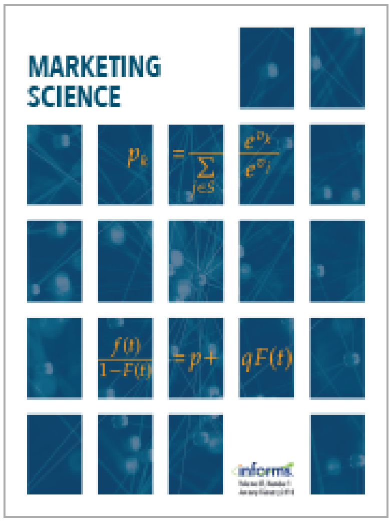

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Competitor See, Competitor Do: Incumbent Entry in New Market Niches

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The ability to keep up with changing technology is critical for a company's long-term survival. However, companies have to balance the risk of rushing into new areas and potentially cannibalizing their existing business against the risk of missing the emerging market. This paper investigates when incumbents enter into new market niches created by technological innovation. We argue that market conditions and company-specific characteristics do not suffice to explain incumbents' entry timing, but that entry is a contagious process. Our results demonstrate that incumbents are more likely to respond to innovations in their industry when their counterparts do so. In particular, we show that incumbents are affected by the entry of firms that are similar in size and resources. When a highly similar company enters the new market, it raises the probability that the company enters itself beyond levels based solely on the attractiveness of the market.

Key words: market entry; competition; new product research
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1. Introduction

Retail brokers confronted with online brokerage, integrated mills confronted with minimills, offset press manufacturers confronted with digital printing... examples abound of incumbents encountering new technologies into their markets. Technological change can transform a market, often creating great turmoil in an industry and enabling successful entry of new firms (Han et al. 2001). Accordingly, it poses a significant challenge for established firms. When confronted with competitors' new products, companies need to decide how long they can remain passive. Innovations provide opportunities for growth but may also undermine existing competitive advantages and investments and distract from current operations. This paper presents a conceptual and empirical model to explain the timing of an incumbent's response to disruptive technology.

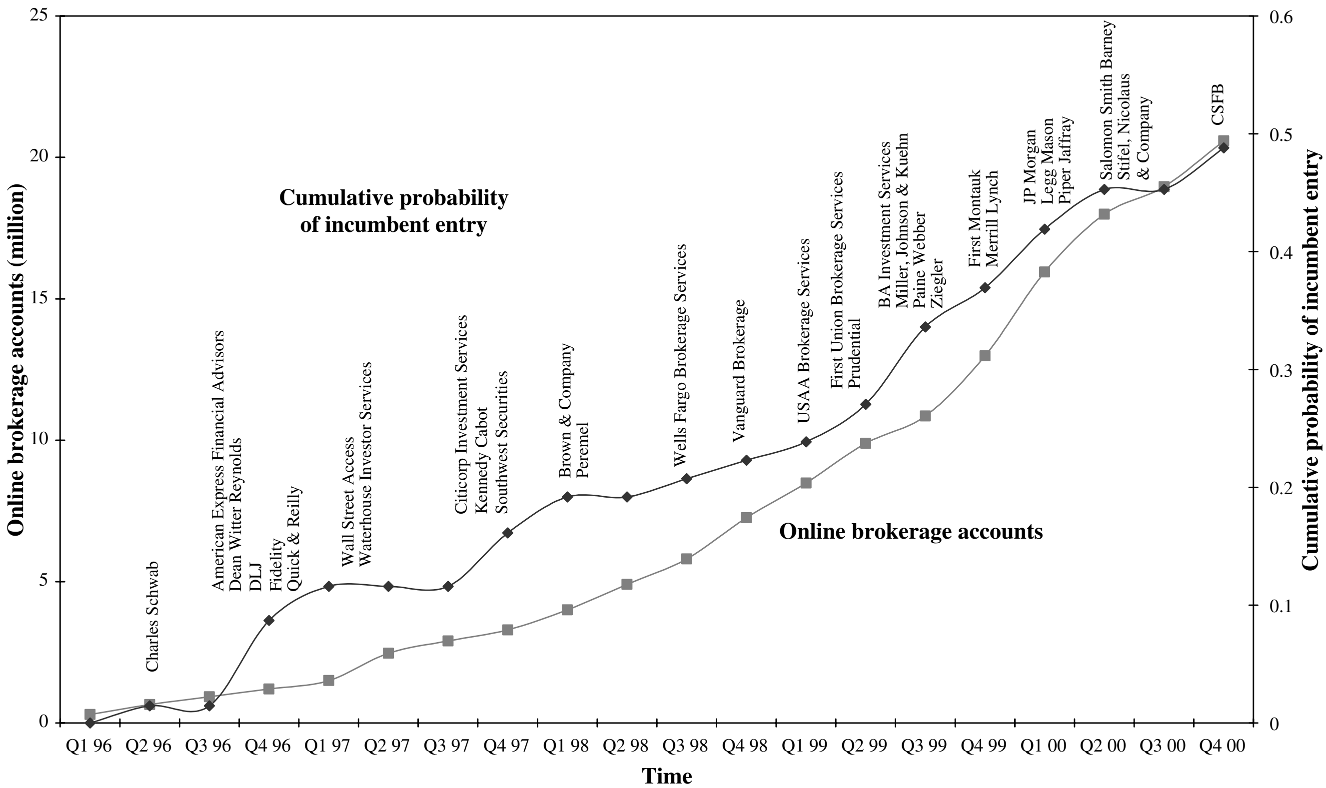
The research questions this paper addresses include: What factors determine when incumbents enter into a new market niche created by disruptive innovation, and how can we explain the variety in timing of incumbents' responses? *Specifically, this study investigates whether the entry time of different incumbents is interdependent*. An argument can be made that as a competitor enters the market, it makes it less attractive to all subsequent entrants. We discover a positive effect resulting from other companies' entry, suggesting a contagion effect within market entry.

The structure of this paper is as follows. In the next section, we define the context of this paper. We then present our empirical setting in §3. The fourth and fifth sections discuss the concept of contagion and integrate it within an empirical model of market entry. Next, we discuss the data, estimation, and empirical results. We conclude by exploring the implications of this analysis for a firm's potential reaction to disruptive innovation.

2. Definitions

Recent research has focused attention on the competitive effect of *disruptive niche innovation* (Adner 2002, King and Tucci 2002). Niche innovation occurs when a new technology creates a new market opportunity within an existing industry. As introduced by Christensen (1997), an innovation can be termed disruptive if it introduces new performance dimensions. Compared to existing technology on standard performance attributes, disruptive innovations actually perform worse (Christensen 1997). The concept of disruptive innovation therefore deviates from the default notion of technological change as the embodiment of progress on existing performance dimensions. Disruptive innovation infringes upon the existing market by appealing to lower-end customers

Figure 1 **Market Growth and Incumbent Entry**



who value their lower price points (see Adner 2002 for a breakdown of the demandside foundations of disruptive innovations). This paper adds to the existing literature on the timing of incumbents' entry in emerging technology-created niches (King and Tucci 2002, Mitchell 1989). Throughout this paper, when we refer to "incumbent entry" or "market entry," we mean the entry of incumbents[1] into a new market area that results from disruptive niche innovation.

3. Empirical Setting

The empirical setting of this study is the retail brokerage industry. In the mid-1990s, this industry faced the emergence of online brokerage, which has been recognized as a disruptive innovation (Christensen and Oberdorf 2000). Online brokerage possesses key characteristics of a disruptive innovation: (1) It introduces a new technology and new performance dimensions to the industry (e.g., website ease of use, online stock quotes, speed of processing); (2) it is inferior to the established offering on the key performance dimensions of this market segment (e.g., quality of advice, personalized relationship, etc.); (3) it operates at a lower price point than the existing market; (4) it invades the established market at the low end; and (5) some customers from the existing market switch to the new market.

Central characteristics of online brokerage provide the context for this empirical study. First of all, entry barriers are low. Typically, strategic reasons motivate a company's entry into the online brokerage area. Amidst the e-commerce frenzy of the nineties, the emergence of online brokerage has attracted many new entrants to the industry. By January 2001, more than 150 companies had entered the online brokerage area, including retail brokerage incumbents, start-ups, banks, and technology providers. Market uncertainties have, however, been high, as highly diverging market projections testify. Thus, incumbents have faced significant uncertainty about the impact of online brokerage, although their entries have generally not been obstructed by technological limitations.

Since its inception, online brokerage has made significant inroads in the retail brokerage market. Figure 1 shows the development of the online brokerage market from 1996 to the end of 2000.

Within our five-year observation period, the market grew to more than 20 million brokerage accounts. Online accounts held about $1 trillion in assets, which accounted for over 5% of household's liquid financial assets, and 12% of the assets held in equities.

[1] In defining incumbency, we follow Chandy and Tellis (2000) in assuming that incumbency reflects whether a firm participated in the previous generation of products.

Industry reports claim that by the end of the year 2000, more than one-third of retail brokerage trades were done online. The growth of the market coincided with a gradual influx of incumbent companies into the online market. Charles Schwab was the first major incumbent to take the plunge in May 1996. Many others followed, as shown in Figure 1.

In this paper, we introduce the idea that, aside from idiosyncratic company characteristics and the attractiveness of the market, the actions of other incumbents play a role in a company's decision to enter. Anecdotal evidence suggests such a contagion effect. For example, the entry of Fidelity Brokerage came right on the heels of Schwab's entry into online brokerage. Similarly, after denying any plans just a couple of months earlier, Piper Jaffray entered the online brokerage area right after major competitors Merrill Lynch and Paine Webber had done so. These examples suggest that entry may be a contagious process: The entry of competitors increases the likelihood that a company enters as well. In the next section we explore this idea further by discussing existing research on organizational contagion. Additionally, we lay out arguments to establish that the actions of similar competitors are most conducive to contagion.

4. Organizational Contagion

4.1. Literature Review

In the process of contagion, each adoption of a new practice or product makes the subsequent adoption from a potential adopter more likely (Burt 1987). *It does not presuppose a decision-making process that causes the phenomenon* (Greve 1998). Contagion has been documented extensively as a dynamic behind the diffusion of new products (Bass 1969, Rogers 1983). When it concerns the behavior of organizations, this phenomenon has also been labeled herd behavior, bandwagon effect, demonstration effect, or organizational imitation (Kennedy 2002). The hypothesis of contagion does not imply a specific rationale. Contagion can result from blind imitation of others' behavior. Others' decisions can carry informational value that may affect potential followers' decisions. With uncertainty as to the outcome, decision makers may turn to others' behavior as a signal of the value of an action (Gilbert and Lieberman 1987). Imitative behaviors also result when decision makers are risk averse and are evaluated on their relative performance in comparison to others (Palley 1995). In some cases the existence of previous actors could actually increase the utility of an action when network externalities are present. Population growth models claim that increased entry into a new market attracts new entry in turn (Gort and Konokayama 1982, Hannan and Freeman 1977, Lambkin and Day 1989). However, (1) these models are at an aggregate level, and (2) they attach an equal influence to every company's entry on subsequent entrants.

4.2. Contagion Effect of Incumbent Entry

The contagion effect induced by other incumbents' entry is driven by three factors: positional advantages, substitution, and the reduction of uncertainty about the attractiveness of the market.

Other Incumbents' Entry Affects Expected Positional Advantages. The incentive to enter the new market depends on the company's ability to capitalize on positional advantages, but also to avoid laggard disadvantages. To deal effectively with postentry competition, incumbents need to consider the expected competition from companies with resource profiles similar to their own. An incumbent's performance will be affected mainly by its order of entry relative to other incumbents, rather than by its overall entry order (Mitchell 1991, Narasimhan and Zhang 2000). The entry of similar competitors thus creates the impetus to respond likewise.

Other Incumbents' Entry Increases the Extent of Substitution. The entry of other incumbents not only changes the expected competition in the new market, but it also changes the competition between the existing and new markets. Because of their transferable assets and capabilities, incumbents entering a new market niche can develop the new market further and accelerate the level of substitution between the old market and the new market (King and Tucci 2002). This increases the extent of external market encroachment on the existing market players. Because of the similarity in complementary assets, this market penetration mainly affects incumbents who have the same assets, but have not yet entered the new market. For these companies, the expected substitution effect increases and the incentives to enter the new market increase accordingly (Narasimhan and Zhang 2000).

Other Incumbents' Entry Reduces Uncertainties About the Value of Entry. With market uncertainty lingering, companies rely on rivals' behavior to signal market opportunities. Gilbert and Lieberman (1987) show that in uncertain conditions, contagious investment behavior is an equilibrium outcome. Not every incumbent's entry carries a similar signal of the market potential. Competitive cognition theory claims that interpretation of competitive events is affected by a firm's mental model of the competition, developed mainly by examining the most similar competitors (Porac and Thomas 1990). This means that similar companies receive more attention. Firms perceived as dissimilar to the company are viewed as less threatening, monitored less closely, and understood less. Companies are therefore more likely to imitate the actions of their most similar peers (Haveman 1993, Kraatz 1998). The more uncertainty surrounds a decision, the more peer comparison becomes a guide (Haunschild and Miner 1997). Entry into a new market carries a great deal of uncertainty. We expect the entry of similar competitors to be particularly significant and influential for the entry decision.

5. Model Development

5.1. Base Model

In order to test the hypothesis of contagion, we must develop a model for incumbent entry into a new technology-created market niche. We start from the notion that the utility of entry depends on the opportunity that the new market represents. Incumbents, in contrast to new entrants, may have little incentive to develop a new area, for fear of cannibalizing their existing market. They may delay acting on the new situation until other entrants force their hand. The point at which the opportunity cost of nonentry counterbalances the expected self-cannibalization determines when incumbents respond to innovations. This depends on the size of the new market niche and the extent to which it invades a company's existing market.

Opportunity. An incumbent can regard disruptive niche innovations as a threat to existing business, but such innovations also represent an opportunity for new business. Unlike newcomers, incumbents possess certain assets that are required to operate successfully in an industry and that maintain their value from one product generation to another (Mitchell 1991). Examples include existing distribution systems, the ability to produce complementary goods or services, efficiency advantages, the possession of human capital, experience, etc. In addition, incumbents possess critical marketing capabilities—including existing customer relations, customer knowledge, and market power—that give them an advantage over new entrants in successfully marketing new products (Chandy and Tellis 2000). The difficulty in replicating these assets should give incumbents the advantage in new market areas. A developing new niche therefore represents a source of opportunity for incumbents. Given the advantage of entry in a growing market, growing adoption of the innovation should motivate entry into this new market (Bowman and Gatignon 1995, Lilien and Yoon 1990).

Susceptibility to Substitution. Incumbents may delay acting upon new technologies because they fear self-cannibalization. When other companies enter the new market, however, this cannibalization happens from the outside (Narasimhan and Zhang 2000). Disruptive innovations usually start at the low end of the market, but gradually invade upon the existing mainstream market (Adner and Zemsky 2005). We define an incumbent's susceptibility to substitution as the extent of profit reduction an incumbent experiences due to the development of the new market niche. Substitution can occur when other competitors develop the new market while the incumbent remains absent. This makes the incumbent vulnerable to customers defecting. The extent of overlap between target segments of the new technology and of an incumbent determines the magnitude of the innovation's impact on the incumbent (Adner 2002). Substitution is thus larger if the positioning of the existing product resembles that of the new product (Moorthy and Png 1992, Deleersnijder et al. 2002). This threat to the incumbent's core market motivates its entry into the new field (Mitchell 1989).

We investigate when incumbents enter a new market, and consider the time-dependent dynamics that account for that entry. The phenomenon of interest is a time-dependent binary event modeled by survival analysis or hazard modeling (Cox and Oakes 1984, Jain and Vilcassim 1991, Helsen and Schmittlein 1993).

Based on the discussion above, the hazard of entry for an incumbent, then, can be expressed as:

$$h_{it} = \lambda_0(t)\exp(\beta_1 MGR(t) + \beta_2 SUBST_i + \bar{\beta}_3 IC_i)$$

with:
$MGR(t)$: market growth of the new market,
$SUBST_i$: susceptibility to substitution, and
IC_i: vector of incumbent characteristics.

The market growth variable $MGR(t)$ captures the general entry dynamics that can be attributed to the development of the new market. $\lambda_0(t)$ captures the time trend that exists after controlling for this market growth. The individual covariates $SUBST_i$ and IC_i represent the shift from the baseline hazard that specific observations experience due to individual differences (see Table 1 for definitions of the variables). To control for these internal factors, covariates for the incumbent characteristics are added to the model (because of space constraints not discussed in detail).[2] Aside from the incumbent characteristics that we included, other unobservable traits may influence the timing of response to innovation (e.g., willingness to cannibalize Chandy and Tellis 1998),

[2] Because the main interest and contribution of this study lies in investigating the contagion effect of incumbents' entry, the empirical context of the study is chosen to reflect this optimally and to reduce the confounding effect of pure technological capabilities. This excludes industries in which a firm's innovation decisions are mainly determined by patent protection issues.

or technological opportunism (Srinivasan et al. 2002)). To correct for unobserved heterogeneity, we let λ_0 be distributed according to a gamma distribution with mean r/a (Jain and Vilcassim 1991). This distribution is quite flexible, and results in a closed-form solution for the log-likelihood function (Dekimpe et al. 1998).

It is difficult to distinguish between the apparent contagion effect and the effect of common unobserved shocks. By integrating longitudinal evolutions and firm-specific conditions in an individual-level model, we are able to separate the contagion effect from common external influences.

5.2. Adding Contagion

Contagion is commonly operationalized within a hazard model by a covariate that captures the influence of previous actors on subsequent actors. To account for a contagion effect on entry, we can thus add $n(t-1)$, the number of previous entrants, to the model (Strang 1991).[3] However, this measure of contagion is crude because it does not differentiate among previous entrants. The contagion effect evoked by different previous entrants is assumed to be equal. Also, this contagion specification acts as a common influence on all potential entrants, which may create difficulties in distinguishing it from other common time-varying effects.

An alternative approach allows for heterogeneity in the effects of previous entrants and introduces cross-sectional variation in the contagion variable. This effect is accomplished by adding lagged endogenous autocorrelation terms of the following form (Hedstrom 1994, Van den Bulte and Lilien 2001):

$$\beta \sum_j w_{ij} y_{j,\,t-1}.$$

The weight w_{ij} expresses the extent to which j exerts an influence on i.[4] Based on the arguments for contagion developed above, we represent this weight by the similarity between i and j, sim_{ij}.

The contagion factor thus becomes:

$$\beta \sum_j sim_{ij} y_{j,\,t-1}.$$

Even though the marginal contribution of each previous entrant is now customized, the assumption that contagion increases with each additional entrant remains an issue in this operationalization of contagion (Van den Bulte and Lilien 2003). The weights of different previous entrants are simply added up. In other words, if an unimportant entrant acts after a highly influential one, the contagion factor is still assumed to increase, although we may expect the significance of this event to be nonexistent. If previous entrants do have an effect, it may not matter as much how many acted as how important those entrants are. Therefore, we adjust the operationalization to express that the marginal contribution of an entrant is zero when its influence is not higher than that of previous entrants. The contagion effect is then identified in terms of the most influential previous entrant, SIM_i.

$$\beta\,\mathrm{Max}(sim_{ij} y_{j,\,t-1}) = \beta\, SIM_i(t).$$

Aside from the contagion effect evoked by similar incumbents entering, we also need to control for nonincumbents entering the market. Therefore, $ENTRY(t)$, the number of nonincumbent entrants at any point in time, is included in the model. As is apparent from the discussion in §4.2, based on the similarity among incumbents, we expect that the incumbent contagion effect will be stronger than the effect of new entries.

Adding contagion to the base model, the hazard of entry at time t for observation i then can be formulated as:

$$h_{it} = \lambda_0(t) \exp\big(\beta_1 MGR(t) + \beta_2 SUBST_i + \bar{\beta}_3 IC_i + \beta_4 SIM_i(t) + \beta_5 ENTRY(t)\big).$$

6. Data

We collected data for this study by examining secondary data, following the principles of historical analysis (Golder 2000). The measurement sample of incumbents for this study consists of the 70 biggest retail brokerages, as identified by the Securities Industry Association. These represent 82% of the entire industry in terms of number of accounts. The measurement window for this study covers quarterly data for the period 1996–2000, which represents the growth stage of the market. The beginning of 1996 marks the takeoff of the online brokerage market. Of the total sample, 44.3% had entered the online brokerage market in the period before January 2001. There is no left censoring. The first incumbent entry happened in the second quarter of 1996.

The measures in the empirical model are specified in Table 1, together with the descriptive data from the sample. The online brokerage market data consist of quarterly observations of the number of online brokerage accounts, compiled from market research and industry reports. This study uses account data rather than trading-volume data because the latter are more

[3] This approach conforms to aggregate adoption models such as logistic growth models and the Bass diffusion model. According to these, the rate of adoption is positively related to the cumulative number of previous adopters.

[4] Innovation diffusion models base these weights on spatial or social networks between potential adopters.

Table 1 Summary of Discrete-Time Data

	MGR	*SUBST*	*ENTRY*	*BANK*	*STATES*	*OFF*	*RETTOT*	*ACCOFF*	*ACC*
Mean	0.08	0.54	6.23	0.20	0.17	0.14	0.87	0.01	0.05
St. Dev.	0.07	0.64	4.23	0.40	0.16	0.44	0.21	0.01	1.12

Variable	Description
$MGR(t)$	Market growth in number of online brokerage accounts (divided by 10,000)
$SUBST_i$	Number of customer accounts per retail representative (divided by 1,000)
$SIM_i(t)$	Maximum similarity with incumbent entrants
$ENTRY(t)$	Number of nonincumbent entrants
IC_i	Vector of incumbent characteristics
$BANK_i$	Dummy variable stating whether the brokerage is affiliated with a bank
$STATES_i$	Number of U.S. states in which the company has a physical presence (divided by 100)
$OFFICES_i$	Number of retail brokerage offices (divided by 1,000)
$RETTOT_i$	Ratio of number of retail on total brokerage representatives
$ACCOFF_i$	Number of customer accounts per office (million)
ACC_i	Number of customer accounts (10 million)

likely to be affected by fluctuations in the stock market. We had no direct measurement of the susceptibility to substitution for each company. The measure we use as a proxy relies on the argument that the extent to which companies are affected depends on their positioning. New products represent the greatest threat to competitors most closely positioned to them (Gruca et al. 2001). The extent of substitution is thus reflected in the proximity of positioning between the existing product and the new product (Moorthy and Png 1992, Deleersnijder et al. 2002). The number of brokerage accounts per retail representative is a good measure for the closeness of an incumbent's positioning to online brokerage. A larger number of accounts per representative corresponds to less personal relationships with customers, a characteristic typical of online brokerage.[5]

The basis for the contagion measures is a matrix that contains the similarity between all companies in the population. We construct three similarity matrices between incumbents, based respectively on the size, market scope, and resources of the companies (Porac and Thomas 1990). Appendix 1 contains further details on the contagion measures. The similarity between two companies is contained between one and zero. One represents total equality, while zero represents maximum dissimilarity.[6] The size-similarity measure captures the similarity between companies in terms of market share in the incumbent market. The market similarity measure captures the overlap in the geographical scope of companies. The resource similarity measure captures the company's organizational resources. Because of the overlap between organizational resources and the products offered—an overlap typical for services industries—the organizational resources of the company closely reflect its position in the retail brokerage market. Appendix 2 contains additional details about the calculation of these similarity matrices. The average similarity of a company to its rivals is 0.74 for size similarity, 0.18 for market similarity, and 0.39 for resource similarity. The respective average standard deviations of these similarities are 0.27, 0.20, and 0.15.[7] For example, firms most equal to Schwab in terms of resource similarity include Fidelity (0.86) and Quick & Reilly (0.83). In contrast, the similarity to DLJ (0.42), Dean Witter Reynolds (0.51), and Merrill Lynch (0.52) is considerably lower. Merrill Lynch, on the other hand, is most similar to Dean Witter Reynolds (0.82).[8] The resulting contagion measures show longitudinal as well as cross-sectional variation (see Table 2).

All incumbent characteristics are based on figures from January 1996 and are treated as time-independent covariates. Choosing the start of the measurement window of the hazard model as the time to measure the company covariates allows for

[5] For example, discount brokers, who are much closer positioned to online brokers than full-service brokers, generally have more customer accounts per retail representative.

[6] This operationalization is in line with spatial diffusion models.

[7] These figures indicate the variation in similarity of a company to its rivals. The reported numbers are calculated by averaging the standard deviation of the similarity of a company to its rivals over the entire sample.

[8] The validity of the resource similarity measure was tested by correlating the resulting similarity matrix with other sources. The ability of this measure to discern different types of companies was reflected in the fact that it differentiates among the different types of brokerage firms identified by the Securities Industries Association. This test confirmed that these measures are industry-accepted and are actually used to distinguish companies with a different positioning. As a second validation, the similarity matrix was cross-validated with content analysis of industry publications in which similar sets of companies are mentioned.

Table 2 Descriptive Statistics for Contagion Measures

	SIMSIZE	*SIMMARKT*	*SIMRESS*
Mean	0.85	0.38	0.51
Longitudinal variation	0.15	0.17	0.11
Cross-sectional variation	0.06	0.25	0.14

Notes. The longitudinal variation is calculated as the standard deviation of the variable over time for every observation, averaged over the entire sample. The cross-sectional variation is calculated as the standard deviation of the variable over the sample for every time point, averaged over all discrete time points.

conformity among all cases (a later time would create a problem with uncensored cases). The company characteristics used to construct the contagion measures are also included as covariates in the model.

7. Estimation

7.1. Model Specifications

We explore alternative model specifications to ascertain the stability of the results. We report models with a parametric baseline and a nonparametric baseline. For the parametric baseline model, a series of nested models determined the optimal specification of $\lambda_0(t)$. Likelihood ratio tests demonstrated that a constant term λ_0 is optimal (corresponding to an exponential process). The nonparametric baseline model does not require a decision on the nature of the duration dependence of the data. The nonparametric baseline hazard is a step function that can take on different values in each time interval. The model can be expressed as:

$$h_{it} = \lambda_0 \exp\big(\delta D(t) + \beta_2 \, SUBST_i + \bar{\beta}_3 \, IC_i + \beta_4 \, SIM_i(t)\big)$$

with $D(t)$: dummy variables for different time periods.

The nonparametric baseline incorporates all the changes over time that can influence incumbents' timing of entry. These may reflect changing market characteristics (e.g., market size and profitability, adopter characteristics, etc.) or the characteristics of new entrants in the market (e.g., scale and performance of new entrants, etc.).

All in all, the model contains the following elements to rule out rival effects that could cause a spurious contagion effect: (1) the impact of measured (parametric baseline model) or unmeasured (nonparametric baseline model) conditions common to all observations, (2) the impact of measured characteristics of the observations, and (3) the impact of unmeasured characteristics of the observations. Together these elements control for longitudinal and cross-sectional effects. In particular, the model with nonparametric baseline and unobserved heterogeneity contains the maximum amount of flexibility in controlling for measured and unmeasured conditions that influence incumbent entry.

Because the data are measured on a quarterly basis, we estimate the model as a continuous-time formulation with interval censored data. The log-likelihood function for this model with nonparametric baseline and gamma-distributed unobserved heterogeneity (Dekimpe et al. 1998) can be written as:

$$LL = \sum_{i=1}^{N} \ln\left\{(1+d_i)\left[\frac{a}{B_i(T_i-1)+a}\right]^r - \left[\frac{a}{B_i(T_i-1)+(1-d_i)e^{\beta X_i(T_i)+\delta D_i(T_i)}+a}\right]^r\right\}$$

where:
T_i: time until entry or censoring
d_i: indicator for censoring
a, r: parameters of gamma distribution
$X_i(t)$: vector of covariates
D_i: vector of time-period dummy variables[9]
β: vector of parameters for covariates
δ: vector of parameters for time-dummies
N: number of observations
and $B_i(t) = \sum_{t=1}^{T} e^{\beta X_i(t)+\delta D_i(t)}$.

Table 3 contains the estimation results. The results of the nonparametric baseline models are generally consistent with the results obtained with the parametric specification. We report results for the base model and then add all three forms of contagion (size, market, and resource) to it. A likelihood-ratio test against an intercept-only model rejects the hypothesis that all parameters equal zero ($p < 0.001$). There are several factors that lead to a firm's decision to enter the new market. What is important here, based on the likelihood-ratio tests, is that adding contagion is significant. Based on the BIC-criterion, the base model with resource contagion added is the best model.

7.2. Specification Tests

We found no violations against the basic assumption of proportionality. Additionally, the results remain robust when a proportional odds model is specified instead of a proportional hazard model. A concern that similar exogenous variables may influence similar firms can also constitute a claim for nonproportionality. These effects cannot be absorbed as common trends in the baseline hazard. Interactions of the company characteristics and duration allow for a nonproportional effect of exogenous time-varying variables on different companies (Wedel et al. 1995).

[9] This vector is absent in the parametric baseline specification.

Table 3 Estimation Results for Parametric and Nonparametric Baseline Models

		Parametric baseline				Nonparametric baseline			
		Base model	+ Size contagion	+ Market contagion	+ Resource contagion	Base model	+ Size contagion	+ Market contagion	+ Resource contagion
Time	Year 1					−2.011***	−0.919	−1.896***	−1.399*
	Year 2					−1.753***	−1.356***	−1.723***	−1.618**
	Year 3					−1.769***	−1.700***	−1.754***	−1.703**
	Year 4					−0.499*	−0.462*	−0.494**	−0.395
Market growth	$MGR(t)$	6.840**	4.724*	6.522***	5.588***				
Nonincumbent entry	$ENTRY(t)$	0.048*	0.029	0.045	3.614				
Substitution	$SUBST_i$	1.625***	1.436***	1.280***	1.230***	1.291***	1.433***	1.350**	1.220**
Size contagion	$SIMSIZE_i(t)$		3.003*				4.068**		
Market contagion	$SIMMARKT_i(t)$			0.347				0.339	
Resource contagion	$SIMRESS_i(t)$				2.223***				2.559**
Incumbent characteristics	$BANK_i$	0.211	0.223	0.208	0.475	0.252	0.278	0.235	0.552
	$STATES_i$	4.538***	4.594***	4.038***	4.422***	4.734***	4.620***	4.199***	4.645***
	$OFFICES_i$	−2.799	−3.253	−2.843	−2.053	−2.817***	−3.297***	−2.985**	−1.971
	$RETTOT_i$	4.107***	4.709***	4.233***	3.306**	4.302***	4.884***	4.640***	3.333
	$ACCOFF_i$	8.483***	5.733	7.700	11.558	12.682**	10.370	9.854	16.375
	ACC_i	1.625	1.996	1.634***	0.514	1.450*	2.038***	1.535	0.209
	r/a	0.00005	0.000003	0.00005	0.00004	0.0003	0.000004	0.0002	0.0002
	LL	−116.662	−114.916	−116.531	−114.566	−114.174	−112.148	−114.125	−111.780
	BIC	253.5	252.0	255.2	251.3	252.3	250.1	254.1	249.4

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

These interactions were tested one by one, but none were statistically significant.

The nonparametric baseline allows for discrete shifts of the baseline hazard in different time periods. A sufficient number of events in a given time interval is required to allow for reliable estimation of the associated parameters (Dekimpe et al. 1998). Therefore, we aggregate time periods to allow for yearly shifts instead of quarterly shifts. Seasonal dummies were added to test for heterogeneity of the parameter estimates of the baseline within the yearly time intervals, but were found to be insignificant.

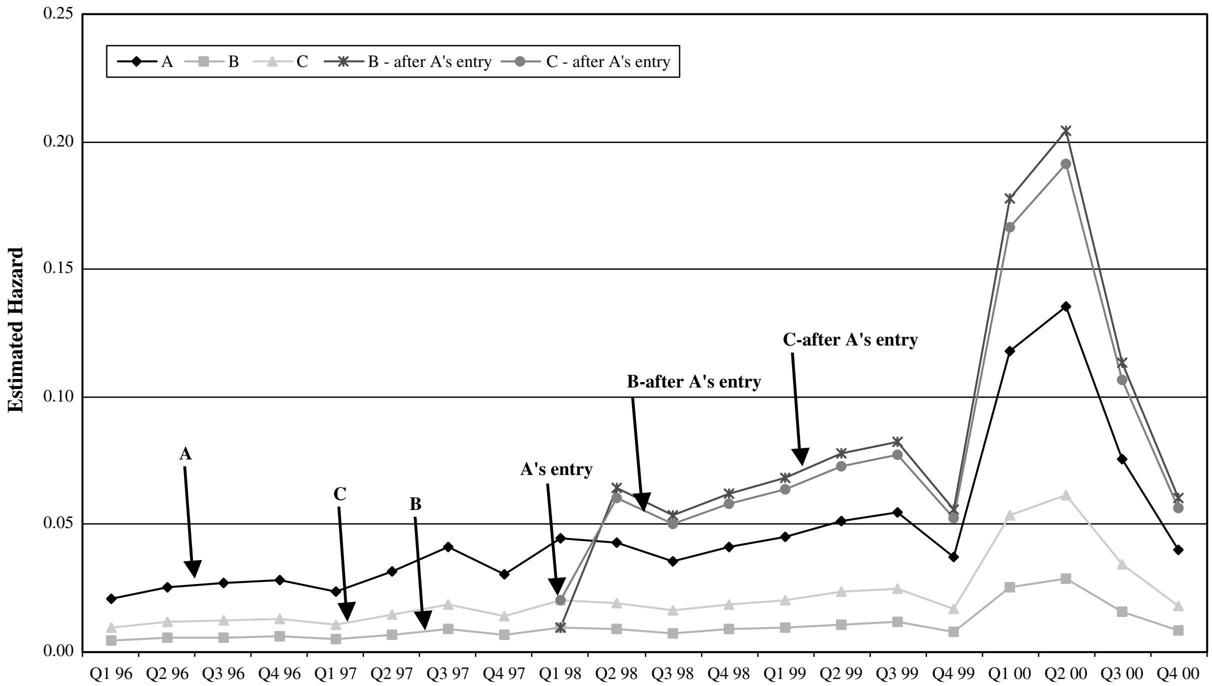
The hazard models we estimate assume that the entire population will eventually experience the event (as time $\rightarrow \infty$). As such, these models estimate the timing of an event, not the probability that it happens. In our case, this assumes that at infinity, all incumbents will enter online brokerage. To test the robustness of the obtained results empirically to this assumption, we estimated a split-hazard specification (Dekimpe et al. 2000). A split-hazard model enables the joint estimation of the timing and probability of an event. It divides the population into two latent groups: one group for which the event will happen and another group for which it will never happen. The splitting parameter indicates the proportion of the population that belongs to the former category (Sinha and Chandrashekaran 1992). The parameter estimate for the splitting parameter converged to one, making us feel comfortable with our original assumption.

8. Results

The parameter estimates demonstrate that market and company characteristics, as well as contagion effects, determine the timing of an incumbent's entry into a new market niche. We find confirmation that the growth of the new market ($MGRT(t)$) and its cannibalization upon a firm's existing market ($SUBST_i$) stimulate incumbents to enter. Market growth captures the effect of both market expansion and substitution. The effect of $SUBST_i$ reflects the additional effect of an incumbent's individual proneness to be affected by substitution. Although nonincumbent entry also stimulates incumbent entry, its effect is not significant, as we expected. The more geographic markets in which a firm is present ($STATES_i$), the more likely it is to respond. Likewise, the more there is a retail customer base in the business ($RETTOT_i$), the more likely the firm was to enter into the new technology.

The key finding is the existence of contagion between incumbents. The model demonstrates that the difference in timing among incumbents' responses is not solely determined by the companies' characteristics, but also depends on other companies' actions. The results confirm that incumbents are more likely to respond to disruptive niche innovations in

Figure 2 **Estimated Hazard Without and With Contagion**



their industry when their similar counterparts do so. We used three different measures of incumbent similarity in three different estimations because of their high intercorrelation. For the similarity in terms of size and in terms of resources, we found that the higher the competitor similarity, the more likely the incumbent was to follow into the new market. This was not the case for the similarity of the market they served (although there was no significant effect in any direction). The contagion effect has managerial significance as well as statistical significance. Applying the average cross-sectional deviation from Table 2, one standard deviation change in size-, market-, and resource-similarity changes the instantaneous hazard of entry by 20.8%, 8.9%, and 36.5% respectively. This implies that the variance in contagion effects influencing different companies at any point in time creates a considerable amount of difference in their likelihood of entry.

9. Discussion

9.1. Conclusions and Implications

We identify competitive contagion as one of the drivers of an incumbent's entry into new market niches created through disruptive innovation. The approach used in this paper differs from a deterministic explanation of incumbent reaction based on the company and the innovation's characteristics. Instead, we introduce a path dependency into the entry decision by incorporating dynamic competitive effects through contagion. Our study is the first to concentrate on how competition affects an incumbent's response to innovations. The results suggest that when similar competitors enter the market, incumbents experience increased urgency to respond to the new niche. To further illustrate the effect of entry contagion, we selected three observations from our dataset (labeled A, B, and C). A and B share a high resource similarity (0.88), but A and C are less similar (0.52). Figure 2 shows the predicted empirical hazard for these observations, using the parametric baseline model and leaving out the effect of contagion. The change in entry hazard over time is due to the effects of market growth and nonincumbent entry. The difference between A, B, and C can be explained by their individual characteristics. Based on these, A has the highest probability of entering the market at each point in time, and B the lowest. Figure 2 also shows the predicted hazard, assuming A enters in the first quarter of 1998. Because of the contagion effect, the entry of A significantly increases the probability that B and C follow. Due to the larger effect that A's entry has on B, B's hazard of entry exceeds C's from that moment on. This example illustrates the power of contagion. Although the intrinsic characteristics of C make it a more likely candidate to enter the market then B, B is more likely to enter than C once A has entered the market. The results demonstrate empirically that incumbents respond to disruptive innovations when their similar counterparts do the same thing. In other words, comparable companies imitate each other's actions, thereby restoring their equality.

Three important implications emerge. First, incumbents should not expect their presence in the new market to deter competitors. In fact, they attract competition by their entry into the new market. This postentry change in competition should be anticipated. Second, the expectation of increasing competition from similar counterparts can change the optimal entry time for incumbents. Incoming incumbents help to develop the new market and increase the competition within the market. The former accelerates the cannibalization on the existing market, whereas the latter makes the new market less attractive. These considerations decrease the expectation of positive gains from entering the new area. Third, incumbents should consider alternative approaches to avoid attracting competition in the new market. They might do so by entering the market through acquisition and operating it as a separate unit, therefore sending a weaker signal to competitors. Also, this entry strategy reduces the learning effect for competitors because they cannot make inferences about their own entry from this move. In other words, the acquisition entry has less diagnostic value for competitors. Of course, this advantage should be balanced against the financial sacrifice and the loss of utility from complementary assets that retain their value in the new market.

9.2. Limitations and Future Research

Several caveats emerge, as well as opportunities for future research. The analysis of intercompany influence was limited to past behavior only. We ignored contemporaneous and anticipated future reactions. We were limited in our measures of the market's attractiveness, which would have been helpful for further exploring which market factors expedite entry. Also, it is important to note that our results are not intended to convey normative implications about the appropriateness of contagion in market entry. It would have been helpful to determine whether the firms that did imitate their competition fared better than those that did not. Unfortunately, we did not have performance data. Rather, this paper carries managerial implications for the assessment of postentry competition.

We have presented a methodology for studying the factors leading to the entry decision in other industries. It would clearly be worthwhile to replicate this analysis in other industries. We would expect to find similar results in many of the industries that have gone from bricks and mortar to online, as in this case. For example, Barnes and Noble may have waited before responding to Amazon.com, but felt they had no choice but to respond once Borders went online. Additionally, it would be interesting to compare our findings to competitive entry behavior for nondisruptive innovations.

This study introduces the concept of contagion within a competitive setting. The results trigger new questions about the roots of the contagion effect and the context in which it occurs. Our arguments are based on two theoretical perspectives. The contagion effect can be defended from the perspective of resource-based competition (Narasimhan and Zhang 2000). Accordingly, we argued that the entry of similar competitors affects companies' expected positional advantages in the new market and also exacerbates substitution. At the same time, arguments for a contagion effect can be made from a decision-theoretic perspective, based on the attention, relevance, and credibility attached to competitors' actions. Additional research is needed to investigate the decision process that lies behind the apparent contagion effect and to disentangle different motivations that lie behind it.

Also, the contagion effect could be contingent upon other factors. For example, it could be a time-dependent effect. One might argue that entry contagion is a phenomenon restricted to the growth stage of the market, but disappears in the mature stage when uncertainties fade and the competitive battlefield becomes more established. Furthermore, it would be useful to know if previous entrants can manipulate the contagion effect that their entry prompts.

Finally, our empirical investigation rests on secondary data, which enabled us to gather unbiased and complete data but also carried certain limitations. For example, because there are no secondary measures for the extent of substitution of online brokerage, we used the company's positioning relative to online brokerage as a proxy measure. Also, secondary data do not enable us to dig deeper into company traits previously mentioned in the literature that may affect their responsiveness to new technology (e.g., willingness to cannibalize; see Chandy and Tellis 1998), or technological opportunism (Srinivasan et al. 2002). We could only account for these by incorporating unobserved heterogeneity into the model. Similarly, the effect of market evolutions or new entrant characteristics could be investigated in more detail with additional data.

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Appendix. Incumbent Similarity Matrices

1. Size Similarity

The size similarity of an incumbent with the entered incumbents is based on the number of customer accounts the company has.

Δ_{Sij} is the difference between the logarithms of the number of accounts of company i and j.

The elements of the size similarity matrix are:

$$Sim_{ij} = 1 - \frac{\Delta_{Sij}}{\text{Max}_{i,j}\Delta_{Sij}}.$$

2. Market Similarity

The market similarity between two companies is based on the U.S. states in which the company has a physical presence (i.e., a bricks-and-mortar office).

The market similarity $SMKT_{ij}$ between company i and company j is calculated as the proportion of shared markets to the total number of markets in which either of the two companies i or j are present. The elements of the market similarity matrix are:

$$Sim_{ij} = \frac{\sum_m D_{im} D_{jm}}{\sum_m (D_{im} + D_{jm} - D_{im} D_{jm})}.$$

D_{im} is a dummy variable denoting whether company i is present in market m.

3. Resource Similarity

The resource similarity of an incumbent with entered incumbents is based on a composite measure that contains different elements of the resource endowment of each company. Δ_{Rij} is a vector of the standardized differences of company i and company j on eight variables that profile the company.[10] The distance between two companies on these variables is defined as a Euclidean distance:

$$DISRES_{ij} = \Delta'_{Rij} \Delta_{Rij}.$$

The eight variables are:

1. *STATES*: number of states with physical presence (reflects regional presence of the company);
2. *ACC*: number of customer accounts (reflects existing customer relationships);
3. *OFF*: number of offices (reflects bricks-and-mortar dependence);
4. *RETTOT*: retail to total ratio (reflects dependence on retail market);
5. *ACCOFF*: accounts per office (reflects scattered localized presence);
6. *ACCREP*: accounts per representative (reflects personalization of customer relationships);
7. *DESC*: activity description (reflects positioning within retail brokerage market);
8. *BANK*: bank affiliation (reflects complimentary banking relationship).

[10] None of the correlations between these eight variables are statistically significant.

The elements of the resource similarity matrix are:

$$Sim_{ij} = 1 - \frac{DISRES_{ij}}{\text{Max}_{i,j} DISRES_{ij}}.$$

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