The Impact of Marketing-Induced vs. Word-of-Mouth Customer Acquisition on Customer Equity

by

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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 that each acquired customer makes to overall customer equity. We 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. We illustrate our findings with some dynamic simulations of the long-term impact of different resource allocations for acquisition marketing.

INTRODUCTION

Customers are valuable assets for the firm, but they can be costly to acquire and to retain. Customers' differences in the course of their relationship with the firm are reflected in their price sensitivity, lifetime duration, purchase volume, and even word-of-mouth generation. This causes differences in customers' lifetime value (CLV, hereafter), defined as the discounted stream of cash flows generated over the lifetime of a customer. To the extent that different acquisition strategies will bring different "qualities" of customers, the acquisition effort will have an important influence on the long-term profitability of the firm. Indeed, both practitioners and scholars have emphasized that firms should not spend to acquire just any customer, but 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 (CE).[1]

Optimizing the acquisition budget for long-term profitability is particularly relevant for start-ups and for firms competing in growth markets, where acquisition spending is the most important expense in the marketing budget. In these scenarios, the firm could have an illusion of profitable growth, when in fact it is 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

[1] For a general discussion of the CE concept we refer to Blattberg, Getz and Thomas (2001) and Rust, Zeithaml and Lemon (2000). Though there exist various definitions of CE, it is defined in this paper as the sum of all existing and expected customers' CLVs.

linkage between acquisition spending and long-term profitability was poorly understood (Reinartz, Thomas, and Kumar 2005).

In order to grow their businesses, companies acquire customers in various ways, including marketing actions such as broadcast media, public relations and direct mail (i.e., marketing-induced customer acquisition), and word-of-mouth (i.e., spontaneous customer acquisition). The cost and effectiveness of these acquisition routes may be expected to vary widely, so the purpose of our paper is to investigate the impact of such marketing-induced vs. word-of-mouth customer acquisition on CE. We do so with specific reference to long-term effects, using metrics that are financially related.

The importance of measuring the long-term effects of marketing has been emphasized by managers and academics alike (e.g., MSI 2004-2006 Research Priorities). Managers are often criticized as myopic in their spending decisions because they tend to maximize the short term and neglect the long-term profitability of the firm. The reason for this myopia may lie in that many times managers' incentives are linked to short-term metrics such as market-share, or in that some managers lack the necessary tools to measure the long-run effects of their decisions. Indeed, the difficulty of measuring the future consequences of current decisions increases the uncertainty of future payoffs, especially in turbulent markets that are difficult to forecast. By contrast, short-run metrics such as current market share have a strong credibility at all levels of management and are easy to justify (Keil, Reibstein, and Wittink 2001). Nonetheless, neglecting the long-term effects of current actions can lead to suboptimal spending decisions, resulting in inferior long-run profitability and shareholder value creation (Doyle 2000; Venkatesan and Kumar 2004). For example, some banner ads that appear ineffective in the short-run

(when measured by click-throughs) may generate higher consumer awareness and become effective in the long run by sifting attitudes towards a brand that result in future purchases (Briggs and Hollis 1997; Drèze and Zufryden 1998). Similarly, word-of-mouth effects may take some time to materialize as early customers gain experience with and appreciation for the product or service provider. Therefore, acquisition effectiveness should be measured with models that can quantify short-run as well as long-run effects.

Furthermore, we sustain that, whenever possible, acquisition effectiveness should be measured not by "soft" metrics of communication effectiveness (e.g., brand awareness) but by "hard" metrics of profitability (Greyser and Root 1999). We operationalize such "hard" metric by measuring the effectiveness of acquisition methods with respect to their long-term financial contribution to the firm in the form of customer equity. Each time a customer is acquired, customer equity increases through several effects. First, this customer adds a stream of future cash-flows generated through her relationship with the firm, which could be captured by the CLV metric. Second, this customer may generate word-of-mouth (positive or negative) and act as a salesperson to the firm. Hence, we could think of assigning to the profitability of a new customer, the expected CLV of future customers acquired by virtue of word-of-mouth. Finally, by improving current firm's performance, a new customer may start a future performance reinforcement effect. Hence, our model does not measure the expected CLV of a customer, but rather her *contribution* to customer equity (CE). This CE 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 apply the VAR modeling methodology to develop such a metric.

The paper is organized as follows. First, we compare the two major different customer acquisition vehicles (i.e., marketing induced vs. word-of-mouth acquisition) and investigate the short-run and long-run differences in their impact on CE. Second, we propose an econometric time-series model to estimate the long-run 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 discuss managerial implications of the proposed methodology by scenario analysis. Lastly, we present our conclusions and an agenda for future research.

RESEARCH DEVELOPMENT

In its simplest form, marketing is a fast but expensive acquisition method, whereas word-of-mouth 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, which includes mass media (e.g., TV advertising) and more personalized contacts (e.g., emails or promotion calls). Marketing spending on acquiring customers represents for many firms one of is most important expenses, and it is widely known that the acquisition process has an important effect on the customer base 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).

On the other hand, customers can be also acquired spontaneously from word-of-mouth communications, newspaper articles, user reviews, or internet search results. An

increasing number of firms use word-of-mouth with or without monetary incentives. For instance, 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, spends on online ad banners; places free trial coupons in the DVD-players cartons of some manufacturers; mails other free-trial coupons to targeted audiences and encourages referrals; although without any monetary incentive.

While these types of customer acquisition are less controlled by the firm, they may be more likely to succeed, for various reasons. First of all, these communications have higher credibility than conventional marketing activities that are designed and implemented by the firm. For instance, word-of-mouth communications have been suggested to be more persuasive than conventional advertising (Brown and Reingen 1987; Herr, Kardes, and Kim 1991). Secondly, following contingent persuasion knowledge theory (Friestad and Wright 1994, 1995), customers realize that the main goal of marketing-induced communications is to influence their beliefs and/or attitudes about the firm, and therefore cope with these attempts. Thirdly, since these communications can be spread without using the firm's marketing resources, the firm can enjoy much better financial gains from the customer acquisition. Under this scenario, satisfied customers assume the role of enthusiastic sales representatives who work for the firm free of charge.

Measuring Acquisition Effectiveness

In this research we develop a metric that links acquisition efforts to long-run profitability by measuring the impact of a single customer acquisition on customer equity, which has

been suggested as a powerful metric for the value of a firm (Gupta, Lehmann and Stuart 2004).

Our model investigates the difference between customer cohorts at the acquisition channel level. Previous work has assumed that customers are homogeneous in their 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 will investigate how different types of acquisition contribute to the firm's customer equity in the short run and in the long run. Although we focus our analysis on the difference between marketing-induced vs. word-of-mouth customer acquisition, our methodology can be applied to any particular acquisition media. This difference has important implications for optimal resource allocation, as firms want to allocate their limited acquisition budget so as to maximize customer equity and therefore shareholder value. For instance, firms may choose to increase the buzz level among customers by encouraging referral activities. In addition, we emphasize the difference between short-term and long-run effectiveness and we illustrate the importance of maximizing the latter when allocating marketing resources.

Our metric assesses the impact a new customer has on the total customer equity of the firm. This metric can be interpreted as a *customer equity elasticity*, rather than the CLV of a newly acquired customer (as in Venkatesan and Kumar 2004). We believe this metric is superior to the CLV metric, because the latter may underestimate the return on acquisition spending as it excludes effects such as the generation of word-of-mouth that a newly acquired customer may generate throughout his lifetime, or the reinforcement

effects of acquisition on the firm's performance. Traditional deterministic models cannot capture these effects, because they are not directly observable.

METHODOLOGY

Linking Customer Acquisition and Long-Run Performance

The acquisition process and its link with the firm's performance should be examined as a complex system in which many interactions could take place over time. For example, when computing the marginal contribution on CE of one new customer, we want to measure not only her expected CLV but also all the indirect influences that this acquisition will cause in the firm's performance.

We propose a vector-autoregressive (VAR) model to investigate these interactions which we characterize as follows:

(1) *Direct effects* of acquisition on the performance of the firm. We are interested in measuring the impact of a person being acquired through a given acquisition channel on the firm's performance;

(2) *Cross-effects* between two types of customer acquisition. For instance, we are interested in how the marketing-induced customer acquisition affects future acquisitions generated through word-of-mouth;

(3) *Feedback effects*. The firm's current performance may affect the future number of customers. For instance, firms that develop stronger reputations through better performance could increase future customer acquisitions;

(4) *Reinforcement effects*. Both firm's performance and customer acquisitions may have a future effect on themselves. For instance, if there is inertia in the firm's marketing

resource allocation, the time series of marketing-induced acquisitions will have an autoregressive component.

We propose a three-variable VAR system to capture the dynamic interrelationships between the number of customers acquired and the firm's performance such that:

$$\begin{pmatrix} AM_t \\ AW_t \\ V_t \end{pmatrix} = \begin{pmatrix} a_{10} \\ a_{20} \\ a_{30} \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} a_{11}^l & a_{12}^l & a_{13}^l \\ a_{21}^l & a_{22}^l & a_{23}^l \\ a_{31}^l & a_{32}^l & a_{33}^l \end{pmatrix} \begin{pmatrix} AM_{t-l} \\ AW_{t-l} \\ V_{t-l} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{1}$$

where AM stands for the number of customers acquired through the firm's marketing actions, AW stands for the number of customers acquired from word-of-mouth, and V 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 $N(\mathbf{0}, \mathbf{\Sigma})$, the direct effects are captured by a_{31}, a_{32}, cross effects by a_{12}, a_{21}, feedback effects by a_{13}, a_{23} and finally, reinforcement effects by a_{11}, a_{22}, a_{33}. We could, of course, include additional exogenous variables (e.g., a deterministic trend) and impose restrictions on some of these parameters if there is an a priori reason for doing so. Instantaneous effects are not included directly in this VAR, but are reflected in the variance-covariance matrix of the residuals ($\mathbf{\Sigma}$).

Note that we do not need to include marketing activity data (e.g., advertising expenditures, price promotions) since at this point we are not interested in measuring how these marketing efforts lead to number of customers acquired. Instead, we want to measure how much a specific customer contributes to both present and future firm

performance. This function linking the number of customers acquired to the contribution to the firm's customer equity will be called the *value generating function*. The interactions between marketing spending and number of acquisitions will be captured by a separate *acquisition response function*[2] (see Figure 1).

Insert Figure 1 here

Impulse Response Functions and Customer Equity

Given data availability, a VAR model not only captures the direct, cross, feedback and reinforcement effects, it also measures the dynamics of each. We are interested in disentangling the immediate and the long-run effects, and in determining the total cumulative effects. This is accomplished by Impulse Response Functions (IRFs) that trace the present and future response of a variable to an unexpected shock in another variable. 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; Srinivasan, Bass, and Popkowski 2000). They are used here to assess how one unexpected customer acquisition impacts customer equity over time. To the best of our knowledge, this is the first use of the VAR method to measure the financial contribution of newly acquired customers.

Assuming data stationarity, we can rewrite the VAR model in equation (1) as a moving-average representation (see Enders 2004):

$$\begin{pmatrix} AM_t \\ AW_t \\ V_t \end{pmatrix} = \begin{pmatrix} \overline{AM} \\ \overline{AW} \\ \overline{V} \end{pmatrix} + \sum_{i=0}^{\infty} \begin{pmatrix} \phi_{11}(i) & \phi_{12}(i) & \phi_{13}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \phi_{23}(i) \\ \phi_{31}(i) & \phi_{32}(i) & \phi_{33}(i) \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-i} \\ \varepsilon_{2,t-i} \\ \varepsilon_{3,t-i} \end{pmatrix} \tag{2}$$

[2] If complete matching records of marketing spending and acquisition are available, the two functions may be combined in one extended VAR model. That is not the case in our empirical example.

The coefficients $\phi_{jk}(i)$ are called impact multipliers and measure the impact of a one-unit change in $\varepsilon_{k,t-i}$ on the jth variable. The different sets of coefficients $\phi_{jk}(i)$ for $i = \{0,...,\infty\}$ are called impulse response functions and are usually plotted to visualize the dynamic behavior of the variables of interest as a function of shocks in other variables. We can calculate the cumulated long-run effect of unit impulses in any error shock on another variable by accumulating the impact multipliers,

(3) $$Total\ Effect\,(k \rightarrow j) = \sum_{i=0}^{\infty} \phi_{jk}(i)$$

When variables are stationary, the impact multipliers tend to zero for sufficiently high numbers of *i* and therefore the total effect is finite. When variables are evolving, the standard procedure is to estimate the VAR model with variables in first differences (see Dekimpe and Hanssens 1995b for more discussion on the VAR modeling).

In order to estimate the effect of one new customer acquisition on the long-run performance of the firm we take the following steps: (1) estimate the impulse response functions defined as the effect of a one-person acquisition on the firms' performance; and (2) select the impact multipliers that are significantly different from zero. Thus the long-run impact multiplier for a direct effect is obtained as

(4) $$\gamma_k = \sum_{i=0}^{m} \phi_{vk}(i)$$

where *m* is the number of periods to include in the calculation, and $\phi_{vk}(i)$ is the impact multiplier measuring the response of the *V* variable to the shock of the kth variable *i* time units ago.

So long as V is a good proxy for the firm's performance, this impact multiplier can be interpreted as the contribution of one incremental customer acquired to the firm's customer equity, before accounting for differences in acquisition costs. In other words, γ_k does not take into account the cost that was necessary for customer acquisition. In the case that V cannot be expressed in monetary value, the impact multiplier needs to be translated to profit contribution, for example,

$$\lambda_k = \tau(\gamma_k) \tag{5}$$

where $\tau(\bullet)$ is a function that translates the direct effects (as measured by the impact multipliers) to the firm's profits. This approach may be necessary, for example, for an online newspaper that generates revenue from advertising but can only observe the login behavior of its users. That login behavior may be expected to be positively correlated with advertising exposure and, therefore, the firm's financial performance.

In conclusion, our customer equity elasticity, estimated from a VAR model, captures the expected contribution of a new customer acquisition on the firm's short-term and long-term value.

EMPIRICAL ILLUSTRATION

Data Description

We study an internet firm that provided free web hosting to registered users during a 70-week long observation period. At the time of registration, individuals 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]. Since this particular firm

[3] One limitation of these data is that it was 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.

did not allow for multiple responses in this question, we study the *predominant* channel that brings a customer to the firm. Once registered, individuals' unique behavior was tracked as they logged in to use the firm's services (e.g., changing the content or appearance of their web site, or checking on the number of site visits).

From these records, we calculate the weekly number of logins as well as the number of registrations per acquisition channel. These channels are classified as marketing-induced or as word-of-mouth acquisition channels. The marketing-induced acquisition channel includes online ad banner, TV, radio, magazine or newspaper advertisement, email links, and direct mails. The word-of-mouth 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. A very small number of registrants who indicated "Other" as their acquisition channel was discarded from this analysis. Other demographic variables are also collected at the time of registration such as a business type (e.g., retailers), country of origin, and number of employees. Some descriptive statistics on these variables are also shown in Table 1.

Insert Table 1 here

Specifying and testing the value generation function

We use the number of logins as a proxy for the firm's performance, i.e., V in Equation (2), given the characteristics of this business. Most free-service internet companies generate advertising revenue based on logins or click-throughs. Therefore, high login intensity provides the firm with more revenue. Furthermore, we expect that intensity of login behavior will be 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 familiarized with the site, and thus perceive higher switching costs that lead to consumer lock-in (Zauberman 2003). In addition, high login intensity may make customers be committed to 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 login 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 the firm intended to change that policy later on. Two weeks after the end of our observation period, the firm announced by email that, in two months' time, users would either agree to pay subscription fees for different service levels, or face the termination of their accounts. We obtained data on which customers declined the fee for service and which ones 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 predict subsequent willingness to pay.

The hypothesis is tested using a binary logit model of customer choice, using individual data on login behavior and various demographic characteristics as independent variables. The logit model includes the following covariates:

(1) ***LOG20****:* total binary logins (that is, the number of weeks when a customer logs in the service at least once) during the first 20 weeks of a relationship. Therefore, given the 70-week observation period, we study the login behavior of customers who registered between week 1 and week 50 of the observation period.

(2) ***WEEK****:* week in which the customer registered. This variable allows us to test whether early adopters (customers who joined early) have a different conversion probability than late adopters.

(3) ***RETAILER**:* 1 if retailer, 0 otherwise. Most of the firm's customers are small companies trying to advertise or sell through the internet. Therefore, these retailers are expected to have higher conversion rates than others (e.g., individuals).

(4) ***COUNTRY**:* 1 if US, 0 otherwise. This dummy variable tests for a difference in conversion probability among nationalities.

(5) ***EMP**:* number of employees. We expect small firms to have a higher conversion rate than large firms because they may not have the resources to staff their web-hosting internally.

Since the total conversion rate is very 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.[4] In both models, all parameter estimates are found to be statistically significant, and our focal construct LOG20 has a positive impact on the probability of paying (see Table 2). The choice-based sampling model correctly classifies 90.8% of those who terminate and 86.5% of those who agree to pay[5]. The average predicted probability of retention for our choice-based sample is 0.475, which is very similar to the observed 0.484. Using the revised intercept, the predicted average retention probability for the population is 0.0107, which is also very close to the observed value of 0.0111.

The results support our hypothesis of a significant and positive effect of a customer's login activity on her subsequent willingness to pay. Therefore, acquisition

[4] This technique does not yield consistent maximum-likelihood estimates of the intercept. Following Manski and Lerman (1977), we adjust the estimated intercepts for each alternative by subtracting from the exogenous maximum likelihood estimates of the intercept the constant $\ln(S_g/P_g)$, where S_g is the percentage of observations for alternative g in the sample, and P_g is the percentage of observations for alternative g in the population (see also Ben-Akiva and Lerman 1985).

[5] We also estimated the model with 60% of the observations and used the estimates to check the predictive accuracy with an out-of-sample dataset. The original model correctly classifies 90% of the sample. When used in the out-of-sample, the correct classification is 88%.

channels with a higher level of subsequent usage (login) activity will increase the subsequent average conversion rates. We also test the relative predictive strength of customer usage levels by estimating a logit model with and without the demographic covariates. The demographic variables are found to add only 0.3 and 2.1 percentage points for correctly classified defectors and paying customers, respectively. Additionally, a model with only demographic variables as covariates correctly classifies 75.9% of the defectors and only 59.0% of the future buyers. Thus it is login activity, and not customer demographics, that is the leading indicator of subsequent willingness to pay.

Insert Table 2 here

Based on the above analysis, we construct three endogenous variables in the VAR system as follows.

- $\boldsymbol{AM_t}$: number of new registrations at time t resulting from marketing activities
- $\boldsymbol{AW_t}$: number of new registrations at time t from word-of-mouth
- $\boldsymbol{V_t}$: total number of binary logins at time t

We also include in the model other covariates to control for the effect that a different profile of customers could have on login activity, namely:

- $\boldsymbol{RC_t}$: the percentage of U.S. based customers among the new registrants at time t
- $\boldsymbol{RB_t}$: the percentage of retailers among the new registrants at time t
- $\boldsymbol{RE_t}$: the percentage of firms with more than 4 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 (see Dekimpe & Hanssens 1995b for a detailed explanation). We use the augmented Dickey-Fuller (ADF) unit root test with the null hypothesis of unit

root. We apply the iterative procedure proposed in Enders (2004, pp. 181-183) to decide whether to include a deterministic trend in the test. Since it has been argued that conventional unit root tests (e.g., ADF) tend to under-reject the null of unit root, we validate our results with the KPSS test (Kwiatkowski et al. 1992) that uses the null of stationarity. The ADF test statistics have values from -4.07 to -4.89, all above the 5% critical value. KPSS statistics vary from 0.08 to 0.11, all below the critical value. Hence, we can reject the null hypothesis of a unit root using the ADF test, and we cannot reject the null hypothesis of stationarity, using the KPSS test (see Table 3).

Insert Table 3 here

Since 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. The dummy variable is included in order to control for outliers.[6] Finally, the variables adding demographic information allow us to control for the effects that different profiles of customers may have on the results. We also estimated a model without demographics, but both the log likelihood and the AIC 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 (SUR) estimators. However, a log-likelihood ratio test confirms (at the 5% of significance level) that the restrictions do not improve the model performance.

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

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 (Lutkepohl 1993, p.150-152) and find that the null hypothesis of white noise cannot be rejected. The estimation results are reported in Table 4, and the impulse response functions are shown in Figure 2. Note that we use orthogonalized IRFs given a contemporaneous ordering of the variables in that first, marketing-induced acquisitions impact word-of-mouth acquisitions, and finally these two impact login activity. Following the procedure in Dekimpe and Hanssens (1999), IRFs with the absolute value of t-statistics exceeding one are plotted in Figure 2.

Insert Table 4 and Figure 2 here

Direct Effects

These IRFs measure the total or net effect of an unexpected acquisition on the firm's performance, defined as the total number of logins over time. The net effect includes not only a new customer's own login activity, but also the effect on the login 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 term than customers acquired through word-of-mouth,* viz. the former generate approximately 3.35 logins during the first week, while the latter generate only 2.82 logins. Note that these login generations may be decomposed in three ways, e.g. 3.35 logins due to marketing-induced customer acquisition during the first week originate as follows: 1 login from the acquired customer, 1.06 logins from buzz generation during the

first week (buzz effects), and 1.29 incremental logins from the existing pool of customers.

However, this short-term effect does not directly translate into a long-term impact. We calculate the long-term multipliers (equation (4)) to be used in our value generating function[7] by accumulating the effects as long as they are statistically significant. We find that the cumulative impact (after ten weeks) of word-of-mouth channels (γ_{AW} = 10.31) is about *twice* that of marketing-induced channels (γ_{AM} = 5.21)[8]. Moreover, the effect of the marketing-induced acquisition settles down after only three weeks, while the effect from word-of-mouth channels lasts for about 6 weeks. These time 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 his efforts sub-optimally. Customers acquired through marketing activities are found to focus more on "trials" (i.e., short-term effects) while customers through word-of-mouth tend to provide the firm with more "repeats" (i.e., long-term effects).

Word-of-Mouth Effects

Next, we investigate the cross effects between marketing-induced acquisition and word-of-mouth acquisition. Panel B of Figure 2 shows that customers acquired through word-of-mouth are better at future word-of-mouth generation than those acquired by marketing induced channels. For example, each customer acquired through marketing is expected to bring around 1.59 new customers throughout his lifetime, while a customer acquired through word-of-mouth is expected to bring 3.23 customers (including himself). However,

[7] We do not make any assumptions on $\tau(\bullet)$ yet, as expressed in Equation (5). Therefore, these multipliers should be interpreted as the contribution to the firm's total login activity, not to the monetary value of the firm.

[8] We tested for the differences in the cumulative impulse response function using Monte-Carlo simulations following the procedure suggested in Lutkepohl 1993 (p. 495).

there is no significant difference between 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 cohorts.

Which factor is more important in explaining the future dynamics of word-of-mouth acquisition? We measure how much of the forecast error variance in future word-of-mouth acquisition can be attributed to a change in current marketing-induced acquisition (*AM*), word-of-mouth acquisition (*AW*), and firm value (*V*) by decomposing the forecast error variance of *AW*. 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 instance, 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 shown in Figure 3, shocks in marketing-induced customer acquisition (*AM*) explain about 60% of the changes in word-of-mouth acquisition (*AW*) in the short-term (i.e., in one or two weeks). However, in the long term *AW* becomes more important in explaining future word-of-mouth generation (its impact stabilizes at about 50%). By contrast, firm value (*V*) explains only 1.3% of the variance in the long-run. Overall, this analysis confirms that *current word-of-mouth customer acquisition is the most important predictor of future word-of-mouth generation.*

Insert Figure 3 here

Other Effects

In addition, we find significant *reinforcement effects* for both acquisition channels. For example, marketing-induced channels have a cumulated reinforcement effect of 1.4, i.e.

each new customer acquired through marketing generates a total of 1.4 customers in the long term. On the other hand, we find no evidence of *feedback effects*, i.e., the response of future acquisitions to a shock in logins is insignificant. Therefore the mere fact of observing more intense login activity among existing customers does not in and of itself increase future acquisition levels.

ECONOMIC-IMPACT SIMULATION

In this section, we demonstrate a numerical simulation to highlight the economic impact of acquiring customers through either marketing activities or word-of-mouth. Under some assumptions on model parameters, we compare the financial impact of acquiring 1000 new customers through the two channels. The simulation is implemented as follows.

First, we calculate the expected increase in the number of customers and logins over 10 weeks, attributed to the current acquisition of 1000 new customers, using the IRFs from the VAR model. Since the IRFs in Figure 2 show the impact of one customer acquisition, we multiply these IRFs by 1000 to obtain the effect of 1000 new customer acquisitions. Second, we convert the increase in login activities to a dollar value by assuming each login is worth two dollars[9]. In other words, we define the $\tau(\bullet)$ function in Equation (5) as a simple multiplicative form such that $\lambda_k = 2 \cdot \gamma_k$. Third, we calculate the present value of this financial change using a weekly time discount factor of 0.2%. Finally, the financial contribution per increased customer is calculated. The simulation results are presented in Table 5.

[9] This value may be different across firms and industries. It may be obtained by comparing customer subscription revenue to average login activity.

Insert Table 5 here

The simulation shows the different financial contribution of two customer acquisition channels, both in the short run and in the long run. For instance, this firm can increase its short-run revenue more through marketing-induced customer acquisition ($6,695) than through word-of-mouth customer acquisition ($5,631). However in the long run (i.e. over 10 weeks), the latter has a bigger financial impact ($20,554 of present value) than the former ($10,419 of present value). This difference is mainly due to the fact that customers acquired through word-of-mouth tend to stay longer as an active customer and thus generate more value over time. Since this comparison is done 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 marketing, the net value of one customer through marketing will be $1.04 while that of one customer through word-of-mouth (assuming there is no cost associated with word-of-mouth acquisition) will be $20.55. Therefore, managers can use such simulation results in determining an appropriate level of customer acquisition spending. As an illustration, if the firm wants to use financial incentives to boost word-of-mouth acquisitions, incentives of up to $20.55 per acquired customer would be justified.

CONCLUDING REMARKS

This paper has developed a statistical model capable of measuring the long-run impact of customer acquisitions through different channels on customer equity. The VAR model allowed us to measure the financial impact of an additional customer on the firm's performance (V). Thus, we did not explicitly measure the marketing effort (i.e.,

spending), but rather the result of that effort (i.e., an acquired customer) and how that acquired customer increases the customer equity of the firm. We constructed a metric called the long-term impact multiplier, which generates the intrinsic value of the "typical" customer coming from a specific acquisition channel. This metric, based on impulse response functions, not only captures the dynamic effects that a customer will exhibit in her lifetime, but also the customer's effect on other customers (e.g., generating word-of-mouth). As such, our metric captures the impact of an additional customer on the customer equity of the firm.

The limitations of our work offer areas for future exploration. First, our data on acquisition channels were self-reported. In general, this limitation is difficult to overcome in any study that incorporates word-of-mouth, though advances in internet communications tracking may improve the quality of the data. Second, our model does not incorporate marketing spending, only the result of that spending (i.e., an acquired customer). In order to make optimal resource allocation inferences, marketing spending should be added to the model. Third, we use the number of logins as a proxy for profit and not profit itself. While we demonstrated the value of the login proxy in our setting, a similar model could be used with direct profitability data. Finally, more research is needed to understand the dynamics of word-of-mouth generation and how incentivizing word-of-mouth could influence the future behavior of customer cohorts acquired through this channel.

Table 1

Classification of the Acquisition Channels and Descriptive Statistics

Series	Mean	Maximum	Minimum	Standard Deviation
AM	625	1268	72	272.6
AW	1526	2758	170	608.7
V	8895	15842	1183	3997.4
RC	0.78	0.85	0.68	0.04
RB	0.20	0.26	0.15	0.03
RE	0.92	0.94	0.86	0.01

(Notes)

- *AM*: number of weekly new registrations from marketing activities such as online ad banner, TV, radio, magazine or newspaper advertisement, email links, and direct mails
- *AW*: number of weekly new registrations from word-of-mouth channels such as 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
- *V*: number of weekly binary logins
- *RC*: percentage of U.S. based customers among the new registrants at each week
- *RB*: percentage of retailers among the new registrants at each week
- *RE*: percentage of firms with more than 4 employees among the new registrants at each week

Table 2

Binary Logit Model Results

	Total Population (N=93,119)		*Choice-Based Sample (N=2,130)*	
	estimate	*s.e.*	*estimate*	*s.e.*
intercept	-9.713	(0.579)**	-5.120	(0.730)**
intercept (revised)			-9.547	
log20	0.281	(0.006)**	0.324	(0.013)**
week	-0.013	(0.002)**	-0.020	(0.005)**
retailer	0.763	(0.069)**	0.807	(0.152)**
country	3.440	(0.565)**	3.207	(0.690)**
emp	-0.107	(0.051)*	-0.179	(0.089)*
-2 Log Likelihood	7,194		1,287	
Cox & Snell R Square	0.043		0.542	
Nagelkerke R Square	0.379		0.723	

*significant at the 5% level; **significant at the 1% level

Table 3

Unit Root Test Results

Series	*ADF (H_0: unit root)*			*KPSS (H_0: stationary)*		
	Stat	*5%-crit*	*Unit root?*	*Stat*	*5%-crit*	*Unit root?*
AM	-4.89	-3.48	No	0.11	0.15	No
AW	-4.07	-3.48	No	0.08	0.15	No
V	-4.34	-3.48	No	0.09	0.15	No

(Notes)

- ADF: augmented Dickey-Fuller test
- KPSS: Kwiatkowsi-Phillips-Schmidt-Shin test

Table 4

VAR Model Estimation Results

	AM_t		AW_t		V_t	
AM_{t-1}	0.32	(0.17)*	-0.40	(0.22)*	-1.31	(0.74)*
AW_{t-1}	0.03	(0.21)	0.90	(0.28)***	1.71	(0.94)*
V_{t-1}	-0.01	(0.06)	-0.05	(0.08)	0.24	(0.26)
Intercept	1,696.42	(1,828.90)	2,386.34	(2,404.08)	11,497.56	(8,072.60)
Trend	4.31	(7.29)	12.83	(9.58)	109.12	(32.17)***
Dummy	225.70	(89.31)**	-52.67	(117.40)	-198.96	(394.20)
RC_{t-1}	3,952.88	(1,166.39)***	3,838.93	(1,533.22)**	15,256.15	(5,148.36)***
RB_{t-1}	-5,065.28	(1,541.51)***	-5,721.79	(2,026.31)***	-14,015.99	(6,804.11)**
RE_{t-1}	-3,823.34	(2,340.96)	-4,305.66	(3,075.87)	-22,329.33	(10,328.40)**
R Squared	0.55		0.84		0.96	
F Statistic	9.14		40.75		177.45	
Log likelihood: -1,431.72	AIC: 41.68		SC: 42.55			

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table 5

Economic Impact Simulations

A. Case 1: acquiring 1000 more customers through marketing

time (week)	baseline	1	2	3	4	5	6	7	8	9	10	total
# customers (cum.)	60,000	62,056	62,746	62,993	62,993	62,993	62,993	62,993	62,993	62,993	62,993	62,993
# customers increase		2,056	690	247	0	0	0	0	0	0	0	2,993
# weekly logins	8,000	11,348	9,305	8,562	8,000	8,000	8,000	8,000	8,000	8,000	8,000	85,214
# weekly logins increase		3,348	1,305	562	0	0	0	0	0	0	0	5,214
revenue ($, weekly)	16,000	22,695	18,609	17,124	16,000	16,000	16,000	16,000	16,000	16,000	16,000	170,429
revenue increase		6,695	2,609	1,124	0	0	0	0	0	0	0	10,429
PV of revenue increase		6,695	2,604	1,120	0	0	0	0	0	0	0	10,419

B. Case 2: acquiring 1000 more customers through word-of-mouth

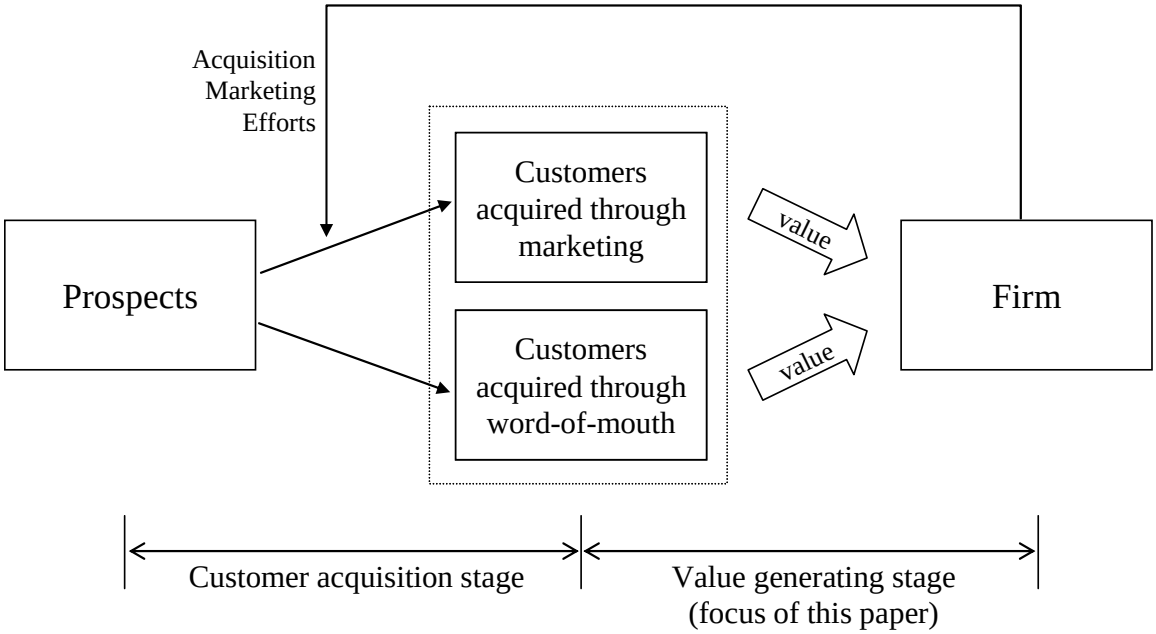
time	baseline	1	2	3	4	5	6	7	8	9	10	total
# customers (cum.)	60,000	61,000	61,754	62,310	62,717	63,012	63,227	63,227	63,227	63,227	63,227	63,227
# customers increase		1,000	754	556	406	296	215	0	0	0	0	3,227
# weekly logins	8,000	10,816	10,391	9,874	9,415	9,049	8,770	8,000	8,000	8,000	8,000	90,314
# weekly logins increase		2,816	2,391	1,874	1,415	1,049	770	0	0	0	0	10,314
revenue ($, weekly)	16,000	21,631	20,782	19,747	18,830	18,098	17,540	16,000	16,000	16,000	16,000	180,627
revenue increase		5,631	4,782	3,747	2,830	2,098	1,540	0	0	0	0	20,627
PV of revenue increase		5,631	4,772	3,732	2,813	2,081	1,524	0	0	0	0	20,554

(Assumptions)

- Monetary value of each login: $2
- Number of current customers: 60,000
- Number of current weekly logins: 8,000
- Time discount factor (weekly): 0.2%

Figure 1

Customer Acquisition and Value Generation



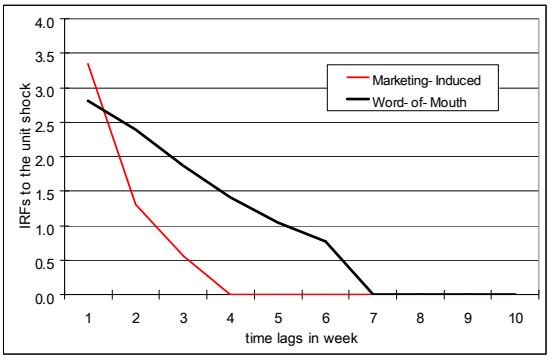
(Note) The effectiveness of marketing efforts on customer acquisition can be measured by an "Acquisition Response Function" in customer acquisition stage. Rather, the current paper focuses on "Value Generating Function" that can measure the impact of new customer acquisitions on the subsequent value generating stage.

Figure 2

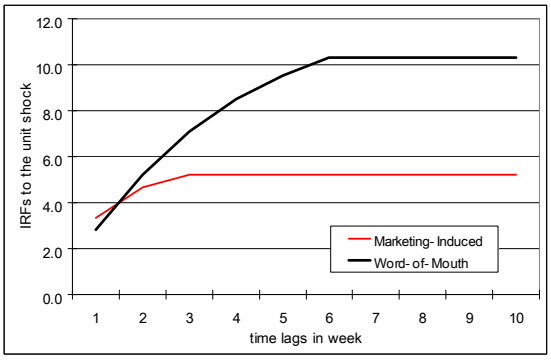
Impulse Response Functions

A. Direct Effects

<Weekly Effects>



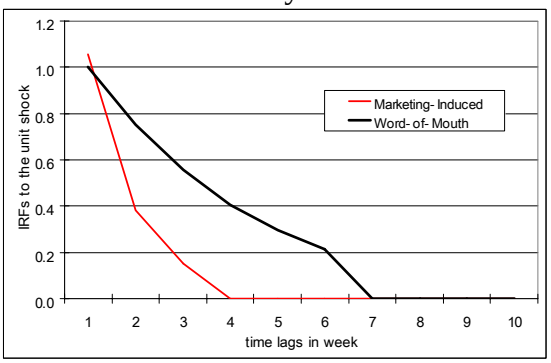
<Accumulated Effects>



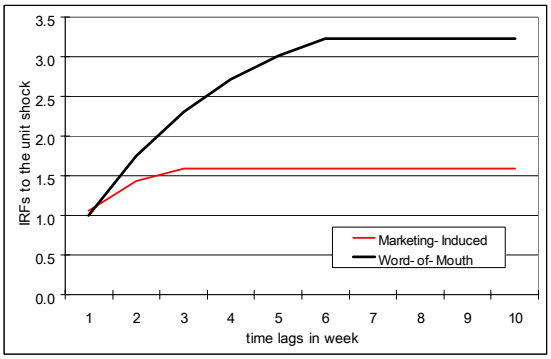
Note: Should be interpreted as the effect of one customer increase from each channel on the total login activity of the firm.

B. Word-of-mouth Effects

<Weekly Effects>



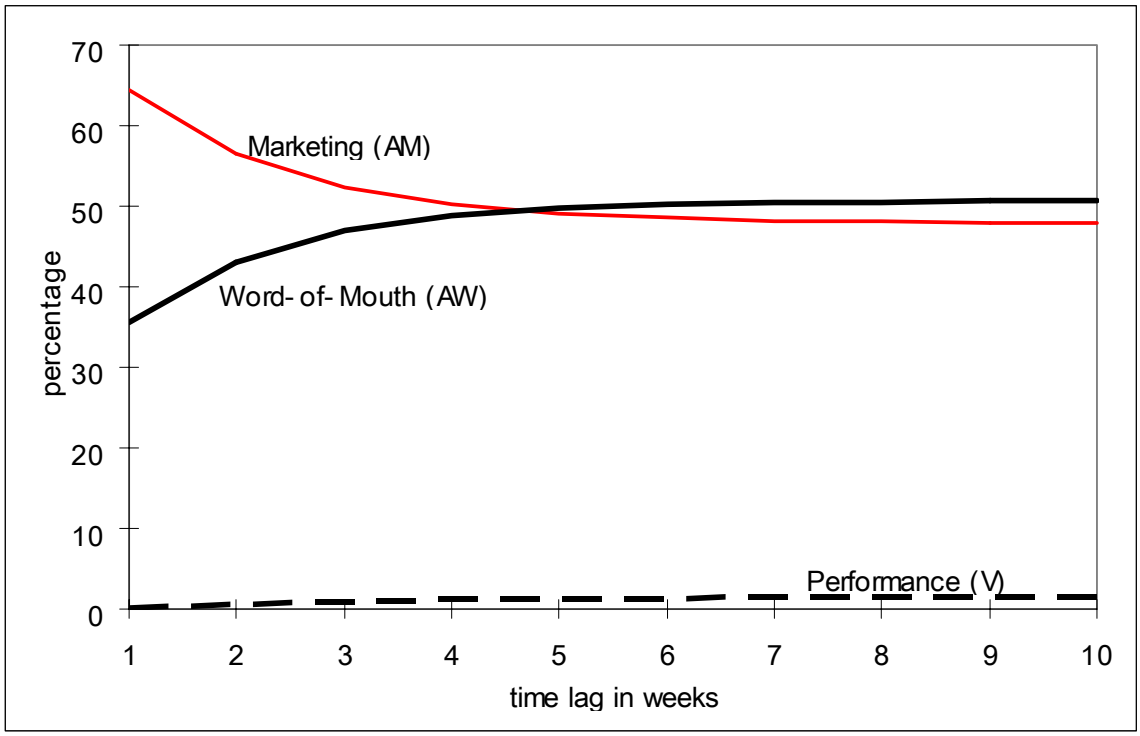
<Accumulated Effects>



Note: Should be interpreted as the effect of one login activity increase on the total number of customers acquired through word-of-mouth.

Figure 3

Word-of-Mouth Forecast Error Variance Decomposition



Note: The graph shows how much of forecast error variance in word-of-mouth acquisition (AW) can be attributed to changes in three endogenous variables (i.e., AM, AW, and V). For instance, about 65% of the one-period-ahead forecast error variance of word-of-mouth acquisition is explained by marketing-induced acquisition (AM). This proportion gradually decreases to about 48% in the long-run, while the proportion explained by AW grows to about 50%.

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