

Measuring the Lifetime Value of Customers Acquired from Google Search Advertising

Tat Y. Chan, Chunhua Wu, Ying Xie

Olin Business School, Washington University in St. Louis, St. Louis, Missouri 63130
{chan@wustl.edu, chunhuawu@wustl.edu, xie@wustl.edu}

Our main objective in this paper is to measure the value of customers acquired from Google search advertising accounting for two factors that have been overlooked in the conventional method widely adopted in the industry: (1) the spillover effect of search advertising on customer acquisition and sales in off-line channels and (2) the lifetime value of acquired customers. By merging Web traffic and sales data from a small-sized U.S. firm, we create an individual customer-level panel that tracks all repeated purchases, both online and off-line, and tracks whether or not these purchases were referred from Google search advertising.

To estimate the customer lifetime value, we apply the methodology in the customer relationship management literature by developing an integrated model of customer lifetime, transaction rate, and gross profit margin, allowing for individual heterogeneity and a full correlation of the three processes. Results show that customers acquired through Google search advertising in our data have a higher transaction rate than customers acquired from other channels. After accounting for future purchases and spillover to off-line channels, the calculated value of new customers using our approach is much higher than the value obtained using conventional method. The approach used in our study provides a practical framework for firms to evaluate the long-term profit impact of their search advertising investment in a multichannel setting.

Key words: customer lifetime value; multiple-channel shopping; customer acquisition; sponsored search advertising

History: Received: August 8, 2010; accepted: April 25, 2011; Eric Bradlow and then Preyas Desai served as the editor-in-chief and Peter Fader served as associate editor for this article. Published online in *Articles in Advance* August 25, 2011.

1. Introduction

With the widespread use of the Internet, online advertising market is soaring. In particular, sponsored search advertising has surpassed display advertising as the most dominant form of online advertising (Greene 2008). The annual revenue of Google, the dominant player in this market with a 77% market share, has increased more than 50-fold, from \$439 million in 2002 to \$21.8 billion in 2008.¹ One of the major advantages of search advertising is that it creates a better fit between potential customers' needs and the advertised message. By reaching out to a large audience with immediate interest in the product advertised, search advertising provides a platform for advertisers not only to stimulate sales among existing customers but to also acquire new customers and grow business. Furthermore, because advertisers pay on a click performance basis, search advertising is also believed to provide more accountability in terms of bottomline performance (e.g., traffic, sales, and profitability) than traditional mass media advertising. These two advantages are especially important

for small firms because of their tight marketing budget.

Along with these advantages, the industry has observed an increasingly intensified competition for popular keywords. As a result, the cost of sponsored search advertising has been rising rapidly in the recent years. According to a 2007 DoubleClick Performics study of 50 large and well-managed paid search campaigns, the average cost per click (CPC) climbed up 42% from December 2005 to December 2006 (Performics 2007). This has made advertisers rethink whether their investments in search advertising are worthwhile (Elgin and Hof 2005).

To decide whether or not any marketing spending is paying off, one needs to understand the corresponding return in sales and profits. The conventional method to measure the return of Google search advertising in industry is to compare the online transaction profit generated from Google referrals with the cost of search advertising within a fixed time period (monthly or yearly).² Although it is straightforward and implementable, this method has overlooked two

¹ From Google Investor Relations: <http://investor.google.com/financial/2003/tables.html> and <http://investor.google.com/financial/2009/tables.html> (accessed June 6, 2011).

² See <http://adwords.google.com/support/aw/bin/answer.py?hl=en&answer=14090> (accessed June 6, 2011).

important factors in the profit calculation. First, multi-channel distribution has become more prevalent with the widespread use of Internet. By focusing only on online transactions, we are not able to account for the potential cross-channel spillover effects. According to ComScore, a substantive portion of customers ends up making purchases off-line even though they are made aware of the retailer through search advertising; for example, only 25% of purchases in the jewelry category generated from search advertising were converted online (Ryan 2006). The conventional method does not capture such positive spillovers from search advertising and therefore might lead to an underestimate of the profit impact.

Second, with the shift from product-centered thinking to customer-centered thinking in marketing research and practice, customer lifetime value has been widely used in many industries as key marketing asset metrics. As firms increasingly target marketing expenditures on the maximization of these metrics, profit measures that only reflect short-term returns are often prejudicial against marketing expenditures (Rust et al. 2004). With a trusted relationship with firms, returning customers may spend more and purchase more frequently in the future. Because the conventional method only considers immediate purchases of customers acquired from Google, it overlooks the value from the same customers whose future purchases are no longer referred from search advertising.

The main objective of this paper is to develop an empirical method to estimate the lifetime value of customers who clicked on Google search advertisements prior to their first-time purchases with the firm, accounting for the cross-channel spillover effect. Building on the current methodology in the customer relationship management (CRM) literature, we develop an integrated model of customer lifetime, transaction rate, and gross profit margin, allowing for individual customer heterogeneity and a full correlation of the three processes, to estimate the customer lifetime value (CLV). The model is estimated using the well-established hierarchical Bayesian method. We apply the model to an individual customer-level panel we obtained from a small-sized U.S. firm that has spent a substantial proportion of its marketing budget on purchasing search keywords from Google in recent years. We view our effort to establish a correct measurement of the customer value as a crucial step to evaluate the returns of investment on Google search advertising.

Our results show that, on average, customers acquired from Google have a higher CLV, mainly because they purchase more frequently relative to customers acquired through other channels. Returning customers tend to increase their purchase quantities

over time. The predicted CLV from new customers after accounting for future purchases and acquisition and sales spillover to the off-line channel is much higher than the CLV obtained when we use the conventional method.³ Assuming all customers acquired from Google would not be acquired from other channels, the breakeven CPC across keywords, above which the firm's expected returns are negative, is \$10.22, significantly higher than the current average CPC at \$0.80 in data. By contrast, the breakeven CPC calculated from the conventional method is \$0.37, much lower than the current CPC. These results show that the firm's management would be seriously misled on their investment on search advertising without accounting for sales spillovers and future purchases from newly acquired customers.

The contribution of this paper is twofold. From the academic perspective, to the best of our knowledge, our empirical study is the first one to apply CRM models to investigate the long-term value of customers acquired from sponsored search advertising in a multichannel context. Managerially, we demonstrate that, by making use of the data sources available to advertisers, a better measurement of the value of customers acquired from search advertising can be constructed to help firms evaluate the true profitability of their investment.

1.1. Literature Review

Marketing researchers have developed a number of models to measure the customer lifetime value. One of the earliest and most impactful models is the Pareto/NBD model proposed by Schmittlein et al. (1987). Their model has been widely adopted and has become the building block for many later models of customer lifetime value (including Schmittlein and Peterson 1994, Reinartz and Kumar 2000, Fader et al. 2005a, and our study here). More recently, Fader et al. (2005b) proposed an alternative beta-geometric/NBD model to reduce the estimation burden. Donkers et al. (2007) compared the performances of competing models for CLV calculation. Venkatesan et al. (2007) and Glady et al. (2009) relaxed the assumption of independence between transaction rate and transaction amount and modeled these two processes jointly. Abe (2009) extended the original Pareto/NBD model to incorporate richer customer heterogeneity in a hierarchical Bayesian fashion. Singh et al. (2009) proposed a similar Markov chain Monte Carlo (MCMC) approach for estimating an extended range of models. In this paper, we follow this rich tradition and develop an

³We note that the estimated value may not be equivalent to the profitability of the firm's investment, because some of these customers could have been acquired later from other methods had Google search advertising not been used.

integrated model for customer lifetime, transaction rate, and gross margin. By incorporating individual-level customer heterogeneity and full intercorrelations between the three stochastic processes, our model is less restrictive than the original Pareto/NBD model, and therefore it is complementary to the existing CLV modeling literature.

Several studies have empirically examined the cross-channel effect in a dual-channel (i.e., online and off-line) setting. Bialogorsky and Naik (2003) showed that online sales did not significantly cannibalize retail sales. Deleersnyder et al. (2002) found that cannibalization was most likely to occur when the online channel closely mimics the off-line setting. Ansari et al. (2008) found a negative impact of Internet usage on long-term purchase incidences. Verhoef and Donkers (2005) explored how retention rates and cross-selling opportunities varied across different acquisition channels. In this study, we quantify the impact of search advertising on customer acquisition in the dual-channel setting and examine how customer lifetime, transaction rate, and gross margin differ among customers depending on acquisition methods, the first-time transaction channel, and other observed customer characteristics.

Search advertising, as one of the newest forms of advertising, has received increased interest in academic research in recent years. The majority of the theoretical literature focuses on advertisers' bidding strategy for keywords and optimal mechanism design for search websites. Examples include Edelman et al. (2007) and Katona and Sarvary (2010). Empirical research on search advertising, on the other hand, has focused on exploring the impact of search advertising on advertisers' click-through and conversion rates. Ghose and Yang (2009) modeled the relationship between click-through rates, conversion rates, CPC, and ad ranks using a simultaneous equations model. Rutz and Bucklin (2011) examined potential spillover effects between generic and branded keywords and found that generic keyword searches affect branded keyword searches, but the reverse effect is not significant. A few recent studies have structurally modeled the competition among advertisers for search keywords. Yao and Mela (2011) developed a dynamic model of advertisers' bidding strategy. Chan and Park (2010) used the method of moment inequalities to estimate the advertisers' profitability generated from consumers' click-through of sponsored search ads. To our knowledge, empirical works on search advertising to date have only focused on the short-term profit impact of search advertising on online sales, which might lead to a serious underestimate of the true profit impact. Our purpose of calculating the long-term value of new customers acquired from search advertising is achieved by constructing a

unique customer panel data set that tracks the search and purchase behavior of individual customers in a multichannel context. As a result, we can build a model based on the well-established CRM modeling literature and apply it to our empirical context.

The rest of this paper is organized as follows. Section 2 describes the data and explains how we construct the customer-level panel data. Section 3 describes in detail how we model and estimate the customer lifetime value. Section 4 reports the estimation results and the value of customer acquisition through Google search advertising. Finally, §5 concludes.

2. Data

We obtained data from a small-sized firm in a Midwest city in the United States that has been in business for about 20 years. It specializes in providing biomedical and chemical lab supplies to the science community primarily inside the United States. Its clients can be divided into two categories: research customers including colleges, universities, and research labs; and commercial customers including small pharmaceutical and biomedical companies. The firm has a dual-channel structure for business—clients can either place orders on its website (online channel) or by phone or fax (off-line channel). The firm has traditionally relied on word of mouth to reach potential customers; however, since late 2003, the owner has started to actively use Google search advertising to acquire new customers it could not reach by traditional methods.

The sample period of our data is from January 2004 to August 2007. The data come from three sources: (i) keyword performance records from Google AdWords, (ii) log files from the firm's website, and (iii) customer transaction records, which are typical data sets often maintained by firms that run online business and use sponsored search advertising. Therefore we believe that the data-merging methods and the empirical model we propose below can be adopted by these firms. The Google keyword performance data record the firm's bid and CPC for each keyword, daily average rankings of its sponsored ads, and number of daily impressions and clicks. The firm typically bids for the generic chemical names of its top-selling products, the majority (71.6%) of which are placed at the first or second position at Google-sponsored links.⁴ The CPC charged to the firm ranges from \$0.01 to \$3.00 in the data, with a mean value at \$0.53 and median at \$0.37. Some summary statistics are provided in Table 1. The firm has become more

⁴The top five keywords of the firm remain active throughout the entire data period. They generated 65% of the impressions and 82% of the clicks, and they accounted for 93% of the costs.

Table 1 Usage of Google Search Advertising

Period	2004	2005	2006	2007 (Jan.–Aug.)
Total amount paid to Google (\$)	493	386	2,414	3,810
Number of keywords bid	90	122	182	208
Number of Google keyword referrals	1,888	2,473	4,480	4,767
Average CPC (\$)	0.26	0.16	0.54	0.80

aggressive in bidding for keywords over time, as the total advertising spending has increased from merely \$400 to \$500 in 2004–2005 to about \$2,400 in 2006 and \$3,800 from January to August in 2007. As a result, the number of referrals from Google search advertising has increased by more than twofold in less than four years. However, consistent with the observation in many industries, the average CPC has also been increasing sharply from about \$0.20 in 2004–2005 to \$0.54 in 2006 and \$0.80 in 2007, perhaps because of the more intensified competition to bid for desirable keywords as sponsored search advertising gains more popularity. The key question faced by the owner, as we have learned, is whether or not it is worthwhile to continue using Google sponsored search advertising given the cost hike.

Log files from the firm's website contain detailed information on every website visit, such as the IP (Internet protocol) address, visit duration, pages viewed, and where the visit is referred (such as Google-sponsored links). This information allows us to distinguish customers by the acquisition method (i.e., whether they are acquired from Google or from other channels), which is the key in determining the value of the Google-sponsored search advertising. During the data period, for the U.S. market alone, Google-sponsored links generated approximately 9,200 visits to the website, accounting for 36% of the firm's total website visits. Consistent with the keyword performance data, we also observe a fast increase in the yearly number of website visits.

The customer transaction data record for each customer the name of his or her organization, shipping address, ordering method, invoice date, invoice amount, and the gross profit margin in dollar terms (i.e., total revenue net of supply cost, without accounting for handling and other costs) for each transaction. During our data period, a total of 883 U.S. customers made 6,813 transactions, generating \$1.08 million gross margin for the firm. Among them, 408 were new customers acquired after 2003, generating 14% of total transactions and 17% of total gross margin. The yearly trend in the number of new customers as well as the number of transactions and the amount of revenues generated by these customers is summarized in Table 2. We observe a strong growth

Table 2 Trends in New Customer Transactions

Period	2004	2005	2006	2007 (Jan.–Aug.)
Number of new customers	80	126	131	71
Number of transactions generated by new customers	97	231	337	255
Gross margin from new customers (in thousand \$)	12.4	39.8	64.2	67.4

along all dimensions. The majority of customers (59%) made multiple transactions during the data period. Among these customers 6% only used the online channel, 31% only used the off-line channel, and the majority (63%) made purchases using both channels.

2.1. Data Merging

To compile panel data that track individual customer's Web browsing and purchases in both the online and off-line channels over time, we need to merge the log files with the customer transaction data. The key challenge is to identify individual customers from their Web browsing history recorded in the log files. Our strategy for customer identification is to check every IP address in the log file and look for the corresponding Internet service provider (ISP) name, organization name, and organization address using a database we subscribed to and from IP2location.com, a leading firm in providing data set technology to help online firms identify the geographical location of their website visitors. We then merge the customer's Web browsing history in the log file with the customer transaction record based on the matching of the customer's organization name and address information.⁵ IP addresses, for example, starting with 66.224.232 have the associated ISP name and organization name of "Alder Biopharmaceutical." We then assign visits from these IP addresses to the client affiliated with Alder Biopharmaceutical and merge them with the purchase history of this client, as recorded in our transaction data.⁶ Four organizations in our data set are affiliated multiple customers (12 in total, accounting for 3% of new customers in the data). This leads to the situation where all customers in the same organization, though having different IP addresses, share

⁵ In addition, we have also matched customers based on the geographical distance of shipping addresses and IP addresses and the time distance between browsing sessions and transaction events. Matches based on organization names and addresses of ISPs are almost exactly the same as matches based on the criteria of 10 miles and seven days prior to purchases. This implies that our matching outcomes are robust under various matching criteria.

⁶ There might be multiple computers used under the same IP address. Given that our data provider is a business-to-business firm, however, this should not be a critical issue for us. Because individual people purchase on behalf of the organization, rather than for their own consumption, we feel they can be treated as a single client.

the same ISP name. In this case we use the time proximity of the Web browsing session of the unique IP address and the transaction date of each individual customer in the organization as the criteria for further matching.

2.2. Conversion Rate and Purchase Behaviors

Based on the browsing history from the merged data set, we classify a customer as acquired by Google search advertising if prior to the first-time purchase he or she has clicked into the firm’s website through one of the advertised keywords on Google.⁷ There are altogether 67 new customers referred from Google in the data and another 16 from other search engines (e.g., MSN, Yahoo!, etc.). Customers acquired from Google made 181 transactions, contributing approximately 20% of the total number of transactions and 18% of gross margin generated from new customers. This merged data set also enables us to differentiate website visits from existing customers and from potential customers.⁸ Among the 6,405 transactions made by existing customers, approximately 18% use search advertising prior to purchasing from the firm.

Conversion rate from search advertising in industry practice is typically calculated as the ratio of observed online transactions referred by search engine to the total number of visits referred by search engine. This calculation overlooks the purchases made through the off-line channel. Table 3 shows that more than three-quarters of the purchases with prior clicks from sponsored links are off-line purchases—the conversion rates for online and off-line are 3.1% and 10.2%, respectively. This could be due to the following reasons: (i) the off-line channel provides consumers an opportunity to negotiate prices and to obtain more information on products and delivery services; and (ii) personal conversation over the phone may help to enhance business-to-business relationships. Table 3 also shows that the conversion rate of returning customers, combining both online and off-line channels, is more than 40 times higher than potential customers (44.5% versus 1.0%, respectively), perhaps because it is difficult for the firm, as a small unknown supplier, to gain trust from the latter group of customers.⁹

⁷ A customer is not counted as acquired by Google search advertising if he or she is referred from Google using search phrases containing the whole or part of the name of the firm.

⁸ Website visits from potential customers are defined as click-throughs from search engines that do not match with the IP address of any existing customer.

⁹ Alternatively, it may be because potential customers are less likely to find the products they need from the firm. We believe such an explanation does not apply in our context because the keywords in our study are all specifically related to generic products that (except for prices) are almost homogeneous among suppliers.

Table 3 Conversion Rates

Conversion rates	Purchases from online channel only (%)	Purchases from off-line channel only (%)	All purchases (%)
Potential customers	0.33	0.68	1.02
Returning customers	9.98	34.52	44.50
All customers	3.06	10.22	13.28

To gain a better understanding of the customer purchase behaviors, we divide the customers acquired during the sample period into cohorts along two dimensions. The first dimension is the customer acquisition method, where we divide customers into Google and non-Google customers. Non-Google customers are mainly acquired from word of mouth; only a few are from other search engines such as Yahoo! and MSN. The second dimension is the channel—online and off-line—where customers made their first-time transactions. Table 4 shows the number of customers, the yearly transaction rate,¹⁰ and the average dollar gross margin per transaction in each cohort. Two-thirds of customers made first-time transactions off-line. Their yearly transaction rate and gross margin are significantly higher than customers who made first-time transactions online (0.76 versus 0.58 for transaction rate and \$238 versus \$146 for gross margin, respectively). Customers acquired through Google (67 out of a total of 408) tend to have a higher transaction rate and gross margin than customers acquired from other methods (1.10 versus 0.63 for transaction rate and \$240 versus \$203 for gross margin, respectively). Based on these observations, we consider acquisition methods and first-time transaction channels to be important factors that may explain the variance in the customer long-term profitability in our model. We also investigate some potential dynamics in customer purchase behaviors from data. The only significant finding, based on simple regressions, is that the gross margin of each transaction is positively correlated with the length of time since customers were acquired, implying that customers tend to be more profitable if a longer relationship is maintained.

3. Modeling the Customer Lifetime Value

For the purpose of this study, we focus on modeling the value of the 67 new customers acquired from Google during the sample period, and we compare it with the value of the 341 customers acquired

¹⁰ The yearly transaction rate is calculated by dividing the total number of transactions by the number of years after acquisition. Although the number is subject to a right-censored bias, it is only shown for illustration purposes.

Table 4 Number of Customers, Transaction Rate, and Gross Margin Across Customer Segments

	First-time transaction channel		Total
	Online	Off-line	
Acquired from Google search advertising			
Number of customers	22	45	67
Yearly transaction rate	0.86	1.21	1.10
Average gross margin per transaction (\$)	135.0	291.4	240.1
Acquired from other methods			
Number of customers	105	236	341
Yearly transaction rate	0.52	0.68	0.63
Average gross margin per transaction (\$)	148.2	227.6	203.2

from other channels. We follow the Pareto/NBD model developed in Schmittlein et al. (1987) to model customer lifetime and transaction rate. Conditional on the occurrence of a transaction, we then model the gross margin for each transaction.¹¹ Our model also incorporates observed and unobserved customer heterogeneity in all three processes. Specifically, we assume that at any time there is a time-invariant hazard function that a current customer i terminates his or her relationship with the firm. This probability function is assumed to be exponentially distributed with a hazard rate μ_i . Conditional on being alive, the customer makes transactions according to a time-invariant Poisson process with parameter λ_i .¹² Based on these two assumptions, previous studies (e.g., Schmittlein et al. 1987) show that sufficient statistics for customer lifetime and transaction rate are $\{x_i, t_{ix}, T_i\}$, which represent the number of repeated transactions (there are altogether $x_i + 1$ observed transactions for each individual i , including the first-time transaction), the time of the last transaction and the total length of observation period,

¹¹ In this study, we choose to use the gross margin per transaction instead of dollar purchase amount in the estimation. The main reason is that, from the firm's perspective, it is more important to understand the profitability per transaction that is better captured by the gross margin.

¹² To test whether the time-invariant hazard rate and transaction rate assumptions are reasonable, we estimate two alternative models. The first model uses a more flexible Weibull distribution assumption for customer lifetime, in which the hazard rate depends on the length of a customer's relationship with the firm. The second model assumes a nonhomogeneous Poisson process for the transaction process, in which the transaction rate depends on the length of time since a customer's last transaction. Model performance measured by either marginal likelihoods (Chib 1995) or Bayes factors favors our proposed model over the alternative models. Detailed estimation and model comparison results of the alternative models are available from the authors upon request.

respectively. Fader and Hardie (2005a) derive the likelihood for $\{x_i, t_{ix}, T_i\}$ as

$$L(\mu_i, \lambda_i | x_i, t_{ix}, T_i) = \frac{\lambda_i^{x_i} \mu_i}{\lambda_i + \mu_i} e^{-(\lambda_i + \mu_i)t_{ix}} + \frac{\lambda_i^{x_i+1}}{\lambda_i + \mu_i} e^{-(\lambda_i + \mu_i)T_i}. \quad (1)$$

The main difference between modeling the customer gross margin and customer lifetime and transaction rate is that we allow for dynamic changes in the former process. We utilize the panel data structure and develop a random effect linear model as

$$\ln z_{ij} = b_i + \beta \cdot \ln(d_{ij}) + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2), \quad (2)$$

where z_{ij} is the gross margin for the j th transaction conditional on the customer being alive, b_i the customer-specific random effect, and d_{ij} the length of time from customer i 's acquisition to his or her j th transaction with the firm. The coefficient β captures the dynamics in customer purchase behavior we discussed before: we expect that customers tend to purchase larger quantities the longer they have been in business with the firm. Finally, ε_{ij} is the idiosyncratic error term that is assumed to be normally distributed.

Let individual parameters $\theta_i \equiv (\ln \mu_i \ln \lambda_i b_i)'$ represent the customer heterogeneity in the three processes. We model the parameters as jointly determined by a vector of covariates X_i as follows:

$$\theta_i = G'X_i + \xi_i, \quad \xi_i \sim N(0, \Sigma), \quad (3)$$

where G is a matrix of parameters and

$$\Sigma = \begin{pmatrix} \sigma_\mu^2 & \sigma_{\mu\lambda} & \sigma_{\mu b} \\ \sigma_{\lambda\mu} & \sigma_\lambda^2 & \sigma_{\lambda b} \\ \sigma_{b\mu} & \sigma_{b\lambda} & \sigma_b^2 \end{pmatrix}$$

is the variance-covariance matrix capturing the interdependence among customer lifetime, transaction rate, and gross margin. The covariates X_i include the following four dummy variables: *google* (which equals 1 if the customer is acquired through Google search advertising), *online* (which equals 1 if the customer's first-time transaction is made from the online channel), *research* (which equals 1 if the customer is from a research organization), and *late-period* (which equals 1 if the customer is acquired after 2006). We include the last variable to investigate whether or not the customer value in the later period, during which our focal firm faced more intense competition for Google search keywords such that new customers might be more difficult to acquire, is systematically different from that in the early period. Abe (2009) used a similar model but only considers customer lifetime and transaction rate. By explicitly allowing gross margin to be dynamically changing over time, and a full correlation between customer lifetime, transaction rate,

and gross margin, our model can be viewed as an extension of the standard CLV models.

The model is estimated using the MCMC method. We run 50,000 iterations with the first 10,000 iterations as burn-ins, and the last 40,000 iterations are used to summarize the posterior distribution for parameters. The convergence is monitored visually and also tested formally using the Gelman and Rubin (1992) method. Details of the estimation are described in the electronic companion, available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

3.1. Calculating CLV

The expected CLV can be calculated directly from the estimate of individual customer parameters θ_i . Let r (we use 0.0043) be the continuous discount rate,¹³ and let S be the length of time in the calculation of the customer value, where $S = +\infty$ is typically assumed in the literature. We normalize the time when the customer is acquired to 0. Let the discounted customer value till the projected period S be $CV_i(S)$. Also, let the discounted total value of (observed) transactions, from the time the customer was acquired to time T_i within the sample period, be V_{i0} .¹⁴

$$V_{i0} = \sum_{j=0}^{x_i} z_{ij} e^{-r \cdot d_{ij}}, \quad (4)$$

where x_i is the total number of repeat transactions of customer i , z_{ij} is the gross margin of transaction j , and d_{ij} is the duration of customer i 's relationship with the firm (since the time of being acquired) by the time of transaction j . The first-time transaction is represented by $j = 0$, and $d_{i0} = 0$ in Equation (4). Let the customer value at any future time point $T_i + s$ be $v_i(T_i + s)$, which we can project using our model estimates. We have

$$CV_i(S) = V_{i0} + \int_0^{S-T_i} E[v_i(T_i + s)] ds. \quad (5)$$

Denote the time when a customer terminates the relationship with the firm as τ_i . We can derive the following expression:

$$v_i(T_i + s) = P(\tau_i > T_i + s) \cdot \gamma_i(T_i + s) \cdot z_{i, T_i + s} \cdot e^{-r \cdot (T_i + s)}. \quad (6)$$

That is, $v_i(T_i + s)$ is a product of $P(\tau_i > T_i + s)$, the probability that the customer is still alive at $T_i + s$; $\gamma_i(T_i + s)$, the transaction rate or probability of transaction; $z_{i, T_i + s}$, the gross margin; and finally, $e^{-r \cdot (T_i + s)}$, the discount factor.

¹³ This continuous time discount rate is equal to a 20% annual discount rate. We choose a high discount rate based on consulting with the firm owner and also to partially account for the uncertainty of competition in the future. Results are qualitatively very similar when we use a 15% discount rate.

¹⁴ Note that V_{i0} can be directly calculated from the data.

Similar to standard CLV models in previous studies, customer lifetime probability derived from our model has a “memoryless” property; i.e., $P(\tau_i > T_i + s) = P(\tau_i > T_i) e^{-\mu_i \cdot s}$. Also, the probability of transaction at any time is fixed at the transaction rate λ_i ; therefore $\gamma_i(T_i + s) = \lambda_i$ in the Equation (6). By plugging in the equation for $z_{i, T_i + s}$ and integrating out the stochastic component ε , we have

$$E[v_i(T_i + s)] = P(\tau_i > T_i) e^{-\mu_i \cdot s} \lambda_i \cdot e^{b_i + \beta \cdot \ln(T_i + s) + \sigma_\varepsilon^2 / 2} e^{-r \cdot (T_i + s)}. \quad (7)$$

Given the observation $y_i = (x_i, t_{ix}, T_i)$, the probability the customer remains to be active with the firm after the observed tenure length T_i in data, $P(\tau_i > T_i)$, is derived in Schmittlein et al. (1987):

$$P(\tau_i > T_i | x_i, t_{ix}, T_i) = \frac{1}{1 + (\mu_i / (\mu_i + \lambda_i)) [e^{(\mu_i + \lambda_i)(T_i - t_{ix})} - 1]}. \quad (8)$$

Finally, we integrate out the CLV for customer i from T_i to the end period S as follows:

$$\int_0^{S-T_i} E[v_i(T_i + s)] ds = \frac{\lambda_i e^{b_i + \sigma_\varepsilon^2 / 2} e^{\mu_i T_i}}{1 + (\mu_i / (\mu_i + \lambda_i)) [e^{(\mu_i + \lambda_i)(T_i - t_{ix})} - 1]} \cdot \frac{\Gamma(\beta + 1)}{(\mu_i + r)^{\beta + 1}} \left[F_\gamma \left(S; \beta + 1, \frac{1}{\mu_i + r} \right) - F_\gamma \left(T_i; \beta + 1, \frac{1}{\mu_i + r} \right) \right], \quad (9)$$

where F_γ is the cumulative distribution function of the gamma distribution. This closed-form expression is different from the previous literature (e.g., Schmittlein et al. 1987) because we have incorporated the dynamics in the model of gross margin.

We use our MCMC iterations in model estimation to compute the expected CLV: we take the values of the last 10,000 iterations¹⁵ and compute the CLV in each iteration for each customer based on the estimates of θ_i and $(\beta, \sigma_\varepsilon^2)$.

4. Results

4.1. Model Estimates

We summarize the estimation results in Table 5. We find that customers acquired from Google have a significantly higher transaction rate than customers acquired from other methods. One possible reason is that Google acquired customers are more likely to be larger organizations, whereas the non-Google customers (mostly acquired through word of mouth) are more likely to be small firms serving the local

¹⁵ To save computational time and storage memory, we use the last 10,000 draws instead of the entire 40,000 draws, which are used to summarize the posteriors of model estimates.

Table 5 Parameter Estimates for the Customer Lifetime Value Model

	Customer lifetime $\ln \mu_i$	Transaction rate $\ln \lambda_i$	Gross margin b_i
<i>Intercept</i>	-5.92* (-7.23, -4.97)	-4.44* (-4.89, -3.98)	4.60* (4.28, 4.91)
<i>Google</i>	-0.11 (-1.66, 1.32)	0.51* (0.08, 0.95)	0.14 (-0.14, 0.42)
<i>Online</i>	-0.15 (-1.63, 1.25)	-0.44* (-0.85, -0.05)	-0.25* (-0.48, -0.01)
<i>Research</i>	-0.73 (-2.14, 0.48)	-0.58* (-0.89, -0.26)	-0.32* (-0.57, -0.05)
<i>Late-period</i>	-0.54 (-1.95, 0.74)	-0.30 (-0.65, 0.04)	-0.04 (-0.25, 0.17)
$\ln d$	—	—	0.038* (0.002, 0.074)
σ_ε^2	—	—	0.66 (0.51, 0.86)
Variance-covariance parameters:			
$\begin{bmatrix} \sigma_\mu^2 & & \\ \sigma_{\mu\lambda} & \sigma_\lambda^2 & \\ \sigma_{\mu\beta} & \sigma_{\lambda\beta} & \sigma_\beta^2 \end{bmatrix}$	1.51 (0.59, 2.86)	1.34 (1.00, 1.70)	0.67 (0.52, 0.83)
	-0.05 (-0.81, 0.69)	0.23* (0.04, 0.42)	
	0.21 (-0.47, 0.79)		
Log-marginal likelihood	-3,305.38		

Note. Numbers in parentheses indicate the 2.5 and 97.5 percentiles.

*Indicates significance at 5% level.

or regional market. Customers who used the online channel for the first-time transaction have a significantly lower transaction rate and gross margin than customers who used the off-line channel for the first-time transaction. We also find that research-type customers tend to have a lower transaction rate and gross margin than commercial-type customers. The coefficient for *late-period* is not statistically significant in any of the three processes, suggesting that there is no systematic difference between the customers acquired before 2006 and those acquired after that.¹⁶ Finally, the significantly positive coefficient for $\ln(d_{ij})$ implies that customers tend to increase the purchase quantity with the length of tenure, perhaps because of their increased trust in the firm.

The last three rows in Table 5 are estimates for the variance-covariance matrix. The correlation between the stochastic components in customer lifetime and transaction rate is insignificant, which is consistent with the independence assumption made in Schmittlein et al. (1987) and the result in Abe (2009). However, we find that the correlation between transaction rate and gross margin is positive and significant, indicating that in our data high-valued customers who purchase more frequently also tend to buy more each time. We also estimated an alternative model assuming no correlation between the gross margin and the other two processes. The log marginal likelihood of the integrated model is -3,305.38 compared with the alternative model at -3,307.42. The Bayes factor calculated from these two likelihoods is 7.69, implying that our model is moderately favored over the latter in terms of data fit (Jeffreys 1961).

To further check the goodness of fit of our model, we plot diagnostic graphs for cumulative number of repeated transactions and cumulative gross margin in Figures 1 and 2. We use each individual's posterior distribution of θ_i to project his or her future transactions after acquisition, and we compare with the actual transaction data to check the model fit. Other than the 44 months of data we used as a calibration sample for model estimation, we also use an additional 28 months out-sample data for validation test. Similar plots for model diagnostics are used in Fader and Hardie (2005b) and Abe (2009). We split customers into two cohorts: customers acquired from Google search advertising and from other methods. Figure 1 compares the model fit of the cumulative number of repeated transactions, and Figure 2 compares the model fit of the cumulative margin of repeat transactions across these two customer cohorts. In both figures, the solid line represents the actual data, the dashed line represents the mean model prediction, and the dotted line represents the 95% confidence intervals of the model prediction. Both figures suggest that our model predictions fit with data reasonably well in both in-sample (before August 2007) and out-sample (after August 2007) periods.

We also plot the time-tracking graphs for the monthly number of repeated transactions and gross margin for in- and out-sample periods on a per-customer basis in Figures 3 and 4. Because the estimation of the customer lifetime value and transaction rate is based on the cumulative numbers rather than the monthly numbers, and because of demand fluctuations that may be due to seasonality, the fit between model predictions and the actual data is expected to be worse than that of the cumulative plots. However, our model still captures the trends of repeated transactions and gross margin in the two

¹⁶ Higher competition for Google search advertising in the later period may have a more significant impact on the acquisition rate, which is not modeled in this paper.

Figure 1 Time-Series Tracking Plot for the Cumulative Number of Repeated Transactions

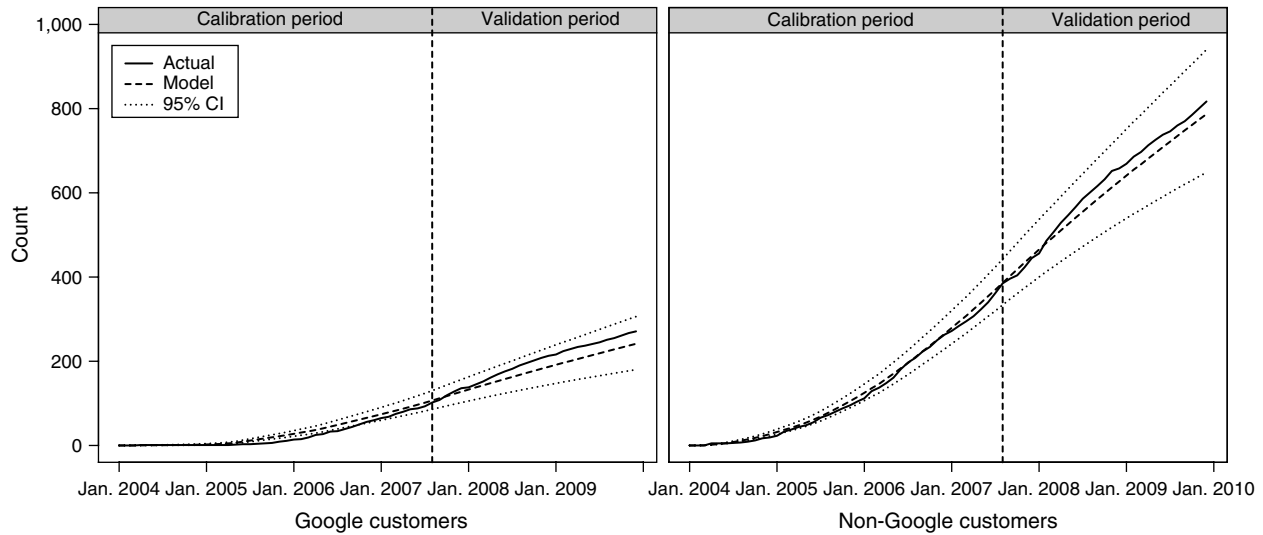
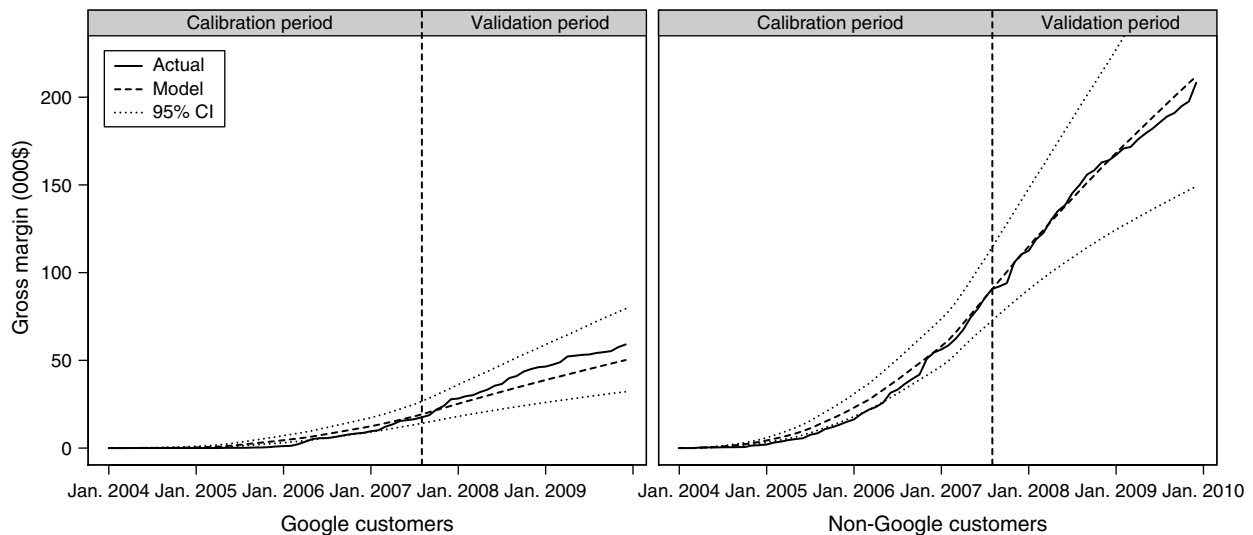


Figure 2 Time-Series Tracking Plot for the Cumulative Gross Margin of Repeated Transactions



figures. Note that the decline of repeated transactions and gross margin in out-sample periods is due to customer dropouts, as customers acquired after August 2007 are not accounted for in this exercise. Both model predictions and actual data suggest that, on a per-customer basis, Google-acquired customers make more repeated transactions and also generate higher gross margins than customers acquired from other methods.

Table 6 presents sample fit statistics at the disaggregate and aggregate levels for the number of repeated transactions and gross margin amount. These statistics have also been used in the previous literature to check the model fit (see Abe 2009, for example). The correlation between predicted and actual transactions across individual customers is used for the disaggregate measure of sample fit. For the calibration

sample, the correlation is high at 0.92 for the number of repeated transactions and 0.86 for the gross margin. The correlations are also reasonably high for the validation sample. We also use time-series mean absolute

Table 6 Model Fit Statistics

	Number of transactions	Gross margin of transactions
Disaggregate measure: Correlation		
Calibration period	0.92	0.86
Validation period	0.73	0.58
Total period	0.88	0.73
Aggregate measure: Time-series MAPE		
Calibration period (%)	21.2	62.8
Validation period (%)	2.8	2.2
Total period (%)	13.7	37.2

Figure 3 Time-Series Tracking Plot for the Average Monthly Number of Repeated Transactions per Customer

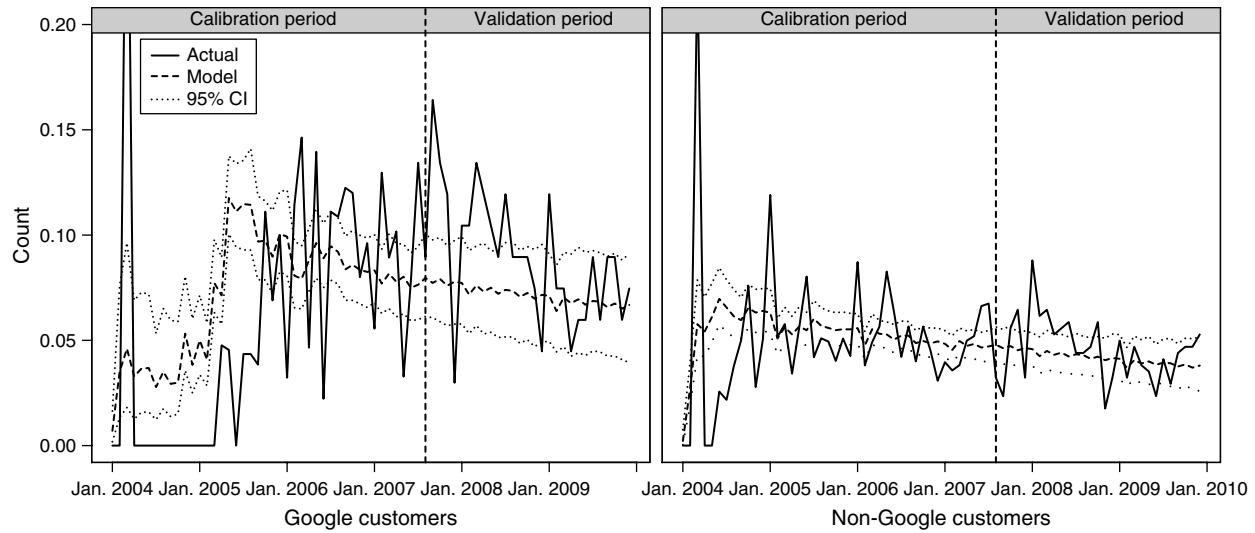
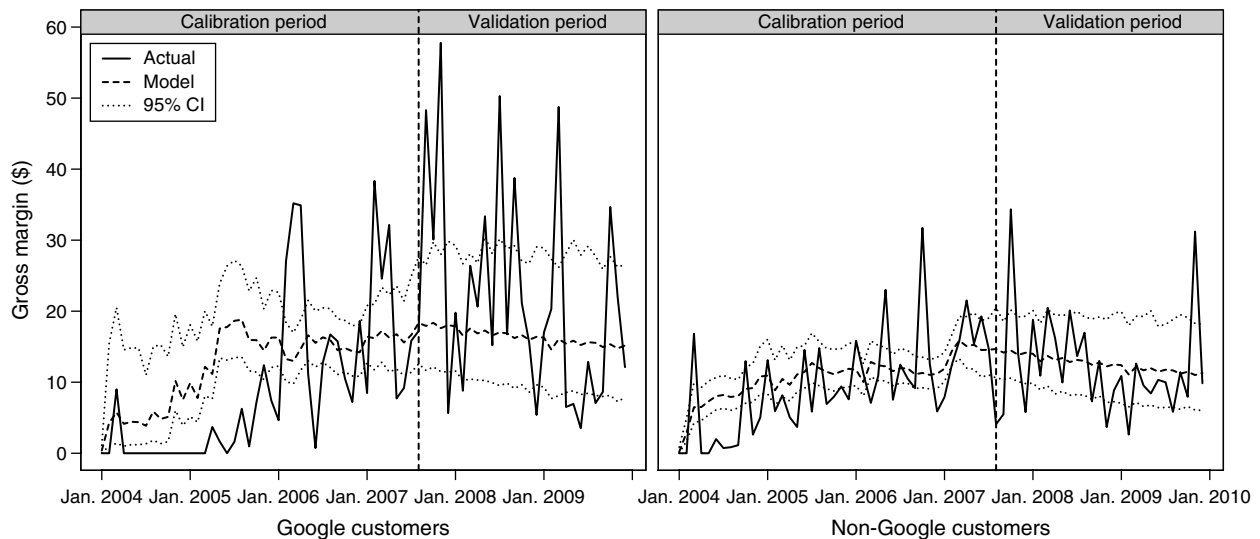


Figure 4 Time-Series Tracking Plot for the Average Monthly Gross Margin of Repeated Transactions per Customer



percentage errors (MAPE) to check the sample fit at the aggregate level. The measure for either repeated transactions or gross margin amount in the validation period is smaller than that in the calibration period. This is because we have few observations in the very early period; hence the prediction errors are larger in the earlier periods than in later periods (see the mismatch of predictions and observed data on the left side of Figures 3 and 4).

4.2. Customer Lifetime Value

Based on estimates θ_i , we can simulate CLV for every customer using Equations (5) and (9). Table 7 presents the median and mean CLV with 95% confidence intervals for customers classified by acquisition method (Google versus non-Google) and first-time transaction channels (online versus off-line). Customers acquired

from Google on average have a higher lifetime value (mean CLV at \$1,002) than customers acquired from other channels (mean CLV at \$808). The difference is even larger for those whose first-time purchase

Table 7 Median and Mean of Projected CLV Across Customer Cohorts (In Dollars)

	First-time transaction channel		
	Online	Off-line	Total
Google	229, 543 (129, 290) (396, 799)	419, 1,226 (257, 523) (825, 2,026)	325, 1,002 (209, 406) (705, 1,568)
Non-Google	157, 470 (99, 213) (356, 623)	279, 959 (197, 304) (689, 1,386)	226, 808 (168, 264) (600, 1,115)

Note. Numbers separated by commas are median and mean estimates of CLV; numbers in parentheses indicate the 2.5 and 97.5 percentiles, respectively.

Table 8 Projected Future Transactions for a Newly Acquired Customer

	Year 1	Year 2	Year 5	Year 10
Probability of being alive at the end of the period				
Google	0.79 (0.52, 0.97)	0.67 (0.35, 0.95)	0.49 (0.15, 0.88)	0.35 (0.06, 0.80)
Non-Google	0.78 (0.63, 0.93)	0.66 (0.46, 0.87)	0.46 (0.24, 0.75)	0.31 (0.10, 0.62)
Expected number of repeat transactions				
Google	1.83 (0.98, 3.08)	1.51 (0.75, 2.61)	1.06 (0.35, 2.08)	0.74 (0.14, 1.71)
Non-Google	1.08 (0.69, 1.61)	0.89 (0.57, 1.35)	0.61 (0.32, 1.05)	0.41 (0.14, 0.82)
Expected gross margin from repeat transactions (\$)				
Google	562 (248, 1,113)	475 (187, 979)	336 (82, 772)	236 (31, 632)
Non-Google	289 (158, 499)	244 (128, 432)	169 (67, 343)	113 (29, 277)

Note. These values are calculated for a “typical” customer who is a commercial customer acquired in the first two years and who used the off-line channel for his or her first-time transaction with the firm; numbers in parentheses indicate the 2.5 and 97.5 percentiles.

was off-line (mean CLV at \$1,226 versus \$959, respectively), implying that the customer value would be underestimated had we only focused on online transactions. Finally, we notice that the mean CLV is always much larger than the median, implying that the distribution of CLV is right-skewed, which is consistent with observations in many industries.

To understand the implications of the coefficients for *google* in Table 5, we assume a typical commercial-type customer who was acquired before 2006 from Google search advertising (Google customer) and made her first-time transaction off-line. We simulate her transactions for 10 years in the future¹⁷ and compare the result with another typical commercial-type customer acquired before 2006 through other methods and made first-time transaction off-line (non-Google customer). The comparison is made along the following three dimensions: probability of being “alive,” expected number of repeat transactions, and the expected gross margin of transactions, in each year. The result is summarized in Table 8. For illustration, the expected transaction rate and gross margin are not conditional on being alive; hence both measurements decline over time. In the first year, the probability of being alive is approximately 80% for both. But the Google customer purchases about 1.8 times, whereas the non-Google customer purchases only once. As a result, the expected gross margin in the first year for the Google customer is 94% higher than the non-Google customer. The probability of remaining as a customer decreases over time. In the 10th year, our model predicts the probabilities of being alive for the two segments are 35% and 31%. The projected gross margin of the Google customer is approximately 108% higher than the non-Google customer.

¹⁷ We utilize the last 10,000 MCMC draws in the model estimation to simulate future transactions. Results in Table 7 are based on the posterior means from those draws.

Table 9 Decomposition of the Google Value

	Expected customer lifetime value	
	Gross margin (\$)	% Increase
Non-Google	1,126 (597, 1,989)	—
Google—Lifetime	1,150 (471, 2,162)	2 (–43, 59)
Google—Transaction rate	1,919 (871, 3,759)	70 (7, 156)
Google—Gross margin	1,300 (651, 2,400)	15 (–13, 52)
Interaction effect	—	11 (–43, 75)
Google	2,227 (853, 4,609)	98 (2, 230)

Note. These values are calculated for a “typical” customer who is a commercial customer acquired in the first two years and who used the off-line channel for his or her first-time transaction with the firm; numbers in parentheses indicate the 2.5 and 97.5 percentiles.

Based on the simulation result, we project the difference in CLV between the above Google customer and non-Google customer to be \$1,101.¹⁸ We further explore the factors driving this Google value by decomposing such incremental value into four parts, the added value resulting from (1) a longer lifetime, (2) a higher transaction rate, (3) an increased gross margin, and (4) the interaction between the above three effects (e.g., a higher transaction rate from the Google customer leads to a larger gross margin). To calculate the first effect, we assume a “Google-lifetime” condition in which only the parameter value of μ for a hypothetical customer is the same as the Google customer, whereas the value of other parameters remain the same as the non-Google customer. We calculate the second and the third effects using a similar method. The last effect is calculated by subtracting the sum of the first three effects from the difference in CLV between the Google and non-Google customers (\$1,101). Table 9 reports the results. The majority of the Google value comes from a higher

¹⁸ In this analysis we use the posterior parameter estimates for a commercial customer. As commercial customers tend to have larger values than research customers, the number reported here is also larger than the pooled mean reported in Table 7.

Table 10 Expected VCA Calculations

VCA and breakeven CPC (\$)	Online transactions only			Transactions from online and off-line channels		
	Total VCA	Average VCA	Breakeven CPC	Total VCA	Average VCA	Breakeven CPC
One-time transaction	-1,045	-48	0.37	9,838	147	2.02
CLV	8,462	385	1.79	63,618	950	10.22
	(5,220, 14,099)	(237, 641)	(1.31, 2.64)	(43,742, 101,584)	(653, 1,516)	(7.19, 16.00)

Notes. Numbers in parentheses indicate the 2.5 and 97.5 percentiles. Because the one-time transaction value is directly summarized over observed data, the corresponding estimates do not have confidence intervals.

transaction rate (70%). The longer lifetime contributes 2%, the larger gross margin contributes another 15%, and the remaining 11% comes from the interaction.

4.3. Value of Customer Acquisition from Google Search Advertising

Under the assumptions that we will further discuss, we can now compute the value of customer acquisition (VCA) as the difference between the CLV and the overall search advertising cost incurred by the company. The advertising cost can be divided into the acquisition cost, which is the cost incurred by acquiring a new customer through Google, and the retention cost, which in our empirical context is the cost incurred by future click-throughs from customers after acquisition. The latter cost is negligible in our data: after matching the transaction records of existing customers with Google referrals, we find that the average click-throughs per transaction for customers acquired from Google in their subsequent transactions is 2.2. As the average CPC is \$0.53, this implies an average retention cost of \$1.2 per future transaction compared with the per-transaction gross margin of \$200.¹⁹ Thus, in the VCA calculation we only consider the acquisition cost. This is calculated as the average CPC divided by the acquisition rate among potential customers, which is 1.02% including both online and off-line purchases in our data (see Table 3).

To address the concern of increasing CPC faced by the owner of the firm, we calculate the corresponding profit breakeven CPC for each of the above scenarios. Using the conventional method, the breakeven CPC is only \$0.37, far lower than the CPC at \$0.80 in the last year of the data. However, when we account for both the cross-channel spillover effect and the long-term effect, the breakeven CPC would increase to \$10.22. The two estimates offer very different policy implications. In contrast to the conventional method, our results imply that investing in Google search advertising has been very profitable to the firm, which the owner of the firm seems to agree. He clearly stated that he would continue his aggressive bidding

for search keywords at Google despite the increasing costs and the economic downturn.

One implicit assumption in our calculation is that customers acquired from Google would not be acquired from other channels if the firm did not invest in Google search advertising. We think this assumption may not be unreasonable because of several observations from the data. First, the firm has only spent a small amount on other marketing promotions and traditionally relied on word of mouth. Google advertising is likely to help the firm reach very different customers. For example, we find from data that the proportion of research-type customers relative to commercial-type acquired from Google is significantly higher than that from other methods (70% versus 45%, respectively). Second, potential customers are unlikely to find the firm's website from organic search results, as we find that its website is consistently placed beyond 20 Google organic search result pages for all the keywords it bid. This implies that any substitution between sponsored search advertising and organic results is negligible. Finally, we find from data that the number of customers generated from other methods has been increasing every year, implying that search advertising may not have cannibalized customer acquisition from other methods. Even if this assumption is incorrect and we have overestimated the true VCA, we believe our policy evaluations will remain valid based on the high estimates presented previously.

5. Conclusions, Limitations, and Future Research

We argue in this paper that the conventional method of measuring the profit impact of search advertising in the industry may be seriously biased for two reasons. First, by focusing only on online transactions, we ignore the potential cross-channel sales spillover from search advertising to off-line channels. Second, the long-term profit impact of new customers has not been considered. Our goal in this study is to develop an empirical method to estimate the value of customers acquired from search advertising by explicitly accounting for these two factors.

¹⁹ This implies that the cost of "reacquiring" existing customers at Google is very small, at least in our empirical context.

To estimate the customer lifetime value, we merge three data sources, all available to advertisers in different industries, to construct customer panel data tracking the online browsing history as well as repeat purchases from both online and off-line channels. We develop an integrated model of customer lifetime, transaction rate, and gross margin. Our model incorporates consumer heterogeneity and allows for a full correlation among the three processes. Based on our model estimates, we find that the firm would incur a loss of \$48 on average to acquire a new customer if using the conventional method. After we account for sales spillovers across channels and the long-term effect, the estimated VCA is as high as \$950 per customer. The increase in CPC in recent years should not prevent the firm from investing in Google search advertising.

There are several limitations in our illustration. First, the time-invariant hazard rate and transaction rate assumptions in the model may not hold in other empirical contexts. We urge researchers to test these assumptions as the first step, as we have done in this study. Second, the data-matching process we describe in this paper may need adjustment when applied to a business-to-consumer context, where each individual consumer may have multiple computers, and multiple individuals may share the same ISP. Third, our study is based on data from a small firm in a specific industry. The results may not be generalized to other firms or industries, where the extent of competition for search advertising is different. Also, the competition in search keywords in this industry may not yet be in equilibrium, as evidenced by the increasing CPC in the sample period. The estimated high value of customers acquired from Google may decrease over time because of the increased future competition.

Our research opens doors to future research in several directions. First, should the firm increase its spending to always occupy the highest ranking at sponsored links? Given the data limitation, we are unable to provide guidance on the optimal level of investment. A field experiment may be required to establish the causal relationship between search advertising ranking and the generated revenue. Future studies may also compare the customer value in different advertising channels (e.g., banner ads versus sponsored search ads). It is also worthwhile to explore how customers make channel choice in subsequent transactions. Finally, we would like to apply our model to other empirical contexts where the data are rich enough that we can estimate the VCA and break even CPC at the individual keyword level. This will provide useful guidelines for firm's bidding strategy in what and how much to bid.

6. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

Acknowledgments

This paper is part of the second author's dissertation work. The authors gratefully acknowledge support from the Boeing Center of Technology, Information, and Manufacturing; and the Center for Research in Economics and Strategy, Olin Business School, Washington University in St. Louis.

References

- Abe, M. 2009. "Counting your customers" one by one: A hierarchical Bayes extension to the Pareto/NBD model. *Marketing Sci.* 28(3) 541–553.
- Ansari, A., C. F. Mela, S. A. Neslin. 2008. Customer channel migration. *J. Marketing Res.* 45(1) 60–76.
- Biyalogorsky, E., P. Naik. 2003. Clicks and mortar: The effect of online activities on off-line sales. *Marketing Lett.* 14(1) 21–32.
- Chan, T. Y., Y. Park. 2010. Position competition in sponsored search advertising. Working paper, Washington University in St. Louis, St. Louis.
- Chib, S. 1995. Marginal likelihood from the Gibbs output. *J. Amer. Statist. Assoc.* 90(432) 1313–1321.
- Deleersnyder, B., I. Geyskens, K. Gielens, M. G. Dekimpe. 2002. How cannibalistic is the Internet channel? A study of the newspaper industry in the United Kingdom and the Netherlands. *Internat. J. Res. Marketing* 19(4) 337–348.
- Donkers, B., P. C. Verhoef, M. G. de Jong. 2007. Modeling CLV: A test of competing models in the insurance industry. *Quant. Marketing Econom.* 5(2) 163–190.
- Edelman, B., M. Ostrovsky, M. Schwarz. 2007. Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords. *Amer. Econom. Rev.* 97(1) 242–259.
- Elgin, B., R. D. Hof. 2005. Keywords for ad buyers: Pay. *Business Week* (February 21), http://www.businessweek.com/magazine/content/05_08/b3921042_mz011.htm.
- Fader, P. S., B. G. S. Hardie. 2005a. A note on deriving the Pareto/NBD model and related expressions. <http://www.brucehardie.com/notes/009>.
- Fader, P. S., B. G. S. Hardie. 2005b. A note on implementing the Pareto/NBD model in MATLAB. <http://www.brucehardie.com/notes/008>.
- Fader, P. S., B. G. S. Hardie, K. L. Lee. 2005a. "Counting your customers" the easy way: An alternative to the Pareto/NBD model. *Marketing Sci.* 24(2) 275–284.
- Fader, P. S., B. G. S. Hardie, K. L. Lee. 2005b. RFM and CLV: Using iso-value curves for customer base analysis. *J. Marketing Res.* 42(4) 415–430.
- Gelman, A., D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences (with discussion). *Statist. Sci.* 7(4) 457–472.
- Glady, N., B. Baesens, C. Croux. 2009. A modified Pareto/NBD approach for predicting customer lifetime value. *Expert Systems Appl.* 36(2) 2062–2071.
- Ghose, A., S. Yang. 2009. An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Sci.* 55(10) 1605–1622.
- Greene, J. 2008. Inside Microsoft's war against Google. *Business Week* (May 8), http://www.businessweek.com/magazine/content/08_20/b4084036492860.htm.
- Jeffreys, H. 1961. *The Theory of Probability*, 3rd ed. Oxford University Press, New York.

- Katona, Z., M. Sarvary. 2010. The race for sponsored links: Bidding patterns for search advertising. *Marketing Sci.* **29**(2) 199–215.
- Performics. 2007. DoubleClick Performics 50 search trend report Q4 2006. Press release (March 21), <http://www.performics.com/news-room/press-releases/doubleclick-performics-50-search-trend/411>.
- Reinartz, W. J., V. Kumar. 2000. On the profitability of long-life customers in a noncontractual settings: An empirical investigation and implications for marketing. *J. Marketing* **64**(4) 17–35.
- Rust, R. T., T. Ambler, G. S. Carpenter, V. Kumar, R. K. Srivastava. 2004. Measuring marketing productivity: Current knowledge and future directions. *J. Marketing* **68**(4) 76–89.
- Rutz, O. J., R. E. Bucklin. 2011. From generic to branded: A model of spillover dynamics in paid search advertising. *J. Marketing Res.* **48**(1) 87–102.
- Ryan, K. M. 2006. Search's role in the buying cycle. *iMedia Connection* (March 29), <http://www.imediaconnection.com/printpage/printpage.aspx?id=8850>.
- Schmittlein, D. C., R. A. Peterson. 1994. Customer base analysis: An industrial purchase process application. *Marketing Sci.* **13**(1) 41–67.
- Schmittlein, D. C., D. G. Morrison, R. Colombo. 1987. Counting your customers: Who are they and what will they do next? *Management Sci.* **33**(1) 1–24.
- Singh, S. S., S. Borle, D. C. Jain. 2009. A generalized framework for estimating customer lifetime value when customer lifetimes are not observed. *Quant. Marketing Econom.* **7**(2) 181–205.
- Venkatesan, R., V. Kumar, T. Bohling. 2007. Optimal customer relationship management using Bayesian decision theory: An application for customer selection. *J. Marketing Res.* **44**(4) 579–594.
- Verhoef, P. C., B. Donkers. 2005. The effect of acquisition channels on customer loyalty and cross-buying. *J. Interactive Marketing* **19**(2) 31–43.
- Yao, S., C. F. Mela. 2009. A dynamic model of sponsored search advertising. *Marketing Sci.* **30**(4) 702–716.