of cross-brand WOM as a positive externality and, in line with prior empirical evidence (Libai, Muller, and Peres 2009), we assume that within-brand influence is greater than cross-brand influence, $\gamma > \delta \ge 0$.

Regardless of whether Firm A experienced exclusivity in period 1, it faces Firm B in period 2. Thus, taking the WOM effects into account, the demand equations for period 2 are

$$(7) \ q_{A12} = \frac{1}{2} \alpha \left[m - \beta p_{A2} + \gamma (q_{A11} + q_{A21}) + \delta (q_{B21} + q_{B31}) \right],$$

$$q_{A22} = \frac{1}{2} (1 - \alpha) \left[m - \beta p_{A2} + \theta (p_{B2} - p_{A2}) + \gamma (q_{A11} + q_{A21}) + \delta (q_{B21} + q_{B31}) \right],$$

$$q_{B22} = \frac{1}{2} (1 - \alpha) \left[m - \beta p_{B2} + \theta (p_{A2} - p_{B2}) + \gamma (q_{B31} + q_{B21}) + \delta (q_{A11} + q_{A21}) \right],$$

$$q_{B32} = \frac{1}{2} \alpha \left[m - \beta p_{B2} + \gamma (q_{B21} + q_{B31}) + \delta (q_{A11} + q_{A21}) \right].$$

Note that Firm B's prior sales boost Firm A's base level demand in period 2; thus, A may benefit from allowing B to sell in period 1. Even though A receives a bigger boost from its own prior sales in Segment 2 than from B's prior sales in that competitive segment (because $\gamma > \delta$), A also benefits from B's prior sales in Segment 3 that A cannot service. Less obvious is whether that boost in base-level demand in period 2 is ever sufficient to give up monopoly profits in Segment 2 in period 1.

Assuming a discount factor ρ to capture both the relative duration of periods 1 and 2 and the time value of money, the present value of total profits of the firms is

$$\begin{split} (8) \, \Pi_{A} &= \Pi_{A1} + \rho \Pi_{A2} \\ &= \big(q_{A11} + q_{A21} \big) \big(p_{A1} - c \big) + \rho \big(q_{A12} + q_{A22} \big) \big(p_{A2} - c \big), \text{ and} \\ \Pi_{B} &= \Pi_{B1} + \rho \Pi_{B2} \\ &= \big(q_{B31} + q_{B21} \big) \big(p_{B1} - c \big) + \rho \big(q_{B32} + q_{B22} \big) \big(p_{B2} - c \big). \end{split}$$

Of course, both the prices and the volumes will be different depending on whether B began commercializing the product in period 1 or 2.

(0) **П**

To identify when Firm A should forgo temporary exclusivity, we compare the equilibrium profits with and without exclusivity. Without exclusivity, A and B first set their prices for period 1 and then, after the period is concluded, set their prices for period 2. So, the game is a two-period simultaneous-move game. With temporary exclusivity, only A sets its price for period 1 and then, after the period is concluded, both A and B set their prices for period 2 simultaneously. We solve the game by identifying the Nash equilibrium pricing strategies through backward induction. The Web Appendix identifies the equilibrium strategies and resulting profits and identifies when it is profitable to forgo exclusivity. Here, we present only the main insights.

Insights

The game-theoretic model provides three insights. The first and most important is that firms may want to forgo temporary exclusivity even when (1) there is price competition, (2) WOM affects sales volume rather than timing, and (3) firms care equally about current and future profits. This is especially true when cross-brand WOM is strongly positive and there is little overlap in customer bases. Forgoing exclusivity can be optimal even with complete overlap in customer bases, provided that cross-brand contagion is strong enough. The basis for this first result is that allowing a competitor to enter early generates a WOM externality that shifts a firm's own demand curve upward, enabling it to sell more or to charge higher prices. These results are consistent with the key insights from the simulation and show that the latter do not hinge on the mechanism at work (demand acceleration vs. demand expansion) or the absence of price competition.

The second insight from the game-theoretic model is that intense price sensitivity tends to favor exclusivity, at least when it goes hand in hand with high overlap in customer bases. This is unsurprising and simply provides additional face validity to our assumptions and results.

The third insight is that in markets with price-sensitive demand, a small fraction of shared customers, and strong within-brand WOM, firms may want to forgo temporary exclusivity even in the absence of cross-brand WOM. Suppose that Firm A has temporary exclusivity in the early stage of market development. When WOM is strong within brands but very weak or inexistent across them, Firm B, entering later, has a major WOM handicap. It is forced to set very low prices to generate any sales and, when customers are very price sensitive, A must follow suit. This depresses A's profit so much that it prefers forgoing temporary exclusivity and competing against B immediately rather than keeping B out of the market initially but then having to compete against it aggressively later on. This pattern is consistent with the insight that within-brand contagion can sometimes intensify competition (e.g., He, Kuksov, and Narasimhan 2012). The pattern is also reminiscent of the famous result by Klemperer (1987) that loyalty programs and switching costs can have a deleterious effect: even though they decrease competition and increase profitability when customers have been made loyal, they induce firms to compete intensely when acquiring customers in the early stages of market development. The ferocious competition to attract new customers can more than dissipate the benefits of reduced competition later on. Our model shows that something similar can happen with temporary exclusivity as well, although the sequence of ferocious versus softened competition is reversed and lock-in is exogenous. Because the simulation did not involve price competition, this result is unique to the game-theoretic analysis.

Discussion

Recapitulation of Main Insights

We considered a puzzling business decision by NTT managers and—building from these practitioners' theory in use (Zaltman, LeMasters, and Heffring 1982)—investigated whether WOM dynamics and customer lock-in can affect the profitability of temporary product exclusivity. We develop six new insights.

First, forgoing temporary exclusivity can be more profitable than taking it, and the most profitable course of action depends not merely on the strength of cross-brand WOM but also on customer lock-in. The right decision cannot be reached by considering one without the other. This interplay between cross-brand WOM and customer lock-in is our most important and novel insight.

Second, firms that count the OLs among their locked-in customers or brand aficionados gain more from exclusivity than firms that do not. Companies and brands that do not have strong and exclusive bonds with OLs are typically viewed as weaker. Thus, our result that such companies and brands gain less from exclusivity—often intended as protection against competition—may seem paradoxical. The paradox is resolved, however, in that those weak players stand to gain most from cross-brand WOM.

Third, a short exclusivity period can be worse than both no exclusivity and long exclusivity. That is, the impact of exclusivity duration on profits can be nonmonotonic. Fourth, firms might consider forgoing temporary exclusivity even in the absence of cross-brand WOM but only in markets with price sensitive demand, a small set of shared customers, and strong within-brand WOM. Although this is a special case, it may be our most surprising result. The next two results are, in our estimation, less important or novel than the preceding four.

Fifth, facing a larger number of competitors increases the profit impact of making the wrong decision but need not affect the decision itself significantly. This is because in fragmented markets with more competitors, both the harm from business stealing and the positive externality of WOM increase. In our simulated markets, both factors ultimately counterbalanced each other. Sixth, forgoing exclusivity for a new product is especially attractive when customers are slow to adopt without WOM and when within-brand WOM alone cannot generate sales quickly.

Contributions to Theory

We make three theoretical contributions. First, we show how WOM and market structure *jointly* affect whether a firm should take or forgo exclusivity. As we discuss subsequently, cross-brand WOM turns competitors' locked-in customers into a complementary asset (Teece 1986) that the firm does not have access to but is able to capitalize on by forgoing exclusivity. Second, unlike previous research, we show that forgoing exclusivity can be profitable even when exclusivity is only temporary, competitors offer products of equal quality, and WOM is weaker across than within brands.

Third, we show how a sound marketing decision can hinge on the interlock between a "vertical" and a "horizontal" network (Van den Bulte 2010). Our two focal considerations, lock-in and WOM, can be integrated into a network view of markets featuring both a vertical network of commercial ties between firms and customers and a horizontal network of WOM ties between customers (Figure 1). The interlocking of horizontal and vertical networks has received little attention so far. Each type of tie has been the focus of separate research streams, with vertical ties being the focus in the channels and business marketing literature streams (e.g., Wuyts et al. 2004) and horizontal ties being the focus in the diffusion and social network literature streams (e.g., Ivengar, Van den Bulte, and Valente 2011). Our results illuminate some of the complex interactions between the two: exclusivity protects firms from rivals vying for the same set of customers (i.e., in network-theoretic terms, from other structurally equivalent firms), but it does so to the detriment of a positive externality stemming from social contagion in the horizontal network.

Implications for Practice

Although our models are theoretical, our results provide useful qualitative guidance to managers. For example, they indicate that NTT's intuition was sound. Word-of-mouth dynamics among customers, and specifically spillover across competitors' customer bases, can reverse the common view that exclusivity is valuable. However, our results also show that NTT's decision is not always best. A systems integrator such as NTT often has many locked-in customers, a situation that favors forgoing exclusivity. A firm that does not have such lock-in may be better off choosing temporary exclusivity, as telephone service provider AT&T did with the early iPhone. Our findings also have implications beyond those motivating examples.

New product marketing. Firms launching a new product can increase their profitability by enabling competitors to enter the market as well. When positive cross-brand WOM accelerates or increases the demand for the product at a given price, this externality can more than compensate for the loss of market share from forgoing an exclusive firstmover position. Customer lock-in is critical, however. The greater the fraction of locked-in customers, the less intense the competition and the greater the boost in cross-brand WOM; thus, the greater the increase in profits from forgoing temporary exclusivity.

Exclusive distribution. Distributors should not always strive for temporary product exclusivity. Our results show that a sound decision takes into account WOM and customer lock-in. Distributors should also take into consideration channel-specific motivations for exclusivity, such as

the need to protect transaction-specific investments or the boost in bargaining power in driving down the manufacturer's wholesale price. Another important consideration is that social contagion often drives growth for risky new products and technologies but is less important than advertising, service, and other distributor efforts for low-risk products in mature industries.

Benchmarking. When exclusivity lowered financial performance in our analyses, it did so because the boost in profit share was not enough to compensate for the decrease in total industry profits. Thus, companies that judge their financial performance against their competitors (e.g., through profit or market share) may mistakenly conclude that exclusivity boosts financial performance when it actually depresses financial performance. This implies that using competitor-oriented objectives when making decisions to accept exclusivity can hurt financial performance, consistent with broader claims by Armstrong and Collopy (1996) and Luo, Rindfleisch, and Tse (2007).

Business marketing. The decision to exploit or forgo exclusivity is especially consequential in markets in which influential customers consider dealing with only one key supplier. The interlock between the vertical network of commercial ties (i.e., which customers consider buying from which firm) and the horizontal network of WOM ties (i.e., which customers are most influential) may be especially important in business markets, in which customers such as Boeing, Goldman Sachs, BMW, or Toyota can have a major impact in legitimizing new technologies and solutions.

Fashion and lifestyle industries. The strategic trade-offs involved in product exclusivity are especially challenging in fashion industries (Appel, Libai, and Muller 2013; Barnett 2005; Hemphill and Suk 2009; Siggelkow 2001). Our results imply that allowing rivals to enter immediately can be beneficial even without cross-brand WOM as long as there are high levels of customer lock-in, within-brand WOM, and customer price sensitivity. Markets for fashion apparel and other products with a strong social or lifestyle identity can exhibit this combination of lock-in (brand aficionados), high within-brand WOM (strong insider buzz), and low cross-brand WOM (indifference to outsiders). Our result that lack of exclusivity can boost profits is relevant to the debate among legal scholars on the merits of laws such as the proposed Innovative Design Protection and Piracy Prevention Act (Barnett 2005; Hemphill and Suk 2009).

Implications for Research

Networks in marketing. Our study considers two mechanisms, competition and WOM, each operating over a different set of ties, vertical commercial ties between firms and customers and horizontal WOM ties between customers. Focusing on vertical and horizontal networks jointly may be an effective research strategy to better distinguish mechanisms that are often difficult to tease apart in a single type of network (e.g., Burt 1987). Further research may benefit from similarly matching different processes to different kinds of ties to gain deeper understanding of social network processes, not only various contagion mechanisms

in new product diffusion, as Iyengar, Van den Bulte, and Choi (2011) discuss, but also other processes such as competition, as illustrated in the present study.

Marketing strategy. Several studies have documented how network externalities and other contagion dynamics can affect the benefits of early versus late entry (e.g., Joshi, Reibstein, and Zhang 2009; Srinivasan, Lilien, and Rangaswamy 2004). Our work suggests that distinguishing the effects of contagion within and between brands may provide more refined insights into that important question.

The positive impact of competition on market size is a phenomenon that has received considerable attention in the areas of technology standards, licensing, category building, and social legitimation dynamics (e.g., Agarwal and Bayus 2002; Roberts and Samuelson 1988). Our work suggests that such positive aspects of competition exist at the intersection of channel strategy and new product diffusion as well. There is a dearth of research at this intersection (Gatignon, Anderson, and Lajos 2007), and we hope our work will motivate more investigations in the area.

Commercialization of new technologies. Influential contributions by Teece (1986) and Itami (1987) note that (1) bringing new technologies to market often requires not only a product and customers but also complementary assets and (2) customer lock-in boosts the firm's ability to appropriate the profits of the innovation. We contend that the presence of cross-brand WOM adds an important dynamic. The locked-in customers of a firm's competitors now become a complementary asset that the firm does not have access to but can nonetheless capitalize on. To do so, the firm must allow its competitor to sell the technology. Forgoing exclusivity is then a form of cooperation with competitors in which access to technology or product is exchanged for WOM. Note that this dynamic can be at work even without any competing standard and so provides a new rationale for technology licensing.

Multimethod research. Our work illustrates how agentbased modeling and game theory can be used complementarily. Combining the two can leverage the strength of each and provide confidence that key insights are not driven by assumptions specific to either method.

Unresolved issues. Like any research effort, our simulation and game-theoretic models provide a purposively selective representation of the phenomenon of interest. The analyses did not consider that customers may interpret exclusivity as a quality signal. In such cases, exclusivity may boost the intrinsic tendency to adopt early or increase the size of the market regardless of WOM. Furthermore, we focus on sellers and their direct customers, without taking into account other constituents upstream or downstream in the supply chain. For example, we did not consider that a reseller or original equipment manufacturer (OEM) may accept an exclusivity offer from an upstream supplier because the reseller or OEM knows that if it does not accept, the offer will go to a competitor, and that if the competitor accepts, the reseller or OEM will be worse off. Therefore, if the upstream supplier makes the mistake of offering exclusivity, a rational reseller or OEM may be induced to accept it even if it would have preferred that no such offer be extended to anyone. In addition, when downstream resellers or OEMs are vertically differentiated in the quality they provide to customers, the upstream supplier should take this information into account when deciding to which of these downstream firms to extend the exclusivity offer (Subramanian, Raju, and Zhang 2013). More generally, allowing for asymmetry between competitors may produce notable new results, as would allowing for price discrimination between locked-in and other customers and allowing for endogenous customer lock-in that springs into existence only *after* a customer buys the product (Klemperer 1987).

The decision to use exclusivity in a vertical supply chain or distribution channel context has several additional facets. On the one hand, exclusivity provides the upstream company with better control and coordination (Frazier and Lassar 1996), signals commitment to its downstream part-

REFERENCES

- Agarwal, Rajshree and Barry L. Bayus (2002), "The Market Evolution and Sales Takeoff of Product Innovations," *Management Science*, 48 (8), 1024–41.
- Anderson, Eric T. and Duncan Simester (2013), "Advertising in a Competitive Market: The Role of Product Standards, Customer Learning, and Switching Costs," *Journal of Marketing Research*, 50 (August), 489–504.
- Ansari, Asim, Oded Koenigsberg, and Florian Stahl (2011), "Modeling Multiple Relationships in Social Networks," *Journal of Marketing Research*, 48 (August), 713–28.
- Appel, Gil, Barak Libai, and Eitan Muller (2013), "The Short- and Long-Term Impacts of Fashion Knockoffs on Original Items," MSI Report No. 13-108, Marketing Science Institute.
- Armstrong, J. Scott and Fred Collopy (1996), "Competitor Orientation: Effects of Objectives and Information on Managerial Decisions and Profitability," *Journal of Marketing Research*, 33 (May), 188–99.
- Barnett, Jonathan M. (2005), "Shopping for Gucci on Canal Street: Reflections on Status Consumption, Intellectual Property, and the Incentive Thesis," *Virginia Law Review*, 91 (6), 1381–1423.
- Burt, Ronald S. (1987), "Social Contagion and Innovation: Cohesion Versus Structural Equivalence," *American Journal of Sociology*, 92 (6), 1287–1335.
- Centola, Damon (2010), "The Spread of Behavior in an Online Social Network Experiment," *Science*, 329 (5996), 1194–97.
 and Michael Macy (2007), "Complex Contagions and the Weakness of Long Ties," *American Journal of Sociology*, 113 (3), 702–734.
- Chen, Yuxin and Jinhong Xie (2007), "Cross-Market Network Effect with Asymmetric Customer Loyalty: Implications on Competitive Advantage," *Marketing Science*, 26 (1), 52–66.
- Christakis, Nicholas A. and James H. Fowler (2007), "The Spread of Obesity in a Large Social Network Over 32 Years," *New England Journal of Medicine*, 357 (4), 370–79.
- Condon, Anne and Richard M. Karp (2001), "Algorithms for Graph Partitioning on the Planted Partition Model," *Random Structures and Algorithms*, 18 (2), 116–40.
- Conner, Kathleen R. (1995), "Obtaining Strategic Advantage from Being Imitated: When Can Encouraging 'Clones' Pay?" Management Science, 41 (2), 209–225.
- Desai, Preyas S., Oded Koenigsberg, and Devavrat Purohit (2010), "Forward Buying by Retailers," *Journal of Marketing Research*, 47 (February), 90–102.

ners (Fein and Anderson 1997), and enables the latter to recoup transaction-specific investments more quickly (e.g., Dutta, Heide, and Bergen 1999). On the other hand, it increases the downstream partner's bargaining power and limits the product's availability (e.g., Subramanian, Raju, and Zhang 2013). Although these considerations affect the governance of supply chains and distribution channels, we did not incorporate them into our analyses. Conversely, existing channel research provides little to no insight into how WOM should affect channel design and management. It is possible that WOM among customers facilitates market learning by channel or supply chain partners, which in turn affects the decision of how to structure the pattern of ties between upstream and downstream companies (Wuyts et al. 2004). This would be an example of how marketing strategy can actively shape the interlock of horizontal and vertical networks.

- Dockner, Engelbert and Steffen Jørgensen (1988), "Optimal Pricing Strategies for New Products in Dynamic Oligopolies," *Marketing Science*, 7 (4), 315–34.
- Dodds, Peter Sheridan, Roby Muhamad, and Duncan J. Watts (2003), "An Experimental Study of Search in Global Social Networks," *Science*, 301 (5634), 827–29.
- Dutta, Shantanu, Jan Heide, and Mark Bergen (1999), "Vertical Territorial Restrictions and Public Policy: Evidence from Industrial Markets," *Journal of Marketing*, 63 (October), 121–34.
- Eyuboglu, Nermin and Andreas Buja (2007), "Quasi-Darwinian Selection in Marketing Relationships," *Journal of Marketing*, 71 (October), 48–62.
- Fein, Adam and Erin Anderson (1997), "Patterns of Credible Commitments: Territory and Brand Selectivity in Industrial Distribution Channels," *Journal of Marketing*, 61 (April), 19– 34.
- Fershtman, Chaim and Eitan Muller (1993), "The Benefits of Being Small: Duopolistic Competition with Market Segmentation," *Review of Industrial Organization*, 8 (1), 101–111.
- Fortunato, Santo (2010), "Community Detection in Graphs," *Physics Reports*, 486 (3/5), 75–174.
- Frazier, Gary L. and Walfried M. Lassar (1996), "Determinants of Distribution Intensity," *Journal of Marketing*, 60 (October), 39–51.
- Fruchter, Gila E. and Christophe Van den Bulte (2011), "Why the Generalized Bass Model Leads to Odd Optimal Advertising Policies," *International Journal of Research in Marketing*, 28 (3), 218–30.
- Gatignon, Hubert, Erin Anderson, and Joseph Lajos (2007), "New Product Distribution and Inter-Channel Competition: Market-Making, Market-Taking, and Competitive Effects in Several European Countries," working paper, INSEAD.
- Gensch, Dennis H. (1984), "Targeting the Switchable Industrial Customer," *Marketing Science*, 3 (1), 41–54.
- Geroski, Paul and Tassos Vlassopoulos (1991), "The Rise and Fall of a Market Leader: Frozen Foods in the U.K.," *Strategic Man*agement Journal, 12 (6), 467–78.
- Givon, Moshe, Vijay Mahajan, and Eitan Muller (1995), "Software Piracy: Estimation of Lost Sales and the Impact on Software Diffusion," *Journal of Marketing*, 59 (January), 29–37.
- Goel, Sharad, Duncan J. Watts, and Daniel G. Goldstein (2012), "The Structure of Online Diffusion Networks," in EC '12 Proceedings of the 13th ACM Conference on Electronic Commerce. New York: Association for Computing Machinery, 623–38.

- Goldenberg, Jacob, Oded Lowengart, and Daniel Shapira (2009), "Zooming In: Self Emergence Movements in New-Product Growth," *Marketing Science*, 28 (2), 274–92.
- Hacking, Ian (1983), *Representing and Intervening: Introductory Topics in the Philosophy of Natural Science*. Cambridge, UK: Cambridge University Press.
- Haenlein, Michael and Barak Libai (2013), "Targeting Revenue Leaders for a New Product," *Journal of Marketing*, 77 (May), 65–80.
- He, Tingting, Dmitri Kuksov, and Chakravarthi Narasimhan (2012), "Intraconnectivity and Interconnectivity: When Value Creation May Reduce Profits," *Marketing Science*, 31 (4), 587–602.
- Heide, Jan B. and Allen M. Weiss (1995), "Vendor Consideration and Switching Behavior for Buyers in High Technology Markets," *Journal of Marketing*, 59 (July), 30–43.
- Hemphill, C. Scott and Jeannie Suk (2009), "The Law, Culture, and Economics of Fashion," *Stanford Law Review*, 61 (5), 1147–99.
- Ho, Teck-Hua, Shan Li, So-Eun Park, and Zuo-Jun Max Shen (2012), "Customer Influence Value and Purchase Acceleration in New Product Diffusion," *Marketing Science*, 31 (2), 236–56.
- Hu, Yansong and Christophe Van den Bulte (2012), "The Social Status of Innovators, Imitators, and Influentials in New Product Adoption: It's Not Just About High Versus Low," MSI Report No. 12-106, Marketing Science Institute.
- Itami, Hiroyuki (1987), *Mobilizing Invisible Assets*. Cambridge, MA: Harvard University Press.
- Iyengar, Raghuram, Christophe Van den Bulte, and Jeonghye Choi (2011), "Distinguishing Among Mechanisms of Social Contagion in New Product Adoption: Framework and Illustration," MSI Report No. 11-119, Marketing Science Institute.

—, ____, and Thomas W. Valente (2011), "Opinion Leadership and Social Contagion in New Product Diffusion," *Marketing Science*, 30 (2), 195–212.

- John, George, Allen M. Weiss, and Shantanu Dutta (1999), "Marketing in Technology-Intensive Markets: Toward a Conceptual Framework," *Journal of Marketing*, 63 (October), 78–91.
- Joshi, Yogesh V., David J. Reibstein, and Z. John Zhang (2009), "Optimal Entry Timing in Markets with Social Influence," *Management Science*, 55 (6), 926–39.
- Keller, Ed (2007), "Unleashing the Power of Word of Mouth: Creating Brand Advocacy to Drive Growth," *Journal of Advertising Research*, 47 (4), 448–52.
- Klemperer, Paul (1987), "Markets with Consumer Switching Costs," *Quarterly Journal of Economics*, 102 (2), 375–94.
- Krishnan, Trichy V., P.B. "Seethu" Seetharaman, and Demetrios Vakratsas (2012), "The Multiple Roles of Interpersonal Communication in New Product Growth," *International Journal of Research in Marketing*, 29 (3), 292–305.
- Libai, Barak, Eitan Muller, and Renana Peres (2009), "The Role of Within-Brand and Cross-Brand Communications in Competitive Growth," *Journal of Marketing*, 73 (May), 19–34.

—, —, and — (2013), "Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration Versus Expansion," *Journal of Marketing Research*, 50 (April), 161–76.

- Luo, Xueming, Aric Rindfleisch, and David K. Tse (2007), "Working with Rivals: The Impact of Competitor Alliances on Financial Performance," *Journal of Marketing Research*, 44 (February), 73–83.
- McPherson, Miller, Lynn Smith-Lovin, and James M. Cook (2001), "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology*, 27, 415–44.
- Medawar, Peter B. (1979), *Advice to a Young Scientist*. New York: Harper & Row.

(1984), The Limits of Science. New York: Harper & Row.

Moody, James (2009), "Network Structure and Diffusion," working paper, Duke Population Research Institute, Duke University.

- Moorthy, K. Sridhar (1993), "Theoretical Modeling in Marketing," *Journal of Marketing*, 57 (April), 92–106.
- Narasimhan, Chakravarthi (1988), "Competitive Promotional Strategies," *Journal of Business*, 61 (4), 427–49.
- Parker, Philip M. and Hubert Gatignon (1994), "Specifying Competitive Effects in Diffusion Models: An Empirical Analysis," *International Journal of Research in Marketing*, 11 (1), 17–39.
- Rivera, Mark T., Sara B. Soderstrom, and Brian Uzzi (2010), "Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms," *Annual Review of Soci*ology, 36, 91–115.
- Roberts, Mark J. and Larry Samuelson (1988), "An Empirical Analysis of Dynamic, Nonprice Competition in an Oligopolistic Industry," *Rand Journal of Economics*, 19 (2), 200–220.
- Schmitt, Philipp, Bernd Skiera, and Christophe Van den Bulte (2011), "Referral Programs and Customer Value," *Journal of Marketing*, 75 (January), 46–59.
- Serrano, M. Angeles and Marian Boguna (2005), "Tuning Clustering in Random Networks with Arbitrary Degree Distributions," *Physical Review E*, 72 (3, Part 2), 036133.
- Siggelkow, Nicolaj (2001), "Change in the Presence of Fit: The Rise, the Fall, and the Renaissance of Liz Claiborne," *Academy of Management Journal*, 44 (4), 838–57.
- Srinivasan, Raji, Gary L. Lilien, and Arvind Rangaswamy (2004), "First in, First out? The Effects of Network Externalities on Pioneer Survival," *Journal of Marketing*, 68 (January), 41–58.
- Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (January), 2–18.
- Subramanian, Upender, Jagmohan S. Raju, and Z. John Zhang (2013), "Exclusive Handset Arrangements in the Wireless Industry: A Competitive Analysis," *Marketing Science*, 32 (2), 246–70.
- Sun, Baohong, Jinhong Xie, and Henry Cao (2004), "Product Strategy for Innovators in Markets with Network Effects," *Marketing Science*, 23 (2), 243–54.
- Teece, David J. (1986), "Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy," *Research Policy*, 15 (6), 285–305.
- Van den Bulte, Christophe (2010), "Opportunities and Challenges in Studying Customer Networks," in *The Connected Customer: The Changing Nature of Consumer and Business Markets*, Stefan Wuyts, Marnik G. Dekimpe, Els Gijsbrechts, and Rik Pieters, eds. London: Routledge, 7–35.
- (2011), "Bass Model," in Wiley International Encyclopedia of Marketing, Vol. 5, Barry L. Bayus, ed. Chichester, UK: John Wiley & Sons, 9–15.
- and Yogesh V. Joshi (2007), "New Product Diffusion with Influentials and Imitators," *Marketing Science*, 26 (3), 400–421.
- and Gary L. Lilien (1997), "Bias and Systematic Change in the Parameter Estimates of Macro-Level Diffusion Models," *Marketing Science*, 16 (4), 338–53.
- Volz, Erik (2004), "Random Networks with Tunable Degree Distribution and Clustering," *Physical Review E*, 70 (5 Part 2), 056115.
- Wuyts, Stefan, Stefan Stremersch, Christophe Van den Bulte, and Philip Hans Franses (2004), "Vertical Marketing Systems for Complex Products: A Triadic Perspective," *Journal of Marketing Research*, 41 (November), 479–87.
- Xie, Jinhong and Marvin Sirbu (1995), "Price Competition and Compatibility in the Presence of Positive Demand Externalities," *Management Science*, 41 (5), 909–926.
- Yoffie, David B. and Renee Kim (2010), "Apple Inc. in 2010," Case 9-710-467, Harvard Business School.
- Zaltman, Gerald, Karen LeMasters, and Michael Heffring (1982), *Theory Construction in Marketing: Some Thoughts on Thinking*. New York: John Wiley & Sons.

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