The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity

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ABSTRACT

Companies can acquire customers through costly but fast-acting marketing investments or through slower but cheaper word-of-mouth processes. Their long-term success depends critically on the contribution of each acquired customer to overall customer equity. The authors propose and test an empirical model that captures these long-term effects. An application to a Web hosting company reveals that marketing induced customers add more short-term value, but word-of-mouth customers add nearly twice as much long-term value to the firm. The authors illustrate their findings with some dynamic simulations of the long-term impact of different resource allocations for acquisition marketing.

Keywords: customer equity, customer acquisition, word of mouth, customer lifetime value, resource allocation

Customers are valuable assets for the firm, but they can be costly to acquire and retain. Customers' differences in the course of their relationship with the firm are reflected in their contributions to the firm value throughout their tenure. To the extent that different acquisition strategies bring different "qualities" of customers, the acquisition effort has an important influence on the long-term profitability of the firm. Indeed, both practitioners and scholars have emphasized that firms should spend not to acquire just any customer but rather the "right" kind of customer (Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001; Hansotia and Wang 1997; Reichheld 1993). Therefore, the customer acquisition process plays an important role in the newly emerging paradigm of customer equity.[1] The acquisition process is particularly important for start-ups and for firms competing in growth markets. For such firms, acquisition spending is the most important expense in the marketing budget. In this scenario, the firm could have an illusion of profitable growth when instead it is actually acquiring unprofitable customers. This occurred for many Internet start-ups that spent aggressively on acquisition in an effort to maximize "eyeballs," with the hope of locking in customer revenue later. However, that revenue never materialized for many companies, either because their value proposition was not compelling enough or because the underlying linkage between acquisition spending and long-term profitability was poorly understood (Reinartz, Thomas, and Kumar 2005).

To grow their businesses, companies acquire customers in various ways, including marketing actions, such as broadcast media and direct mail (i.e., marketing-induced [MKT] customer acquisition), and more spontaneous referrals alike (i.e., word-of-mouth [WOM] customer acquisition). The purpose of this article is to investigate the impact of MKT versus WOM customer acquisition on the growth of customer equity (i.e., the long-term firm value). Because customers acquired through different channels are expected to generate different value (Lewis 2006), we examine the difference of long-term contributions of customers acquired through MKT methods and WOM. In particular, the latter has recently gained more attention from both managers and academics (e.g., Godes and Mayzlin 2004). Similarly, "the connected customer" has emerged as the overarching theme of the Marketing Science Institute's (2006) "2006–2008 Research Priorities".

We believe that whenever possible, acquisition effectiveness should be measured not by "soft" metrics of communication effectiveness (e.g., brand awareness) but rather by "hard" metrics of profitability (Greyser and Root 1999).[2] We operationalize such a hard metric by measuring the effectiveness of acquisition methods with respect to their long-term financial contributions to the firm in the form of customer equity. Each time a customer is acquired, customer equity increases through several effects. First, the customer adds a stream of future cash flows generated through his or her relationship with the firm. Second, the customer may generate WOM (positive or negative) and act as a salesperson for the firm. Thus, it is possible for a firm to assign the profitability of future customers acquired through WOM (i.e., direct network effect). Finally, by contributing to the firm's performance, a new customer may improve the future acquisition process in both channels (i.e., indirect network effect). Thus, we measure not only the expected customer's value in and of itself but also the customer's net contribution to the growth of customer equity. This customer equity contribution is not directly observable and should be captured by a statistical model capable of tackling the complex interactions among the variables of interest. We use the vector autoregression (VAR) modelling methodology to develop such a metric. The VAR method is a system's approach in which each variable is treated as potentially endogenous. If a sufficient number of time-series data are available, VAR parameters

1 For a general discussion of the customer equity concept, we refer to Blattberg, Getz, and Thomas (2001) and Rust, Lemon, and Zeithaml (2004). Although there are various definitions of customer equity, we define it here as the sum of all existing and expected CLVs.

2 By "acquisition effectiveness," we do not mean the success rate of marketing actions in attracting customers but rather these customers' contribution to the firm's value after acquisition. We discuss this conceptual difference in greater detail in the "Research Development" section.

are estimated, and the long-term effect of an unexpected shock in one variable on the other variables in the system may be derived. To date, VAR models have been used in various marketing-mix settings (for a review of this approach, see Dekimpe and Hanssens 2004).

We organize the rest of this article as follows: First, we compare the two major different customer acquisition vehicles (i.e., MKT and WOM acquisition) and investigate the short-term and long-term differences in their impact on customer equity. Second, we propose an econometric timeseries model to estimate the long-term effect of a customer acquisition on the performance of the company. Third, we provide an empirical illustration using data from an Internet start-up. Fourth, we validate our results with cohort-level analysis and customer-base analysis using disaggregated data. Fifth, we examine the managerial implications of the proposed methodology by a numerical simulation. Finally, we present our conclusions and suggest an agenda for further research.

RESEARCH DEVELOPMENT

In its simplest form, MKT acquisition is a fast but expensive method, whereas WOM acquisition is slow but cheap. We first contrast these two acquisition methods and then discuss metrics to gauge their effectiveness.

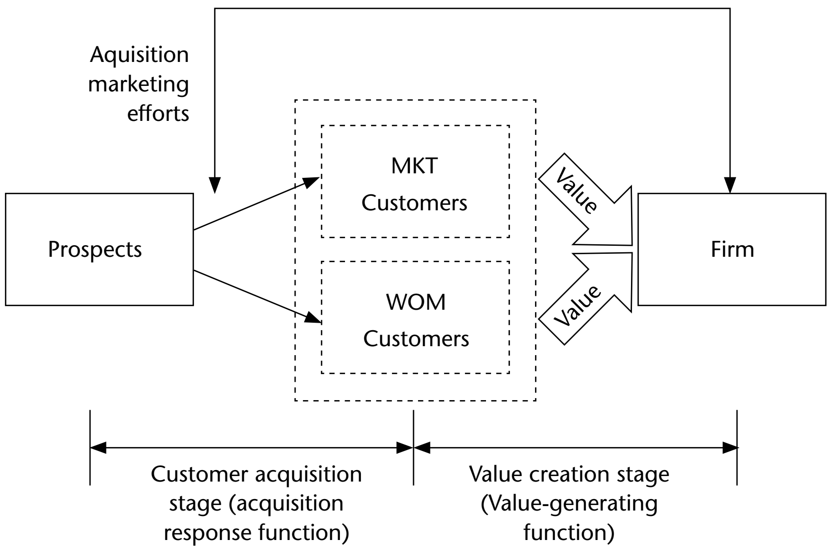
Customer Acquisition Methods

Firms use various types of marketing activities to acquire new customers, including mass media (e.g., television advertising) and more personalized contacts (e.g., e-mails, promotion calls). For many firms, marketing spending on acquiring customers represents an important expense, and it is widely known that the acquisition process has an important effect on future retention probability (Thomas 2001). Researchers have also investigated the effectiveness of different marketing communication channels and have provided models to allocate the acquisition budget for future profitability (e.g., Reinartz, Thomas, and Kumar 2005). Conversely, customers can also be acquired spontaneously from WOM communications, newspaper articles, user reviews, or Internet search results. An increasing number of firms encourage WOM with or without monetary incentives. For example, BMG Music Service not only spends on online ad banners and direct mail but also gives referral incentives (in the form of free CDs) to existing customers to increase the buzz level. Netflix, an online DVD rental firm, encourages referrals without any monetary incentive. Although these types of customer acquisition are less controlled by the firm, they may be more likely to succeed, for various reasons. First, these communications have greater credibility than conventional marketing activities that are designed and implemented by the firm. For example, it has been suggested that WOM communications are more persuasive than conventional advertising (Brown and Reingen 1987; Herr, Kardes, and Kim 1991). Second, contingent persuasion knowledge theory (Friestad and Wright 1994, 1995) suggests that customers realize that the main goal of MKT communications is to influence their beliefs and/or attitudes about the firm and therefore cope with these attempts. Third, because these communications can spread with less support from the firm's marketing resources, the firm can enjoy larger financial gains from customer acquisition.

Measuring Acquisition Effectiveness

In this research, we develop a metric that links customer acquisition to long-term profitability by measuring the impact of a single customer acquisition on the firm's value. Our model investigates the difference between customer cohorts at the acquisition channel level. Previous work has assumed that customers are homogeneous in their

Figure 1: Customer acquisition and value generation



Notes: The effectiveness of marketing efforts on customer acquisition can be measured by an acquisition response function in the customer acquisition stage, but this article focuses on a value-generating function that can measure the impact of new customer acquisition on the subsequent value-generating stage.

expected future value (e.g., Blattberg and Deighton 1996) or longitudinally heterogeneous depending only on the period of acquisition (e.g., Gupta, Lehmann, and Stuart 2004). We investigate how different types of acquisition contribute to the firm's customer equity in both the short run and the long run. Although we focus our analysis on the difference between MKT and WOM customer acquisition, our methodology can be applied to any particular acquisition media. This difference has important implications for optimal resource allocation because firms want to allocate their limited acquisition budget to maximize customer equity and, therefore, shareholder value.

Recent work on customer equity has studied the link between acquisition and profitability. For example, Lewis (2006) finds that promotionally acquired customers have lower repurchase rates and smaller customer lifetime values (CLVs). He offers empirical illustrations of this phenomenon for the customer base of a newspaper and an online grocer. Reinartz, Thomas, and Kumar (2005) develop a model to allocate acquisition and retention resources optimally for long-term profitability. The CLV metric has also been used in a model for customer selection and resource allocation (Venkatesan and Kumar 2004). Venkatesan and Kumar (2004) develop a panel-based stochastic model that predicts purchase frequency and contribution margin at the customer level. In their illustration, when customers are selected for contacts using the proposed model, the company generates 83% more long-term profitability than when it uses its previous allocation method.

Our work fits into this emerging literature that connects acquisition to longterm performance. Specifically, we develop a metric that assesses the impact of a new customer on the growth of total customer equity of the firm. This metric can be interpreted as a customer equity elasticity rather than the lifetime value of a newly acquired customer (as in Venkatesan and Kumar 2004). Indeed, the conventional CLV metric may underestimate the value of a new customer acquisition because it excludes network effects, such as WOM communications generated by a newly acquired customer throughout his or her lifetime. Traditional deterministic models cannot capture these effects either because they are not directly observable. Note that we do not model the firm's marketing actions (e.g., advertising expenditures, price promotions); instead, we focus on measuring how much new customers acquired through different acquisition channels contribute to both present and future firm performance.

We call this function that links newly acquired customers' contributions to the firm's customer equity growth "the value-generating function." In contrast, we call the interactions between marketing spending and the number of acquisitions "the acquisition response function" (see Figure 1). If complete matching records of marketing spending, acquisition, and the customer's contribution to the firm value are available, the two functions may be combined into one extended model. However, the current article focuses on the value-generating process by modeling the interactions between new customer acquisition and the growth of firm value.

METHODOLOGY

Linking Customer Acquisition and Long-Term Performance

The acquisition process and its link to firm performance should be examined as a complex system in which many interactions could take place over time. When computing the marginal contribution of one new customer on customer equity, it is important to measure not only his or her expected value but also all the indirect influences of this acquisition on the firm's performance. This dynamic interaction is particularly important in capturing the impact of WOM acquisition because WOM is both an outcome of prior firm performance and a driver of future performance (Godes and Mayzlin 2004). We propose a VAR model to investigate these interactions, which we characterize as follows:

- *Direct effects of acquisition on the performance of the firm*. We measure the impact of a person being acquired through a given acquisition channel on the firm's future performance.
- *Cross-effects between two types of customer acquisition*. We investigate how the MKT customer acquisition affects future acquisitions generated through WOM, and vice versa.
- *Feedback effects*. The firm's current performance may affect future customer acquisition. For example, a sales increase in one period may increase the number of acquired customers in subsequent periods. This will occur, for example, when the sales increase raises the firm's reputation so that the same marketing budget is now able to acquire more customers.
- *Reinforcement effects*. Both firm performance and customer acquisitions may have a reflexive future effect. For example, an increase in the number of customers acquired through WOM might have an effect on future WOM acquisitions because these customers may generate more referrals than customers acquired through marketing.

By combining these cross-, feedback, and reinforcement effects, the proposed model can capture the network effect of new customer acquisition on customer equity growth. We use the following three-variable VAR system to capture the aforementioned dynamic interrelationships:

$$(1)\ \begin{pmatrix} MKT_t \\ WOM_t \\ VALUE_t \end{pmatrix} = \begin{pmatrix} e_{10} \\ e_{20} \\ e_{30} \end{pmatrix} + \sum_{l=1}^{n} \begin{pmatrix} e_{11}^{\ l} & e_{12}^{\ l} & e_{13}^{\ l} \\ e_{21}^{\ l} & e_{22}^{\ l} & e_{23}^{\ l} \\ e_{31}^{\ l} & e_{32}^{\ l} & e_{33}^{\ l} \end{pmatrix} \begin{pmatrix} MKT_{t-1} \\ WOM_{t-1} \\ VALUE_{t-1} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix},$$

where MKT stands for the number of customers acquired through the firm's marketing actions, WOM stands for the number of customers acquired through word of mouth, and VALUE is the firm's performance. The subscript t stands for time, and p is the lag order of the model. For this VAR model, where $(e_{1t}, e_{2t}, e_{3t})'$ are white-noise disturbances distributed as $N(0,\Sigma)$, the direct effects are captured by a_{31}, a_{32}; the cross-effects are captured by a_{12}, a_{21}; the feedback effects are captured by a_{13}, a_{23}; and the reinforcement effects are captured by a_{11}, a_{22}, a_{33}. We could include additional exogenous variables (e.g., a deterministic trend) and impose restrictions on some of these parameters if there were an a priori reason for doing so. Instantaneous effects are not included directly in this VAR, but they are reflected in the variance–covariance matrix of the residuals (Σ).

Impulse Response Functions and Customer Equity

The dynamic impact of interest is captured by impulse response functions (IRFs) that trace the present and future response of a variable to an unexpected shock in another variable. Although VAR models and IRFs have been introduced to the marketing literature in a marketing-mix context (e.g., Bronnenberg, Mahajan, and Vanhonacker 2000; Dekimpe and Hanssens 1995a; Nijs et al. 2001), we use them to assess how one unexpected customer acquisition affects customer equity over time. To the best of our knowledge, this is the first use of the VAR method to measure the contribution of newly acquired customers to firm value.

EMPIRICAL ILLUSTRATION

Data Description

We study an Internet firm that provided free Web hosting to registered users during a 70-week observation period. At the time of registration, people provided a demographic profile and responded to the question, "How did you hear about our company?" followed by a list of several acquisition channels.[3] Because this particular firm did not allow for multiple responses in this question, we study the predominant channels that bring a customer to the firm. These channels are classified as MKT or as WOM acquisition channels. The MKT acquisition channel includes online ad banner, television, radio, magazine or newspaper advertisement, e-mail links, and direct mail.

The WOM acquisition channel includes links from other Web sites, magazine or newspaper articles, referrals from friends or colleagues, referrals from professional organizations or associations, and referrals from search engines.[4] We discarded a small number of registrants who indicated "other" as their acquisition channel from this analysis. Other demographic variables were also collected at the time of registration, such as a business type (e.g., retailers), country of origin, and number of employees. After people registered, their unique behavior was tracked as they logged in to use the firm's services (e.g., changing the content or appearance of the Web site, checking on the number of site

[3] A limitation of these data is that they were self-reported, and as such, the order in which the list appeared or the ease with which they come to mind could have an effect on customer responses.

[4] The classification between MKT and WOM customer acquisition channels may be different across firms and industries. For example, we do not argue that search engines should always be categorized as a WOM channel. They may be categorized as a MKT channel depending on a firm's marketing activities. Because the data-providing company did not spend any money on search engines, we categorized search engines as a WOM channel.

Table 1: Descriptive statistics

Series	M	Maximum	Minimum	SD
MKT acquisition	625	1268	72	272.6
WOM acquisition	1526	2758	170	608.7
Number of log-ins (Value)	8895	15.842	1183	3997.4
Percentage of U.S customers (RC)	.78	.85	.68	.04
Percentage of retailers (RB)	.20	.26	.15	.03
Percentage of firms wih more than four employees (RE)	.92	.94	.86	.01

visits). From these records, we calculate the weekly number of log-ins and the number of registrations per acquisition channel.[5] Table 1 shows some descriptive statistics, and Figure 2 presents the time series of these variables.

Specifying and Testing the Value-Generating Function

We use the number of log-ins as a proxy for the firm's performance (i.e., VALUE) in Equation 1, given the characteristics of this business. Most free-service Internet companies generate advertising revenue through log-ins or clickthroughs. Therefore, high log-in intensity provides the firm with more revenue. Furthermore, we expect that the intensity of log-in behavior is highly correlated with customers' perceived value of the service and, therefore, their willingness to subscribe to the fee-based service. Indeed, regular users are already familiar with the site and thus perceive higher switching costs that lead to consumer lock-in (Zauberman 2003).

In addition, high log-in intensity may cause customers to be committed and even emotionally attached to the site, which leads to higher willingness to pay (Thomson, MacInnis, and Park 2005). We test the validity of our log-in proxy by studying the relationship between customer usage levels of a free service and the willingness to pay when the service becomes fee based. During the observation period, customers were not charged for the Web-hosting service and did not know that the firm intended to change that policy. Two weeks after the end of our observation period, the firm announced by email that in two months, users would either agree to pay subscription fees for different service levels or face the termination of their accounts. We obtained data on the customers who declined the fee for service and the ones who paid fees for at least one year after the regime switch. We test the hypothesis that free-usage levels are an indication of inherent customer utility for the service and, therefore, that they predict subsequent willingness to pay.

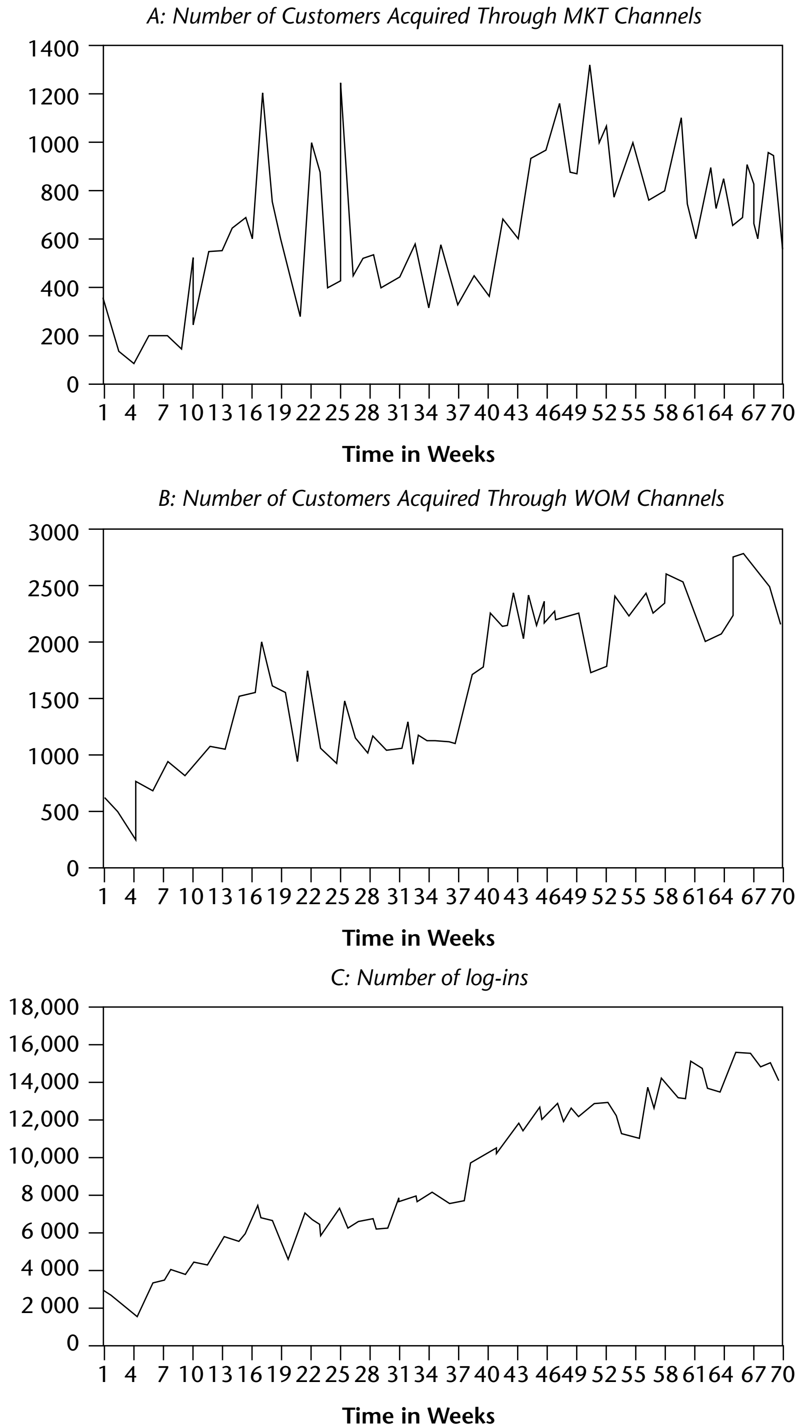
A binary logit model supports our hypothesis of a significant, positive effect of a customer's log-in activity on his or her subsequent willingness to pay (see Table 2). As a result, customers with a higher level of log-in activity are expected to have higher conversion rates to a fee-based service. [6]

On the basis of the preceding analysis, we construct three endogenous variables in the VAR system:

5 We count only the unique log-ins a customer makes in a certain week.

6 We also test the relative predictive strength of customer usage levels by estimating a logit model with and without the demographic covariates. The model with demographic covariates correctly classifies 90.8% of defectors and 86.5% of paying customers. The model without demographics correctly classifies 90.5% of defectors and 84.5% of paying customers. In addition, a model with only demographic variables as covariates correctly classifies 75.9% of the defectors but only 59.0% of the future buyers. Thus, log-in activity, not customer demographics, is the leading indicator of subsequent willingness to pay.

Figure 2: Time series of customer acquisition and number of log-ins



- MKTt: the number of new registrations at time t resulting from marketing activities;
- WOMt: the number of new registrations at time t from word of mouth; and
- VALUEt: the total number of binary log-ins at time t.

We also include other covariates in the model to control for the potential effect of a different profile of customers on the relationship between log-in activity and customer acquisition:

- RCt: the percentage of U.S.-based customers among the new registrants at time t;
- RBt: the percentage of retailers among the new registrants at time t; and
- RE_t: the percentage of firms with more than four employees among the new registrants at time t.

VAR Estimation

The VAR estimation begins with a unit root test to determine whether the series is evolving or stationary (for a detailed explanation, see Dekimpe and Hanssens 1995b). We use the augmented Dickey–Fuller (ADF) unit root test with the null hypothesis of unit root. We apply the iterative procedure that Enders (2004, pp. 181–83) proposes to decide whether to include a deterministic trend in the test. Because it has been argued that conventional unit root tests (e.g., ADF) tend to underreject the null of unit root, we validate our results with the KPSS test (Kwiatkowski et al. 1992), which uses the null of stationarity. The ADF test statistics have values from –4.07 to –4.89, all of which are above the 5% critical value. The KPSS statistics vary from .08 to .11, all of which are below the critical value. Thus, we

Table 2: Factors influencing customer conversion

	Total population (N = 93,119)		*Choice-Based Sample (N = 2130)*	
	Estimate	*(SE)*	*Estimate*	*(SE)*
Intercept	-9.713	(579)**	-5.120	(.730)**
Intercept (revised)			-9.547	
Number of log-ins	.281	(.006)**	3.24	(.013)**
Time trend	–.013	(.002)**	-.020	(.005)**
Retailer	.763	(.069)**	.807	(.152)**
U.S. based	3.440	(.565)**	3.207	(.690)**
Number of employees	-.107	(.051)*	-.179	(.089)*
-2 log-likelihood	7194		1287	

*Significant at the 5% level.

**Significant at the 1% level.

Notes: Dependent variable: 1 if a customer agrees to pay for the service and 0 if otherwise. Independent variables: number of log-ins (total binary log-ins during the first 20 weeks of a relationship), time trend (week in which the customer registered), retailer (1 if retailer and 0 if otherwise), U.S. based (1 if U.S.-based customer and 0 if otherwise), and number of employees. Because the total conversion rate is low (1.1%, we estimate the model with a full sample of customers and with a choice-based sampling method that balances the number of paying customers and defectors. Because the latter technique does not yield consistent maximum-likelihood estimates of the intercept, following Manski and Lerman (1977), we adjust the estimated intercepts for each alternative. (For further information, see the Web Appendix at http://www.marketingpower.com/jmrfeb08.)

Table 3: Unit root test results

Series	ADF (H_o: Unit root)			KPSS (H_o: Stationary)		
	Test statistic	5% Critical Value	Unit Root	Test statistic	5% Critical Value	Unit Root
MKT acquisition	-4.89	-3.48	No	.11	.15	No
WOM acquisition	-4.07	-3.48	No	.08	.15	No
Number of Log-ins (Value)	-4.34	-3.48	No	.09	.15	No

can reject the null hypothesis of a unit root using the ADF test, but we cannot reject the null hypothesis of stationarity using the KPSS test (see Table 3). Because all variables are found to be stationary, we proceed to estimate the VAR in level form, adding five exogenous variables: a deterministic trend t, a dummy variable d, RC, RB, and RE. The deterministic trend variable captures the natural growth observed in the Internet market. We include the dummy variable to control for outliers.[7] Finally, the variables that add demographic information enable us to control for the potential effects of different profiles of customers on the results. We also estimated a model without demographics, but both the log-likelihood and the Akaike information criterion were smaller under the model with demographics, so we conclude that the model with demographics has a better fit.

We find the optimal lag length to be one, using Schwartz' criterion. We also test the possibility of different lags across variables by parameter restrictions and seemingly unrelated regression estimators. However, a log-likelihood ratio test confirms that the restrictions do not improve the model performance at the 5% significance level. Therefore, we assume that all endogenous variables in the VAR model have the same lag lengths. In addition, we test for residual autocorrelation with the Portmanteau test (Lütkepohl 1993) and find that the null hypothesis of white noise cannot be rejected. The estimation results appear in Table 4, and the IRFs for two focal effects (i.e., direct effects and WOM effects) appear in Figure 3. Note that we use orthogonalized IRFs, given a contemporaneous ordering of the variables, such that MKT acquisitions affect WOM acquisitions, which together then affect log-in activity.

Value Creation: Direct Effects

The IRFs measure the total effect of an unexpected acquisition on the firm's performance, defined as the total number of log-ins over time. The effect includes not only a new customer's own log-in activity but also the log-in activity of others (e.g., by encouraging friends to use different service features). The IRFs show that customers acquired through marketing contribute more to the firm's performance in the short run than customers acquired through WOM; namely, the former generates approximately 3.35 log-ins during the first week, and the latter generates only 2.82 log-ins. Note that the short-term effect of MKT on VALUE includes the indirect effect through WOM. Given our causal ordering in calculating instantaneous responses for the IRFs, MKT can contemporaneously affect WOM, but not vice versa.

Therefore, the 3.35 log-ins due to MKT customer acquisition during the first week originate as follows: 1 log-in from the acquired customer, 1.06 log-ins from buzz generation during the first week (buzz effects), and 1.29 incremental log-ins from the existing pool of customers. However, this short-term effect does not directly translate into long-term behavior. We

[7] According to company representatives, these outliers occurred in a few weeks in which the firm experienced server problems.

Table 4: VAR model estimation results

	Equation 1: MKT Aquisition		Equation 2 WOM Aquisition		Equation 3 Number of Log-ins	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Lagged MKT aquisition	.32	(.17)*	-.4	(.22)*	-1.31	(.74)*
Lagged WOM aquisition	.03	(.21)	-.9	(.28)***	1.71	(.94)*
Lagged number of log-ins	-.01	(.06)	-.05	(.08)	-.24	(.26)
Intercept	1696.42	(1828.90)	2386.34	(2404.08)	11.497.56	(8072.60)
Determin-istic trend	4.31	(7.29)	12.83	(9.58)	109.12	(32.17)***
Percentage of U.S. customers	3952.88	(1166.39)***	(3838.93)**	(15,33.22)**	15,256.15	(5148.36)***
Percentage of retailers	-5065.28	(1541.51)***	-5721.79	(2026.31)***	-14,015.99	(6804.11)**
Percentage of large firms	-3823.34	(2340.96)	-4305.66	(3075.87)	-.22,329.33	(10,328.40)**
R^2	.55		.84		.96	
F-statistic	9.14		40.75		177.45	
Log-likelihood: -1,431.72, Akaike information criterion: 41.68, Schwartz critesion: 42.55						

*Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

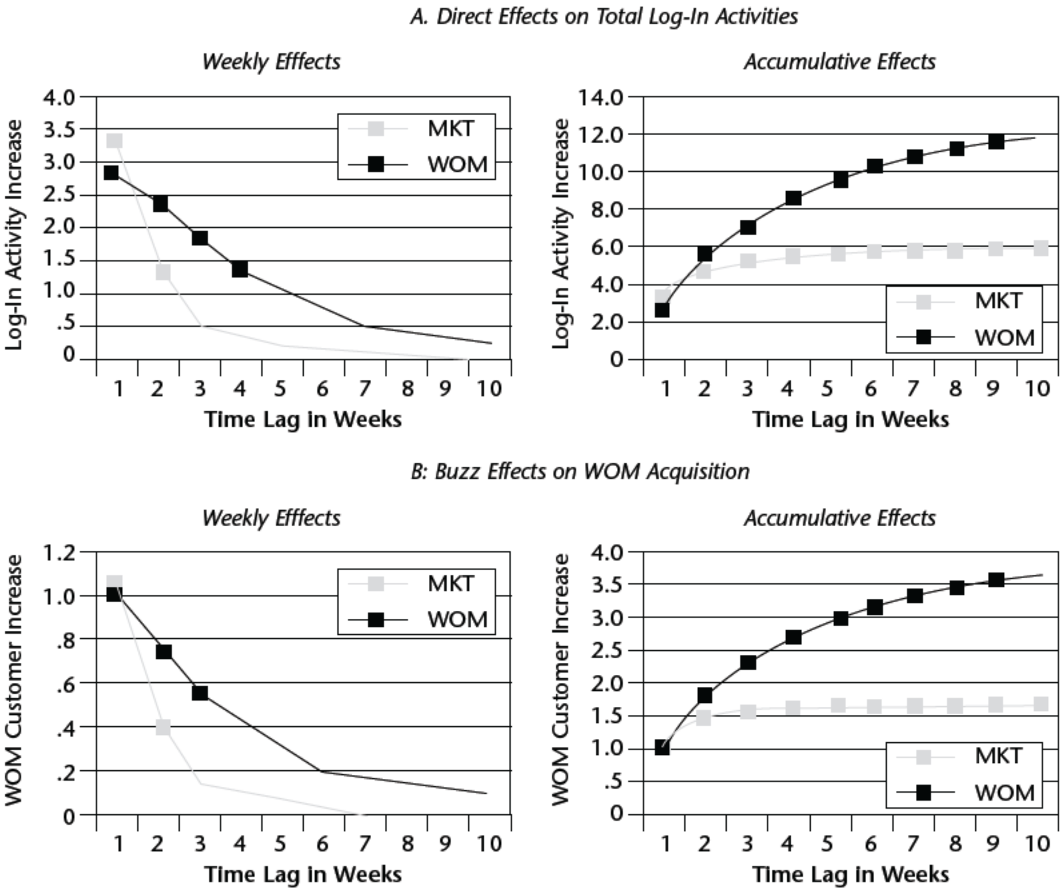
calculate the accumulated IRFs and find that the cumulative impact (after ten weeks) of WOM channels (11.80) is about twice that of MKT channels (5.89).[8] Moreover, the effect of the MKT acquisition settles down after only three weeks, whereas the effect from WOM channels lasts for approximately six weeks. These dynamics are important in a customer acquisition strategy because they show how a manager who focuses only on short-term customer counts per channel will allocate efforts suboptimally. Customers acquired through MKT channels focus more on "trials" (i.e., short-term effects), whereas customers acquired through WOM tend to provide the firm with more "repeats" (i.e., long-term effects).

Buzz Creation: WOM Effects

Next, we investigate the cross-effects between MKT acquisition and WOM acquisition. Figure 3, Panel B, shows that customers acquired through WOM generate more future WOM than those acquired through MKT channels. For example, each customer acquired through marketing is expected to bring approximately 1.77 new customers throughout his or her lifetime, whereas a customer acquired through WOM is expected to bring 3.64 customers. However, there is no significant difference between the two channels in terms of short-term buzz generation. The difference between the short-term and the long-term results is partly attributable to the different lifetime duration of these two customer

8 We tested for the differences in the cumulative IRF using Monte Carlo simulations following the procedure in the work of Lütkepohl (1993, p. 495) (see also Table 5).

Figure 3: Direct effects and buzz effects



Notes: The graphs in Panel A show the effect of one customer increase from each channel on the total log-in activity of the firm over ten weeks. The graphs in Panel B show the effect of one customer increase from each channel on the total number of customers acquired through WOM over ten weeks. Square markers indicate statistically significant values at the 5% level.

cohorts.[9] Which factor is more important in explaining the future dynamics of WOM acquisition? We measure how much of the forecast error variance in future WOM acquisition can be attributed to a change in current MKT acquisition, WOM acquisition, and firm value by decomposing the forecast error variance of WOM. Forecast error variance decomposition analysis is a tool to investigate the relative importance of each endogenous variable in a VAR system in explaining the long-term movements of a focal variable. For example, if a shock in variable X cannot explain any of the forecast error variance of variable Y, then Y is exogenous in the system (Enders 2004).

As Figure 4 shows, shocks in MKT customer acquisition explain approximately 60% of the changes in WOM acquisition in the short run (i.e., in one or two weeks). However, in the long run, WOM becomes more important in explaining future

9 We investigate this issue by calculating each customer's probability of being active and counting those active customers in two customer cohorts. Please refer to the "Customer-Base Analysis" subsection.

WOM generation (its impact stabilizes at approximately 50%). In contrast, VALUE explains only 1.3% of the variance in the long run. Overall, this analysis confirms that future WOM customer acquisitions are better predicted from current WOM acquisitions than from current MKT acquisitions.

Other Effects

In addition, we find significant reinforcement effects for both acquisition channels. For example, MKT channels have a cumulated reinforcement effect of 1.44; that is, each new customer acquired through marketing generates 1.44 customers in the long run. However, we find no evidence of feedback effects; that is, the response of future acquisitions to a shock in log-ins is not significant. Therefore, merely observing more intense log-in activity among existing customers does not increase future acquisition levels.

MODEL VALIDATION

We validate the main results of the proposed model in two ways. First, we check whether our main findings hold within distinctive customer cohorts to verify that our findings are not due to unobserved heterogeneity. Second, we investigate the dropout rates of two customer groups (i.e., MKT customers and WOM customers) by individual-level log-in data to examine possible aggregation bias.

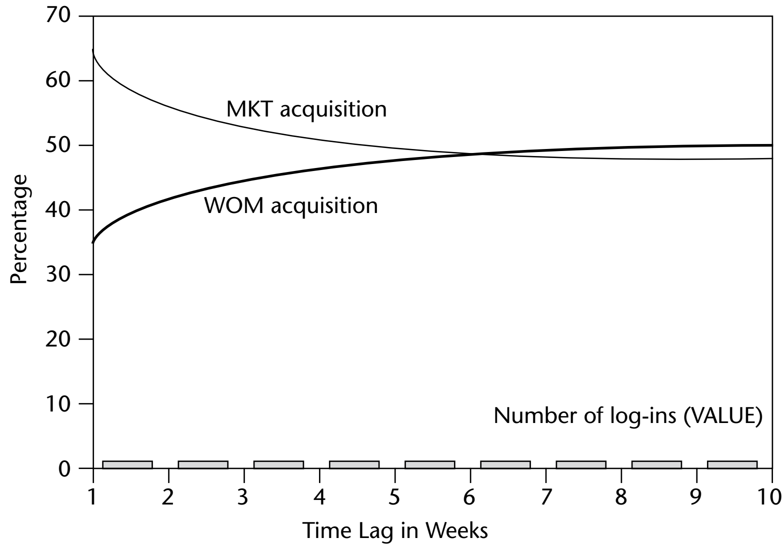
Segment-Level Analysis

We estimate six segment-level VAR models to obtain direct and buzz effects within customer cohorts: large firms (with more than four employees) versus small firms, retailers versus nonretailers, and U.S.-based firms versus non-U.S.-based firms. In each segment-level VAR model, we measure three endogenous variables (i.e., MKT, WOM, and VALUE) within a customer cohort so that the resultant IRFs show the relationship between customer acquisition and firm value for each demographic pool. As Table 5 shows, our main results (i.e., direct effects and buzz effects) hold in the segment-level analysis. Consistent with the results from the main VAR model, customers acquired through WOM create higher firm value in the long run for all but one cohort. The exception is non- U.S.-based firms, which show a nonsignificant difference in the long-term value creation between MKT customers and WOM customers. Because these non-U.S.-based firms are geographically spread out around the world, they are less likely to be close to a WOM generator who could influence their log-in behavior. Regarding buzz effects (i.e., generating future WOM), all but one demographic pool show a pattern consistent with the IRF result from aggregate VAR models. Word-of-mouth customers create more future WOM in the long run within each customer cohort. Again, only non-U.S.-based firms show a nonsignificant difference. Note that we test the statistical significance of these differences by Monte Carlo simulations with 250 replications. In summary, a segmentbased analysis confirms the result that the two customer acquisition channels (i.e., MKT and WOM) bring in different customers in terms of their contribution to firm value and the creation of WOM communications.

Customer-Base Analysis

As a second validation test, we construct individual-level log-in data for the two customer groups–those acquired through MKT channels and those acquired through WOM. Following Fader, Hardie, and Lee (2005), we estimate each customer's probability of being "active" at each point in time on the basis of his or her log-in history, such as (1) the number of past log-ins, (2) the time of the most recent login, and (3) the length of observation period. We provide the details of this analysis in the Appendix.

Figure 4: WOM forecast error variance decomposition



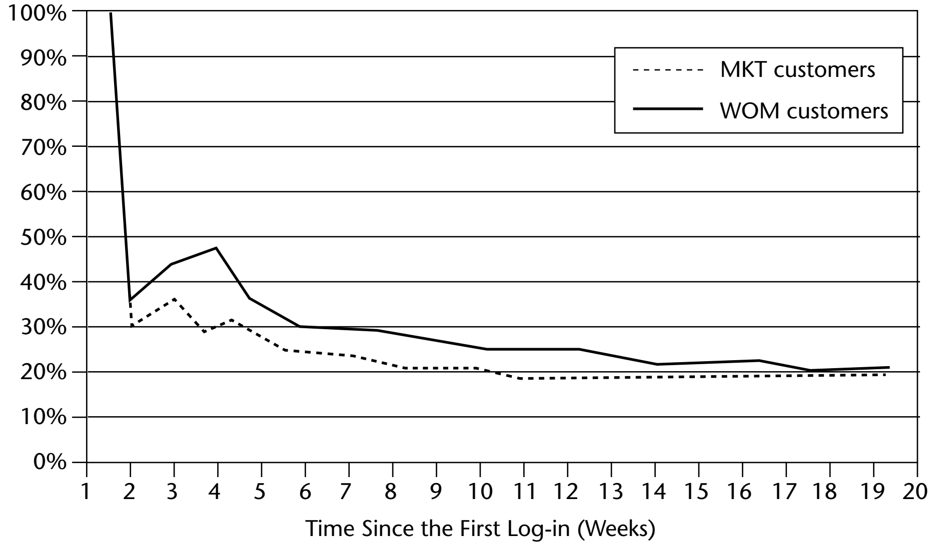
Notes: The graph shows how much of forecast error variance WOM acquisition can be attributed to changes in three endogenous variables (i.e., MKT, WOM, and VALUE). For example, approximately 65% of the one-period-ahead forecast error variance of WOM acquisition is explained by MKT acquisition. This proportion gradually decreases to approximately 48% in the long run, whereas the proportion explained by WOM grows to approximately 50%

Table 5: Segment-levels analysis

		A. Accumulated Direct Effects		
	MKT Acquisition	*WOM Acquisition*	*Difference (WOM – MKT)*	*(t-Statistic)*
Main model	5.89	11.80	5.91	(10.62)
Large firms	7.53	7.85	.32	(3.79)
Small firms	6.96	9.51	2.55	(6.57)
Retailers	11.23	11.93	.70	(2.49)
Nonretailers	6.36	9.32	2.95	(12.32)
U.S. firms	7.53	10.77	3.24	(8.63)
Non-U.S. firms	5.97	5.70	-.27	-(1.38)
		B. Accumulated Buzz Effects		
	MKT Acquisition	*WOM Acquisition*	*Difference (WOM – MKT)*	*(t-Statistic)*
Main model	1.77	3.64	1.87	(10.27)
Large firms	2.87	3.19	.32	(5.19)
Small firms	1.89	3.02	1.13	(9.93)
Retailers	2.27	2.76	.49	(5.04)
Nonretailers	2.11	3.43	1.32	(14.17)
U.S. firms	2.08	3.15	1.07	(9.78)
Non-U.S. firms	2.44	2.54	.10	(.94)

Notes: All numbers are accumulated IRFs over ten weeks after a corresponding shock. We test the statistical significance of the differences by t-statistics obtained from a Monte Carlo simulation with 250 replications. The magnitudes of accumulated IRFs in the main model and those in the segment-level model are not directly comparable, because the latter does not allow between-segment customer interactions such as referrals. The main objective of this segment-level analysis is to confirm whether the difference of value/buzz creation between MKT and WOM customers holds in each customer cohort.

Figure 5: Customer dropout rates



Having obtained the probability of being active for each customer, we calculate customer dropout rates for the two customer groups.[10] As Figure 5 shows and consistent with our main findings, WOM customers stay longer with the company and thus are expected to make a greater long-term contribution to the firm's value. For example, whereas fewer than 30% of MKT customers are active by the fourth week after registration, more than 50% of WOM customers are still active at the same time point. This analysis shows that the main findings from an aggregate VAR model are not due to unobserved heterogeneity or aggregation bias.

ECONOMIC IMPACT SIMULATION

In this section, we demonstrate a numerical simulation to highlight the economic impact of MKT versus WOM acquisition methods. Under some assumptions based on the sample observations and model findings, we compare the financial impact of acquiring 1 000 new customers through the two channels. First, as a basis for the simulation, we calculate the number of active customers, the number of weekly log-ins, and a present value of expected revenue over ten weeks. We assume that each log-in made by active customers is worth $2 for the company.[11] We obtain the baseline values of the number of customers and weekly log-ins from sample averages in the observation period and customer dropout rates calculated in the customer base analysis. We calculate the present value of revenues using a weekly time discount factor of .2%. Second, we calculate the expected increase in the number of customers, log-ins, and revenues over the same ten weeks attributed to the incremental acquisition of 1 000 new customers either through MKT methods (Case 1 in Table 6) or through WOM (Case 2 in Table 6).

We obtain the increase using the IRFs from the main VAR model. Because the

[10] We use a threshold value of .5 to determine an active customer (see Reinartz and Kumar 2000).

[11] This value may be different across firms and industries. In our case, we obtain it by comparing customer subscription fees charged after the observation period with average log-in activity during the observation period.

Table 6: Economic impact simulations

A. Case 0: Status Quo												
Time (Week)	Base-line	1	2	3	4	5	6	7	8	9	10	Total
Number of active customers	20,000	22,000	22,696	23,523	24,350	25,056	25,657	26,219	26,769	27,305	27,796	25,137
Number of weekly log-ins	9 000	9 900	10,213	10,585	10,957	11,275	11,546	11,799	12,046	12,287	12,508	113,117
Revenue (present value in dollars, weekly)	18,000	19,800	20,385	21,086	21,784	22,371	22,862	23,316	23,758	24,185	24,570	224,117
B, Case 1: Acquiring 1 000 More Customers Through MKT Methods												
Time (Week)	Base-line	1	2	3	4	5	6	7	8	9	10	Total
Number of active customers	20,000	24,056	24,075	24,822	25,585	26,207	26,678	27,146	27,653	28,162	28,597	26,298
Increase		2 056	1 379	1 300	1 236	1 151	1 021	927	884	857	801	1 161
Number of weekly log-ins	9 000	13,248	11,518	11,147	11,232	11,427	11,639	11,860	12,089	12,317	12,530	119,007
Increase		3 348	1 305	562	274	152	94	62	43	30	21	5 890
Revenue (present value in dollars, weekly)	18,000	26,495	22,989	22,206	22,327	22,673	23,047	23,438	23,842	24,244	24,613	235,875
Increase		6 695	2 604	1 120	546	302	185	122	84	59	42	11,759
C, Case 2: Acquiring 1 000 More Customers Through WOM												
Time (Week)	Base-line	1	2	3	4	5	6	7	8	9	10	Total
Number of active customers	20,000	23,000	23,811	24,781	25,742	26,448	26,992	27,496	27,998	28,487	28,923	26,368
Increase		1 000	1 116	1 258	1 392	1 392	1 334	1 277	1 228	1 183	1 127	1 231
Number of weekly log-ins	9 000	12,716	12,604	12,459	12,372	12,324	12,316	12,361	12,455	12,584	12,724	124,914
Increase		2 816	2 391	1 874	1 415	1 049	770	562	409	297	216	11,798
Revenue (present value in dollars, weekly)	18,000	25,431	25,158	24,818	24,597	24,452	24,387	24,427	24,545	204,770	24,994	247,597
Increase		5 631	4 772	3 732	2 813	2 081	1 524	1 111	807	585	424	23,481

Notes: The simulation is based on the results from an IRF analysis and a customer-base analysis described in the main text. We assume that each log-in creates $2 of revenue, derived from average customer revenue and log-in levels. We also derive baseline values from sample averages of the observation period. A weekly time discount factor of .2% is used to calculate the present value of revenue.

IRFs in Figure 3 show the impact of one customer acquisition, we multiply these IRFs by 1 000 to obtain the effect of 1 000 new customer acquisitions. The simulation results appear in Table 6. The simulation shows the financial contributions of the two customer acquisition channels both in the short run and in the long run. For example, this firm can increase its short-term revenue more through MKT customer acquisition ($6,695) than through WOM customer acquisition ($5,631). However in the long run (i.e., more than ten weeks), the latter has a greater financial impact ($23,481 of present value) than the former ($11,759 of present value). The primary reason for this difference is that customers acquired through WOM tend to stay longer as active customers and thus generate more value over time. The increases in the number of active customers between Cases 1 and 2 are not significantly different (1161 versus 1231, respectively). Because we compare the financial impact before incorporating acquisition marketing costs, the difference becomes even more pronounced when we consider such costs. For example, if the firm needs to spend $10 per new customer acquisition through MKT channels, the net value of one MKT customer is \$1.76, whereas that of one WOM customer (assuming that there is no cost associated with WOM acquisition) is \$23.48. Therefore, managers can use such simulation results to determine an appropriate level of customer acquisition spending. As an illustration, if the firm wants to use financial incentives to boost WOM acquisitions, incentives of up to \$23 per acquired customer would be justified.

CONCLUDING REMARKS

In this article, we developed a statistical model capable of measuring the long-term impact of customer acquisitions through different channels on customer equity growth. The VAR model enables us to measure the financial impact of an additional customer on the firm's performance. Thus, we do not explicitly measure the marketing effort (i.e., acquisition spending) but rather how the result of that effort (i.e., an acquired customer) increases the customer equity of the firm. We constructed a metric from the IRF analysis to measure the intrinsic value of the "typical" customer coming from a specific acquisition channel. This metric captures not only the dynamic effects of a customer in his or her tenure but also the customer's influence on other customers (e.g., generating future WOM). As such, our metric captures the impact of an additional customer on the customer equity of the firm. We expect that as the quality of customer databases continues to increase, our approach will permit a more careful assessment of the long-term value of adifferent groups of customers. The finding that CLV depends on a customer's acquisition mode has important implications for marketing management, especially for new ventures. If financial needs dictate that new customers need to be acquired quickly, higher initial marketing budgets will be needed. At the same time, higher retention budgets will be required later on because the firm will need to spend more on these MKT customers to preserve their long-term value to the firm. Conversely, firms that can afford to build a customer base organically (i.e., through WOM) face a better long-term profitability outlook and can spend less on customer retention. All else being equal, their shareholder value should be higher. The limitations of our work offer areas for future exploration. First, our data on acquisition channels were selfreported. In general, this limitation is difficult to overcome in any study that incorporates WOM, though advances in tracking Internet communications may improve the quality of the data (e.g., Chevalier and Mayzlin 2006). Second, our model does not incorporate marketing spending, so we investigate only the value creation stage of the customer acquisition process. To make more accurate optimal resource allocation inferences, acquisition response functions with marketing spending data should be added to the model. Third, we use the number of log-ins as a proxy for the firm's profit. Although we demonstrated the face validity of this proxy variable in our setting, direct profitability data, if it were available, would improve model inference. Fourth, because our data set only contains the predominant channel that drove a customer to the firm, we cannot account for interactions among different acquisition channels. It would be worthwhile to investigate the possible synergies among different customer acquisition channels. Fifth, additional research is needed to understand the dynamics of WOM generation. For example, researchers can investigate how "fertilized" referrals may attract different customer cohorts compared with spontaneous WOM communications. Sixth, our results could change with different time windows. For example, the difference between MKT and WOM acquisition could be greater for a start-up than for the same firm after reaching maturity. Given that we had only 70 weeks of data, we could not estimate the metric in different time windows. Finally, because our results are based on a single product category, it is necessary to investigate additional industries to find empirically generalizable differences between the two customer acquisition channels.

APPENDIX: CUSTOMER-BASE ANALYSIS

To investigate dropout rates for two customers cohorts (i.e., customers acquired through MKT methods versus WOM), we calculate the number of "active" customers at each point in time using individual-level log-in data in the observation period. Following Fader, Hardie, and Lee (2005), we assume the following for a customer's log-in behavior:

- The number of log-ins made by an "active" customer follows a Poisson process with occurrence rate λ.
- Customers are heterogeneous in λ, following a gamma distribution with parameters γ and α.
- A customer may become inactive after any log-in with probability p.
- Customers are heterogeneous in p, following a beta distribution with parameters a and b.
- λ and p are independently distributed across customers.

These assumptions yield a beta-geometric negative binomial distribution model. After estimating four parameters (γ, α, a, and b), we can calculate a customer's probability of being active at each time given his or her log-in history, such as (1) the number of past log-ins (x), (2) the time of the most recent log-in (t_x), and (3) the length of observation period (T), such that

$$E[\Pr(\text{active at } T|X = x, t_x . T, \gamma, \alpha, a, b)]$$

$$= \frac{1}{1 + I\{x > 0\} \times \left(\frac{a}{x + b - 1} \times \frac{\alpha + T}{\alpha + t_x}\right)^{x + \gamma'}}$$

where $I\{x > 0\}$ is 1 if $x > 0$ and 0 if otherwise. We conduct the analysis through the following steps:

Step 1. Data Construction

We construct two separate data sets for MKT customers and WOM customers from the original data set. We select customers who have longer than 20 weeks of log-in history, which results in 3 020 customers for MKT acquisition and 6 691 customers for WOM acquisition. For each individual, we measure x, t_x, and T.

Step 2. Parameter Estimation

We estimate four model parameters using Excel Solver. The detailed estimation procedure can be found in the work of Fader, Hardie, and Lee (2005). As a result, we obtain four parameters for each customer group, as follows:

	WOM	*MKT*
γ	2.978	2.746
α	6.036	5.736
a	.630	.698
b	.983	.873

Step 3. Calculating Pr(active)

Using the preceding parameters, we calculate Pr(active) for each customer at each time. These probabilities vary over time depending on a customer's log-in activities. For example, if a customer does not log in for a while, his or her Pr(active) continues to decrease. When this customer logs in again, the probability goes up.

Step 4. Calculating the Number of Active Customers

Using a cut-off value of .5, as Reinartz and Kumar (2000) recommend, we can classify a customer as "active" or "inactive" at each point in time. Then, we can calculate the number of active customers for each customer group.

Step 5. Calculating Customer Dropout Rates

Having obtained the number of active customers, we can calculate customer dropout rates for each customer group.

Because the result in Step 4 does not provide us with each customer's dropout rate, we separately calculate the number of customers for each cohort who are acquired at the same time. In other words, we calculate the number of customers in each customer's first week, second week, and so on. The results appear in Figure 5.

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