Referral Programs and Customer Value

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Abstract

Referral programs have become a popular way to acquire customers. Yet, there is no evidence to date that customers acquired through such programs, referred customers for short, are more valuable than other customers. We address this gap and investigate to what extent referred customers are more profitable and more loyal. Tracking approximately 10,000 customers of a leading German bank for almost three years, we find that referred customers (i) have a higher contribution margin, though this difference erodes over time, (ii) have a higher retention rate, and this difference persists over time, and (iii) are more valuable both in the short and long run. The average value of a referred customer is at least 16% higher than that of a non-referred customer with similar demographics and time of acquisition. However, the size of the value differential varies across customer segments; therefore, firms should use a selective approach for their referral programs.

Keywords: Customer referral programs, customer loyalty, customer value, customer management, word of mouth, social networks.

INTRODUCTION

Word of mouth (WOM) has re-emerged as an important marketing phenomenon, and its use as a customer acquisition method has started to attract renewed interest (e.g., Godes and Mayzlin 2009; Iyengar, Van den Bulte, and Valente 2010). Traditionally, WOM's appeal has lied in the belief that it is cheaper than other acquisition methods. A few recent studies document that customers acquired through WOM also tend to churn less than customers acquired through traditional channels, and that they tend to bring in additional customers for the firm through their own WOM (Choi 2009; Trusov, Bucklin, and Pauwels 2009; Villanueva, Yoo, and Hanssens 2008). One study further suggests that customers acquired through WOM may generate more revenue for the firm than customers acquired through traditional marketing efforts (Villanueva, Yoo, and Hanssens 2008).

From a managerial point of view, these findings are encouraging and suggest purposely stimulating WOM to acquire more customers. However, there are concerns that WOM stimulated by the firm may be substantially less effective than organic WOM in generating valuable customers (Trusov, Bucklin, and Pauwels 2009; Van den Bulte 2010): (i) targeted prospects may be suspicious of stimulated WOM efforts; (ii) such efforts often involve a monetary reward for the referrer who as a result may seem less trustworthy; (iii) programs providing economic benefits tend not to be very sustainable (Lewis 2006); (iv) unlike organic WOM, stimulated WOM is not free, raising questions about cost-effectiveness; and (v) stimulated WOM is prone to abuse by opportunistic referrers.

The uncertainty about the benefits of stimulated WOM in customer acquisition is frustrating for managers facing demands to increase their marketing ROI and wondering whether or not to use this method. Our study addresses this managerial issue by investigating the value of customers acquired through stimulated WOM and comparing it with the value of customers acquired through other methods. We do so in the context of a specific WOM marketing practice that is gaining prominence: referral programs in which the firm rewards existing customers for bringing in new customers. Whereas such programs are generally seen as an attractive way to acquire customers, their benefits are typically considered to be their targetability and cost effectiveness (Mummert 2000). We broaden this view by assessing the value of customers acquired through such a program.

Specifically, we answer four questions. (i) Are customers acquired through a referral program more valuable than other customers? (ii) Is the difference in customer value large enough to cover the costs of such stimulated WOM customer acquisition efforts? (iii) Are customers acquired through a referral program more valuable because they generate higher margins, exhibit higher retention, or both? (iv) Do differences in margins and retention remain stable or do they erode? The answers to the last two questions provide a deeper insight into what might be driving the value differential.

We answer those four questions using panel data on all 5,181 customers that a leading German bank acquired through its referral program (referred customers) between January and December 2006 and a random sample of 4,633 customers the same bank acquired through other methods (non-referred customers) over the same period. For both groups of customers, we track profitability (measured as contribution margin) and loyalty (measured as retention) at the individual level from the date of acquisition until September 2008. The total observation period spans 33 months. We use two metrics of customer value: (i) the present value of the actually observed contribution margins realized within the data window, and (ii) the expected present value over a period of six years from the day of acquisition. Though our study is limited to a single research site as is common for studies requiring rich and confidential data, the methodology and findings are of wide interest. Customer referral programs are gaining popularity in many industries, including financial services, hotels, automobiles, newspapers and contact lenses (Ryu and Feick 2007).

We make the following contributions: First, we provide the first empirical evidence that a referral program, a form of stimulated WOM, is an attractive way to acquire customers. Referred customers exhibit a higher contribution margin, retention, and customer value. Second, based on our finding that differences in contribution margin erode over time whereas those in retention do not, we document that referred customers are more valuable in *both* the short and long run. Third, we show that the referral effect need not be present in every customer segment. Finally, we illustrate how the type of analysis we conduct allows firms to calculate the Return-on-Investment and the upper bound for the reward in their customer referral programs.

We proceed by offering a description of referral programs and developing our hypotheses. A description of the research setting, the data, and the model specifications follows. Then, we report the results. Finally, we discuss implications for practice, limitations, and future research opportunities.

CUSTOMER REFERRAL PROGRAMS

Customer referral programs are a form of stimulated WOM that provide incentives to existing customers to bring in new customers. An important requirement for such programs is that individual purchase or service histories are available so the firm can ascertain if a referred customer is indeed a new rather than existing or former customer.

Referral programs have three distinctive characteristics. First, they are deliberately initiated, actively managed, and continuously controlled by the firm, which is impossible or very difficult with organic WOM activities like spontaneous customer conversations and blogs. Second, the key idea is to use the social connections of existing customers with non-customers to convert the latter. Third, to make this conversion happen, the firm offers the existing customer a reward for bringing in new customers.

Whereas leveraging the social ties of customers with non-customers to acquire the latter is not unique to customer referral programs, their three distinctive characteristics set them apart from other forms of network-based marketing (Van den Bulte and Wuyts 2007). Unlike organic WOM, referral programs are actively managed and monitored by the firm. Unlike most forms of buzz and viral marketing, the source of social influence is limited to existing customers rather than anyone who knows about the brand or event. Unlike multi-level marketing, existing customers get rewarded only for bringing in new customers. They do not perform any other sales function (e.g., hosting parties) and do not generate any income as a function of subsequent sales. Consequently, referral programs do not carry the stigma of exploiting social ties for mercantile purposes like multi-level marketing does (Biggart 1989).

In most referral programs, the reward is given regardless of how long the new referred customers stay with the firm. Such programs are prone to abuse by customers. Though the firm does not commit to accept every referral, the incentive structure combined with imperfect screening by the firm creates the potential for abuse in which existing customers get rewarded for referring low-quality customers. This kind of moral hazard is less likely to occur with WOM campaigns that do not involve monetary rewards conditional on customer recruitment.

Existing studies of customer referral programs have provided guidance about when rewards should be offered (Biyalogorsky, Gerstner, and Libai 2001; Kornish and Li 2010); quantified the impact of rewards and tie strength on referral likelihood (Ryu and Feick 2007; Wirtz and Chew 2002); and quantified the monetary value of making a referral (Helm 2003; Kumar, Petersen, and Leone 2007, 2010). The key managerial question of the (differential) value of customers acquired through referral programs has not yet been addressed.

HYPOTHESES

Because referral programs are a customer acquisition method, an important metric to assess their effectiveness is the value of the customers they bring in. Additional insights come from investigating differences between referred and non-referred customers in contribution margins and retention rates, the two main components of customer value (e.g., Gupta and Zeithaml 2006; Wiesel, Skiera, and Villanueva 2008).

Our hypotheses on these customer metrics of managerial interest are informed by prior work in economics and sociology on employee referral (e.g., Coverdill 1998; Rees 1966), especially the work of Fernandez, Castilla, and Moore (2000), Neckerman and Fernandez (2003), and Castilla (2005) on the quality of employee referral programs. Those studies show that the benefits of such programs are realized through distinct mechanisms, of which better matching and social enrichment appear particularly relevant to marketers. Better matching is the phenomenon that referrals fit with the firm better than non-referrals do, and social enrichment is the phenomenon that the relationship of the referral with the firm is enriched by the presence of a common third party, i.e., the referrer.

Customer referral programs are likely to be subject to similar mechanisms as employee referral programs because they share the three distinctive characteristics of having active management, using the social connections of existing contacts, and offering rewards with the risk of abuse. Better matching and social enrichment are especially likely to be at work in our research setting. Selecting a bank may substantially alter one's financial well being and is a high-involvement decision, like choosing a job is. It also involves a fair amount of uncertainty. Though some basic banking products like checking accounts are well known to most customers, the wider set of financial services provided by banks are considered experience goods rather than search goods (e.g., Bolton, Freixas, and Shapiro 2007; Parasuraman, Zeithaml, and Berry 1985). Recurrent losses by many private investors indicate that many people are not very skilled at assessing complex offerings of banks.

We use the better matching and social enrichment mechanisms only to develop and motivate our hypotheses. Our goal is to document managerially relevant differences in contribution margin, retention and customer value, rather than to test those specific mechanisms. The mechanisms are only possible explanations for the differences we document.

Differences in Contribution Margin

Several characteristics of social dynamics in human networks (e.g., Van den Bulte and Wuyts 2007) imply that referred customers may match up with the firm better than other newly acquired customers. The first is reciprocity. Because referring customers receive a reward, norms of reciprocity may make non-opportunistic customers feel obliged to bring in new customers who they think may be valuable to the firm (Gouldner 1960). This process explains the finding by Neckerman and Fernandez (2003) that referrals for which the referrer claimed a fee had lower turnover than referrals for which no fee was claimed. The second social dynamic likely to be at work is triadic balance. If the main function of the program is simply to nudge customers into making referrals without much consideration for the monetary reward (Thaler and Sunstein 2008), then principles of triadic balance will make existing customers more likely to bring in others who they feel would match well with what the firm has to offer. A third social dynamic likely to be at work is homophily—the tendency for people to interact with people like them. Whereas reciprocity and triadic balance imply that referrers are diligent and active in screening and matching peers to firms, homophily implies that customers are likely to refer others who are similar to themselves. Because existing customers have an above-average chance of being a good match (otherwise, they would not be customers), firms may benefit from referral programs through "passive" homophily-based matching rather than only deliberate "active" screening-based matching by referrers (Kornish and Li 2010; Montgomery 1991; Rees 1966).

Acquisition through referral can also result in informational advantages, making referred customers more profitable than other customers. Referred customers are likely to have discussed the firm's offerings with their referrer. As a result, they are likely to use its products more extensively than novice customers who take a more cautious approach in building involvement. There also can be informational advantages to the firm if people refer others similar to themselves on dimensions that are relevant to the enjoyment of the product or service but that are not immediately observable to the firm (Kornish and Li 2010). Examples for financial services include risk aversion and a sense of fiscal responsibility. In those situations, the firm can make inferences from the observed behavior of the referrers about which products the referred customers will be most interested in (e.g., Guseva 2008). As a result, the firm is able to serve the referred customer in a tailored fashion very early on, something that takes time to learn for other newly acquired customers. Because of this informational advantage, the firm should be able to generate a higher contribution margin from referred customers at the beginning of the relationship.

However, the advantages of better matching and better information should gradually vanish. As non-referred customers accumulate experience with the firm, they should become equally well informed about the firm's offerings and procedures. Likewise, the firm should be able to use the purchase and service history of the non-referred customer to serve them better. Furthermore, non-referred customers who are not a good match for the firm are more likely to leave. Consequently, both revenues and costs of referred and non-referred customer should converge, eliminating the difference in contribution margin over time. Hence we expect:

H1: (a) The average contribution margin of a customer acquired through a referral program is higher than that of a customer acquired through other methods, but (b) this difference becomes smaller over time.

Differences in Retention

Social enrichment is another mechanism that may increase the value of referred customers. The argument is that the relationship with the firm is enriched by the fact that a family member or friend is a customer of the same firm (Castilla 2005; Fernandez, Castilla, and Moore 2000). Having a person close to oneself in a similar position (i.e., being a customer of the same firm) should increase one's trust in the firm and strengthen the emotional bond with it, as both balance theory and social closure theory predict (Van den Bulte and Wuyts 2007). This prediction is also consistent with findings that customers reflecting on their affect towards a firm mention friends who are customers with the same firm (Yim, Tse, and Chan 2008). Such relations should be particularly relevant in a banking context, where emotions and trust play an important role in the customer-firm relationship (e.g., Edwards and Day 2005; Fleming, Coffman, and Harter 2005). In short, referred customers are likely to feel a stronger sense of commitment and attachment to the firm. This implies that referred customers are less likely to churn than non-referred customers, provided that their referrer does not churn either. The latter condition is likely to hold: referrers typically have a higher long-term likelihood to stay, which is why intention to refer is frequently used as an indicator of loyalty (Gupta and Zeithaml 2006).

Whereas the informational advantage of a referred customer decreases over time as direct experience substitutes for social learning, there is no reason to expect erosion in the affective bonding underlying the social enrichment mechanism. Consequently, the erosion of the differential expected in contribution margin need not apply to retention. Therefore, we state:

H2: (a) The average retention of a customer acquired through a referral program is higher than that of a customer acquired through other methods, and (b) this difference does not become smaller over time.

Differences in Customer Value

If hypotheses H1 and H2 hold, *and* if the erosion of contribution margins does not outweigh the initial difference in margins and the persisting difference in retention, the following should hold as well:

H3: The average value of a customer acquired through a referral program is higher than that of a customer acquired through other methods.

H3 can hold even when H1 and H2 do not because it is possible for the differences in both margins and retention to be small but their combined effect to be sizable and significant. Another reason to test H3 on customer value, in addition to hypotheses H1 and H2 on margins and retention, is that customer value is what managers should care about most.

Even though we base our prediction on sound theoretical arguments, the posited effects are not as obvious as they may seem because there are several competing forces at work. First, the prospect of earning a referral fee may induce referrers to pressure their peers to become customers without giving much consideration to whether or not the firm actually matches their peers' needs. Second, the relationship between the referred customer and his referrer, necessary for social enrichment to operate, comes with an inherent risk: When referrers defect, the customers they brought in may become more likely to leave as well. Even though it seems unlikely that referrers as a whole are more churn-prone than the average customer, the risk of contagious defection must not be ignored altogether. Third, an abuse of the referral program by customers only interested in the monetary reward is probably the most important reason for skepticism in the mind of practitioners. This is illustrated by the termination of TiVo's referral program due to frequent abuses (ZatzNotFunny 2008).

Support for our hypotheses would allow one to conclude that the positive effects outweigh the negative ones. In addition, the empirical analysis provides not only a test of the hypotheses but also an estimate of the size of the customer value differential. Firms can use the latter to put a maximum value on the reward to be paid out as part of their referral program.

METHODS

Research Setting

We use data from a leading German bank whose name we do not divulge for confidentiality reasons. The data captures all customers acquired through the bank's referral program between January and December 2006 and a random sample of customers acquired through other methods (e.g., direct mail, advertising) over the same period. The latter group may include customers affected by organic WOM for which the bank did not pay any fee. To the extent that the value of customers acquired through organic WOM is equal to or greater than that of customers acquired through the referral program, our results underestimate the value differential between WOM and non-WOM customers. Regardless, we correctly estimate the value differential between customers acquired through the referral program and all other customers for which no referral fee was paid.

The observation period spans from January 2006 until September 2008 (33 months), and the data on each individual customer includes the day of acquisition, the day of leaving the bank (if applicable), the contribution margin in each year, and some demographics. In total, we have data on 5,181 referred and 4,633 non-referred customers. Because the referral program was only used in a business-to-consumer context, all customers are persons.

The referral program was communicated to existing customers through staff and flyers in the branches and through mailings.[1] The procedure was straightforward: Every existing customer who brought in a new customer received a reward of 25 Euros in the form of a voucher that could be used at several well-known German retailers.[2] Except for opening an account, the referred customer did not have to meet any prerequisites (e.g., minimum amount of assets, minimum stay) for the referrer to receive the reward.

The year 2006 was not unusual in terms of customer acquisition and the bank's management is confident that findings about customers acquired in 2006 are applicable to

[1] These mailings went to the *referring* customers. Mailings to which the non-referred customers responded were sent directly to them.

[2] Whereas confidentiality concerns preclude us from reporting the average cost of acquisition for referral and non-referral customers, we can report that the total acquisition cost for referred customers (including not only the referral fee but also the additional administrative costs of record keeping, paying out, etc.) is on average about 20 Euros *lower* than that for non-referred customers acquired through mailings.

customers acquired in earlier or later years. Proprietary information of the bank shows that its customers are very similar to those of other leading European banks. As to the usage of its referral program and the response of its customers to it, no differences with other firms are apparent either.

Dependent Variables

Daily Contribution Margin is the individual contribution margin on a daily basis. It is the total contribution margin generated by the customer in the observation period, divided by the total number of days the customer was with the bank (Duration). This per diem scaling ensures the comparability of the contribution margin of customers with different observed (and possible censored) durations. The contribution margin equals revenue (interest and fees) minus direct costs (e.g., interest expenses, sales commissions, brokerage and trading costs). The acquisition costs are not subtracted from the contribution margin. We also compute a time-varying version of Daily Contribution Margin by dividing the contribution margin generated by the customer in a particular year (2006, 2007, 2008) by the number of days the customer was with the bank in that year.

Duration is the total number of days the customer was observed to be with the bank. It is the basis for analyzing retention.

We calculate two measures of customer value, one based only on observed data, and the other based on both observed data and predictions. *Observed Customer Value* is the present value of all actual contribution margins the customer generated during the whole observation period (e.g., 33 months for retained customers acquired in January 2006). This metric is affected by both contribution margin and retention because a customer generates no margins after leaving the bank. Our second metric, *Customer Lifetime Value,* is the present value of all contribution margins, both actual and predicted, of the customer within the six-year span following the day of acquisition.[3] For customers who churned during the observation period, *Customer Lifetime Value* equals *Observed Customer Value* because their predicted value is 0. The formulas are:

(1) $$\text{Customer Lifetime Value}_i = \text{Observed Customer Value}_i + \text{Predicted Customer Value}_i$$

(2) $$\text{Observed Customer Value}_i = \sum_{s=1}^{Dur_i} \frac{OM_{is}}{(1+r)^{s/12}}$$

(3) $$\text{Predicted Customer Value}_i = \delta_i \sum_{s=Dur_i+1}^{72} \frac{PM_{is} \times PA_{is}}{(1+r)^{s/12}}$$

where OM_{is} is the observed monthly contribution margin of customer i in the sth month after acquisition (calculated from the observed annual contribution margin and the observed duration), Dur_i is the customer's observed lifetime with the bank in months, δ_i is a dummy censoring variable indicating whether the customer was still with the bank by the end of the observation period, PM_{is} is the predicted monthly contribution margin of customer i in the sth month after acquisition, PA_{is} is the predicted probability that the customer i is still "alive" (i.e., with the bank) in that month, and r is the firm-specific annual discount rate of 11.5%.[4]. The present value reflects what the customer is worth at the day of acquisition.

[3] This way, we do not need to predict margins and retention rates beyond four years after the end of the data window, and the resulting CLV values are unlikely to be overly affected by forecasting error (Kumar and Shah (2009).
[4] We base the discount rate on the CAPM. We assume a risk-free interest rate of 4.25% (Svensson 1994), a 5% market risk rate based on the Institute of German Accountants, and a firm-specific beta 1.45 based on Thomson Financial Datastream.

Independent Variables

The independent variable of central interest is *Referral Program*, a binary indicator taking the value 1 for referred customers, i.e., those customers that were acquired through the referral program, and 0 for non-referred customers.

To improve the comparability of referred and non-referred customers we control for the demographic variables *Age*, *Female* (dummy variable with female coded 1, male coded 0) and *Marital Status* (dummy variables for married, divorced/separated, single, and widowed, with no answer as the base category). We also control for the customer's *Month of Acquisition* (11 dummy variables for each month with December 2006 as the base category).

To assess the robustness of the difference in customer value, we also conduct separate analyses for the two key segments of the bank: retail customers with standard financial needs and non-retail customers with significant assets or requiring more sophisticated financial advice. This segmentation scheme used by the bank is based on a comprehensive analysis of both financial data (e.g., assets invested with the bank, monthly checking account balance) and demographic information (e.g., profession, place of residence). The segments form the basis for all strategic customer-related decisions of the bank.

Descriptive Statistics

The sample includes several customers with an extremely high Daily Contribution Margin that is up to 80 standard deviations above the mean and median. Such extreme data points can influence comparisons of means and regression results, so we purify the data using the standard DFBETA and DFFIT criteria to identify influence points (Belsley, Kuh, and Welsch, 1980). This procedure led to the deletion of 172 referred customers (3.3% of the original 5,181 referred customers) and 147 non-referred customers (3.2% of the original 4,633 non-referred customers). As reported in the sub-section “Robustness Checks”, testing the hypotheses without deleting the influence points results in larger differences and provides stronger support for the hypotheses. Yet, we believe the size estimates obtained without the influence points are more informative.

Table 1 presents the means, standard deviations, and the correlation matrix for the purified sample of 9,495 customers. As indicated by the non-zero correlations between the Referral Program variable and the various demographic and time of acquisition variables, the groups of referred and non-referred customers are not perfectly matched on demographics and time of acquisition. Hence, it is desirable to control for these differences.

[Insert Table 1 about here]

Figure 1 plots the average Daily Contribution Margin for the referred and non-referred customers of the purified sample, for 2006, 2007, and 2008. The pattern is quite encouraging. Referred customers tend to generate higher margins, and the margins tend to erode more quickly among referred customers, such that the margin differential is narrower in 2008 than in 2006 (8 vs. 18 cents/day). Similarly, Figure 2 shows that, after approximately a year, the retention rate of referred customers is higher, and that it is so regardless of duration. Controlling for differences in demographics and time of acquisition is necessary, however, to draw conclusions more confidently.

[Insert Figures 1 and 2 about here]

Statistical Models

To estimate the difference in contribution margin between acquisition modes (H1a) we use a regression model with the following specification:

$$(4) \qquad DCM_i = \alpha + \beta_1 RP_i + \sum_{k=2} \beta_k X_{ik} + \varepsilon_i,$$

where i indexes the customer, DCM is Daily Contribution Margin over the observation period, RP is the binary variable representing the Referral Program, the Xs are control variables, and the errors ε_i have a mean of zero and are independent of the included covariates. We use OLS to estimate the coefficients and compute Huber-White heteroscedasticity-consistent standard errors (Breusch-Pagan test, $p < .001$). The size of our sample implies that we need not assume the random shocks to be normally distributed for statistical inference using t and F statistics (e.g., Wooldridge 2002, pp. 167-171).

To test whether the difference in margin decreases the longer the customer has been with the bank (H1b), we use a fixed-effects specification estimated using OLS:

$$(5) \qquad DCM_{it} = \alpha_i + \beta_2 T_{it} + \beta_3 RP_i \times T_{it} + \eta_t + \varepsilon_{it},$$

where i indexes the customer, t indexes the year (t = 1, 2, 3), DCM_{it} is the Daily Contribution Margin of customer i in year t, i.e., the total contribution margin generated by customer i in year t divided by the number of days that the customer was with the firm during year t, T_{it} is the cumulative number of days the customer i had been with the bank by the end of year t, η_t is a year-specific fixed effect, and the customer-specific intercepts α_i are not constrained to follow any specific distribution but capture all individual-specific, time-invariant differences, including the effect of acquisition through the referral program (RP) and that of the control variables X. The errors ε_{it} have a mean of zero and are independent of the covariates. The β_3 coefficient captures the proper interaction effect because the β_1 effect of RP is now captured through the fixed effects. As before, we use the robust Huber-White standard errors (Breusch-Pagan test, $p < .001$).

To assess the difference in retention between acquisition modes, we use the Cox proportional hazard model. This allows us to analyze right-censored duration data and to exploit the fine-grained measurement of churn at the daily level without imposing any restriction on how the average churn rate evolves over time. Furthermore, the non-parametric baseline hazard makes the model robust to unobserved heterogeneity in all but very extreme cases (e.g., Meyer 1990). The model to test H2a can be represented as:

$$(6) \qquad \ln[h_i(t)] = \alpha(t) + \beta_1 RP_i + \sum_{k=2} \beta_k X_{ik} \ ,$$

where i indexes the customer, t indexes the amount of days since the customer joined the bank, $h_i(t)$ is the hazard rate for the customer's defecting, and $\alpha(t)$ is the log of the non-parametric baseline hazard common across all customers. To test whether the difference in churn propensity changes over time (H2b), we extend model (6) with the interaction between RP_i and $\ln[t]$. The latter is also a test of whether the *RP* effect meets the proportionality assumption (e.g., Blossfeld, Hamerle, and Mayer 1989), but we use it here to test a hypothesis of substantive interest.

To test H3 and assess the difference in customer value, we again use the regression model in Equation 4, but now with Observed Customer Value as the dependent variable. One can subject theoretical claims to empirical validation or refutation only by comparing hypothesized effects against actual data. As a result, one can validly test the truth-content of H3 using the Observed Customer Value as the dependent variable, but not Customer Lifetime Value which itself is based on predictions. Still, given the right-censoring of our data and the hypothesized erosion of the margin differential over time, it is informative to also perform a similar analysis with the six-year Customer Lifetime Value as the dependent variable. To calculate the predicted values entering the Customer Lifetime Value metric, we use (i) predicted annual contribution margins from a fixed-effects model such as specified in Equation 5 but in which we allow all parameters to vary between referred and non-referred customers, and (ii) predicted annual survival rates from a parametric Weibull hazard model because the non-parametric baseline hazard of the Cox model does not allow for forecasts.[5]

RESULTS

Is the Contribution Margin of Referred Customers Higher?

In accordance with H1a, referred customers are on average 4.5 cents per day more profitable than other customers (Mann-Whitney test, $p < .001$). The difference is even larger after we control for differences in customer demographics and time of acquisition, variables on which the two groups of customers are not perfectly matched. The first column of Table 2 reports the coefficients of Equation 4, controlling for Age, Sex, Marital Status, and Month of Acquisition. Whereas the average contribution margin of non-referred customers in our sample is 30 cents/day, customers acquired through the referral program have a margin that is 7.6 cents/day or 27.74 Euros/year higher ($p < .001$), an increase of about 25%. Among the covariates, higher age and being widowed are associated with a higher contribution margin, whereas being married is associated with a lower contribution margin. The pattern in the monthly coefficients suggests that the bank was more successful in acquiring profitable customers in some months than in others. The R^2 is quite low, indicating that other important elements besides acquisition method, acquisition time, and demographics drive customer profitability. Even though the large unexplained variance depresses the power of statistical tests and hence makes it harder to reject the null hypothesis, H1a is strongly supported.

[Insert Table 2 about here]

[5] In-sample parameter estimates from the Cox and Weibull models are nearly identical. The reason for using the Cox model in testing the hypotheses is the absence of a restrictive parametric assumption on the duration dependence.

Does the Contribution Margin of Referred Customers Remain Higher?

H1b predicts that the difference in contribution margin erodes, the longer a customer stays with the bank. Our results support this expectation. Column 2 of Table 2 reports the coefficients of the fixed-effects model in Equation 5. There is a significant negative interaction between Referral Program and the number of days the customer has been with the bank. The difference in Daily Contribution Margin between referred and non-referred customers decreases by 23.1 cents per 1,000 days, or 8.4 cents per year.

The individual-level fixed effects (intercepts) in the model capture the expected Daily Contribution Margin when the included covariates equal zero, i.e., on the day of acquisition in 2006. Regressing these 9,495 fixed-effects estimates on the Referral Program and control variables indicates that a referred customer has an expected contribution margin on the first day of joining the firm that is 19.8 cents higher than the one of a non-referred customer with similar demographics and time of acquisition.[6] This implies that the expected contribution margin advantage of a referred customer disappears after 857 days (= 0.198/.000231), or about 29 months after the customer joined the bank.

Is the Retention of Referred Customers Higher?

To test if the retention rate is higher for referred than for non-referred customers (H2a), we use the Cox proportional hazard model specified in Equation 6. The results indicate that the association between Referral Program and churn (i.e., non-retention) is significantly negative and sizeable. Using only Referral Program as explanatory variable shows that, at any point in time,

[6] This difference in Daily Contribution Margin of 19.8 cents is close but not identical to the 18 cents difference between the two groups of customers in 2006, shown in Figure 1. The small disparity between the two values occurs because the former controls for differences in demographics and time of acquisition, whereas the latter does not. A second reason for the disparity is that the former is the difference on the day of acquisition, whereas the latter is the difference on an average day in 2006.

customers acquired through the referral program who are still with the firm are about 13% less likely to defect than non-referred customers who are still with the firm. After controlling for differences in demographics and month of acquisition (see column 3 of Table 2), the effect size increases to approximately -18% (= exp[-.198] - 1). This multiplicative effect of 18% is relative to a baseline hazard that is very small. As indicated by the survival curves in Figure 2, the probability of being an active customer (i.e., a non-churning customer) after 33 months is 82.0% for referred customers and 79.2% for non-referred customers. Age is associated with a higher churn rate, whereas the opposite holds for being widowed. There is also a trend in the monthly coefficients, indicating that customers acquired late in 2006 (especially in September and later) exhibit more churn than those acquired earlier. This trend is a cohort effect and not duration dependence which is captured in the non-parametric baseline hazard.

Does the Retention of Referred Customers Remain Higher?

We also assess whether the difference in retention varies over the customers' lifetime (H2b). To do so, we extend the Cox model with an interaction between the Referral Program variable and the natural logarithm of the customer's duration with the bank (see column 4 of Table 2). The interaction is not significant and the model fit does not improve significantly ($p >$ .05). So, while there is an eroding difference between referred and non-referred customers in contribution margin, there is no such erosion for customer retention.[7]

[7] Note that in the model with the interaction term included, the coefficient of Referral Program (0.917, $p > 0.05$) is not the average difference between referred and non-referred customers anymore, but the difference between the two groups on the day of acquisition, i.e., when the interaction variable LogDuration equals 0 (Irwin and McClelland 2001). Hence, the insignificant coefficient of Referral Program in the model including the interaction term does not invalidate the finding of a significant difference in retention between the two groups posited in H2a.

Are Referred Customers More Valuable?

Using the Observed Customer Value, we find that referred customers are on average 18 Euros more valuable (Mann-Whitney test, $p < .001$). After controlling for demographics and month of acquisition, the difference increases to 49 Euros (column 5 of Table 2; $p < .001$). A referred customer is roughly 25% more valuable to the bank than a comparable non-referred customer, within the observation period. Taking into account the difference in acquisition costs of around 20 Euros, the difference in customer value is nearly 35%. These results strongly support H3.

Because the margin differential of referred customers erodes over time even though the loyalty differential does not, the question arises whether or not referred customers remain more valuable beyond the observation period. Repeating the analysis for the six-year Customer Lifetime Value indicates it does. The average Customer Lifetime Value of referred customers is about 6 Euros higher than that of other customers (Mann-Whitney test, $p < .001$). After controlling for differences in customer demographics and time of acquisition, the value differential is about 40 Euros (column 6 of Table 2; $p < .001$). Because the average Customer Lifetime Value of a non-referred customer is 253 Euros, a referred customer is roughly 16% more valuable to the bank than a comparable non-referred customer over a horizon of six years. Taking into account the difference in acquisition costs of around 20 Euros, the difference in Customer Lifetime Value is nearly 25%. This value differential is quite considerable.

We also assess to what extent the differences in customer value are robust across various subsets of customers. Table 3 reports the regression coefficients for the Referral Program in models of customer value, with the same controls as in the previous analysis in columns 5 and 6 of Table 2. Row 1 of Table 3 shows that the results for the retail customer segment are nearly identical to those for the entire sample. This is not surprising, as retail customers make up almost 90% of our overall sample. More informative is that the difference in customer value also exists in the non-retail segment (row 2 of Table 3).

Rows 3 and 4 of Table 3 show that the positive referral differential exists among high-margin customers, defined as those in the top decile based on margin, but not low-margin customers, defined as those in the bottom decile based on margin.[8] The remaining rows in Table 3 show that sizable value differentials between referred and non-referred customers exist both among men and women, and among all age ranges except those more than 55 years old. Overall, the acquisition through a referral program is associated with higher customer value for the great majority of customer types, but not all. These results suggest that using referral programs might not be beneficial in all customer segments, an idea we develop further in the Discussion section.

[Insert Table 3 about here]

Robustness Checks

Table 4 shows that the hypothesis tests are robust to including retail versus non-retail segment membership as an additional control variable, and allowing the effect of the referral program to vary as a function of age, sex, marital status and retail segment membership. Given the results of Table 3, we also allowed for a non-linear effect of age.[9] We mean-center all variables interacting with Referral Program, so its coefficient still reflects the main effect. This coefficient keeps its sign and significance in each model, so the hypotheses remain supported. The coefficients are larger than in Table 2 in which we did not control for segment membership

[8] Low-margin customers and high-margin customers are found in both the retail and non-retail segments.
[9] As some readers may be interested in how the effect of Referral Program is moderated by covariates in the time-varying contribution model, we estimate the latter using a random coefficients specification rather than the fixed effects specification used in Table 2.

and non-linear age effects, indicating that our main analysis provides rather conservative estimates of the referral effects.

[Insert Table 4 about here]

As a second robustness check, we repeated the analyses presented in Table 2 for the sample including all outliers. The direction and significance of the referral effect remained the same, but the size of several effects increased. The difference in Daily Contribution Margin increased from 7.6 to 16 cents/day, the margin erosion increased from 23.1 to 45.4 cents per thousand days, the churn hazard reduction remained at 20%, and the difference in Customer Lifetime Value increased from 40 to 66 Euros. These results suggest that our main analysis is rather conservative with regard to the size of the referral differentials.

Though hazard analysis properly accounts for right-censoring, managers are also interested in simply knowing who is likely to have remained with the firm within a certain time frame. We therefore also assessed the relation between referral and the probability of still being with the bank 21 months after acquisition. This time span is the longest duration that is observable without right-censoring for each and every customer, including those who were acquired last, at the end of December 2006. Using logistic regression and controlling for demographics and month of acquisition, we find that referred customers are about 22% less likely to leave the firm within the first 21 months ($p < .01$).

Computing the Customer Lifetime Value over three, rather than six, years after acquisition, and repeating the analysis controlling for demographics and time of acquisition, yields a value differential between referred and non-referred customers of 52 Euros ($p < .001$), rather than of 40 Euros. Both the size and the statistical significance of the latter value is rather robust to re-estimating the model on smaller random samples of 90% (39€, $p < 0.001$), 75% (42€, $p < 0.001$), 50% (48€, $p < 0.001$), and 25% (36€, $p < 0.01$). We also computed the expected value differential if there were no difference in retention between referred and non-referred customers. The differential in six-year Customer Lifetime Value would have decreased from 40 to 33 Euros.

Finally, we extended the model of margin dynamics and allowed the effect of time and its interaction with referral to vary as a function of observed customer demographics, retail versus non-retail status, and normally distributed unobserved heterogeneity. This extended random coefficients model did not fit the data better: the squared correlation between observed and predicted values (pseudo-R^2) increased by only 0.1%, and the BIC even decreased. Most importantly, the coefficients of central interest and the statistical inference were not affected: Customers acquired through referral had a sizable initial margin advantage that eroded to zero after about 1,000 days.

DISCUSSION

Key Findings

Evidence of the economic value of stimulated WOM and of the customers it helps acquire has been sorely lacking. Our study addresses this gap in the context of referral programs and documents the attractiveness of customers acquired through such a program: Contribution margin, retention, and customer value all were significantly and sizably higher for referred customers. In short, referred customers are more valuable in both the short and long run. Yet, we also find that the effect is not uniform across all types of customers, and that the referral program was less beneficial when used to acquire older customers or low-margin customers.

In our application, the value of referred customers in the six years after acquisition was 40 Euros, or 16%, higher than that of non-referred customers with similar demographics and time of acquisition. Considering the initial reward of 25 Euros given to the referrer as an investment, this implies a Return on Investment of roughly 60% over a six-year span. This is a conservative estimate because it does not take into account that the total acquisition costs of referred customers are around 20 Euros lower than those of other customers.

Implications for Practice

Several scholars have expressed cautious skepticism about the value of viral-for-hire and other stimulated WOM (e.g., Trusov, Bucklin, and Pauwels 2009; Van den Bulte 2010). Doubts about the benefits of stimulated WOM have long frustrated managers facing demands to increase their marketing ROI. Our findings are important news for practitioners considering deploying customer referral programs in their own firm. Assuaging prior skepticism, we document a positive value differential, both in the short term and long term, between customers acquired through a referral program and other customers. Importantly, this value differential is larger than the referral fee. Hence, referral programs can indeed pay off.

The positive differential indicates that abuse by opportunistic customers and other harmful side effects of referral programs are much less important than their benefits. The referral program we analyzed was especially prone to exploitation because no conditions, such as minimum stay or assets, applied to the newly acquired customer. Finding a positive value differential of referred customers in this setting is especially compelling. Moving beyond referral programs specifically, our study indicates that a stronger focus on stimulated as opposed to organic WOM is worth considering (Godes and Mayzlin 2009).

Our results, however, also suggest that firms should think carefully about what prospects to target with referral programs and how big of a referral fee to provide. For the program we analyzed, we found that the customer value differential is much larger in some segments than in others. People less than 55 years old and high-margin customers are more attractive to acquire through a referral program. It need not be a coincidence that these also tend to be the more profitable customers for banks (and many other consumer marketers). To the extent that the value differential stems from better matching and social enrichment, as suggested by sociological theory and documented in employee referral programs, referral programs do not "create" higher value customers by transforming unattractive prospects into attractive customers. Rather, they help firms to selectively acquire more valuable prospects and to retain them longer at lower cost. Hence, instead of the currently practiced "all in" approach, firms should design and target referral programs such that attractive customers are more likely to be pulled in.

Managers must also make their customers aware of their referral programs. Bank of America, for example, communicates its referral program at all its ATMs throughout the United States. Connecting referral programs with online activities might help to further increase their reach beyond existing customers' networks of strong ties and face-to-face interactions. Managers must also make it convenient for prospects to actually become a customer. One possible application is to partner with online communities and make it easy for people to start a relationship with the firm online, immediately after they receive a referral from an existing customer in the same community. Our results suggest that such awareness and facilitation efforts should be targeted selectively towards those customers offering the highest value differential.

The referral fee is another issue that requires attention when designing a referral program. Many programs offer the same reward to each referrer (Kumar, Petersen, and Leone 2010). Yet, as we showed, the value of referred customers can vary widely even for one company. Hence, firms may benefit from offering rewards based on the value of the referred customer. However, the question then becomes how to do this without adding too much complexity to the program.

There may be a simple answer: A standard homophily argument suggests that valuable referrers are more likely to generate valuable referrals. Hence, firms may want to make the referral fee a function of the value of the referrer.

A very different approach to take advantage of the referral effect would be to try to generate conditions where non-referred customers become subject to the same mechanisms that make referred customers more valuable. To the extent that the differences we have documented stem from better matching, from social enrichment, or from other mechanisms that firms can actively foster among *all* customers, they may be able to dramatically “scale up” the beneficial referral effect beyond dyads of referring and referred customers. For instance, pharmaceutical companies increasingly involve local opinion leaders in their speaker programs and other medical education efforts. They do so to capitalize on these physicians’ relevance and credibility with practicing physicians.

Firms in the same industry often reward referrers with the same amount. For example, most German banks offer 25 Euros for a referral. So did the one we studied. Our results indicate that managers set the referral fee rather low, allowing the firm to reap attractive returns from its program. Offering higher rewards might lead to even more customer acquisitions while still providing positive returns on investment. Firms should calculate the reward considering their specific program and the customers it attracts instead of merely following their competitors.

Future Research

Our study focuses on referred and non-referred customers of one particular bank. Whereas its customer base and referral program have no unusual characteristics, replications would obviously be very welcome. Such studies require rich, firm-specific data on a large set of customers, with individual profitability observed over a long period. Therefore, we expect replications and extensions to come from other single-firm studies like ours and those by Godes and Mayzlin (2009), Haenlein (2010), Iyengar, Van den Bulte and Valente (2010), and Nitzan and Libai (2010). Because the mechanisms of better matching and social enrichment are likely to be more important for complex products with important experience attributes, rather than simple products with mostly search attributes (e.g., Coverdill 1998; Kornish and Li 2010; Rees 1966), studies of multiple products with varying levels of complexity would be especially informative.

It is quite likely that the quality of the matches with the firm deteriorates as existing customers refer more new customers. It would be of great practical interest to know at what rate the quality of referrals decreases and at what point it tends not to justify the cost of acquisition anymore. It may also be useful to know if the motivation of the referrer changes depending on the reward and if the size of the reward impacts the quality of the referred customer.

Several of the implications for practice point to the benefits of better understanding the drivers of the value differential we documented. Whereas our results are consistent with the better matching and social enrichment mechanisms we used to develop our hypotheses, our analysis focused on the consequences for contribution margin, retention, and customer value, rather than the intervening mechanisms. Research aimed at more directly parsing out the mechanisms is likely to require information about actual dyads of referring and referred customers. This, for instance, would allow one to test the social enrichment argument by matching the referred customer with the respective referrer and analyzing the dependence of their retention. Additional survey data may allow one to document differences in product knowledge over time, and to shed light on the existence of an informational advantage eroding over time. Having matched dyad-level data on both referring and referred customers would also enable one to check whether referral dyads exhibit homophily and whether the value of referred customers varies systematically with that of their referrer (cf. Haenlein 2010; Nitzan and Libai 2010). This would yield valuable insights for the design of individual rewards, instead of the currently practiced “one size fits all”.

CONCLUSION

This study provides the first assessment of economically relevant differences between customers acquired through a referral program and customers acquired through other methods. It documents sizable differences in contribution margin, retention, and customer value; analyzes whether these differences erode or persist over time; and investigates differences across customer segments. The finding that referred customers are on average more valuable than other customers provides the first direct evidence of the financial attractiveness of referral programs and also provides much-needed evidence of the financial appeal of stimulated WOM in general.

Improvements in the targeting, design, and implementation of such programs will require a better understanding of the drivers of the value differential. The dyadic interdependence in the behavior of referrer and referred customer deserves special attention in future research, as it is likely to prove highly relevant to both better theoretical understanding and more effective program management.

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Table 1: Descriptive statistics

	Units	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Referral Program	0-1	0.53	0.50	1.00																					
2. Observed Customer Value	Euros	210.66	336.15	0.02	1.00																				
3. Customer Lifetime Value	Euros	255.75	338.95	0.01	1.00	1.00																			
4. Daily Contribution Margin	Euros/day	0.33	0.50	0.04	0.98	0.98	1.00																		
5. Duration	Days	751.05	119.48	-0.17	0.18	0.21	0.09	1.00																	
6. Age	Years	42.90	17.47	-0.20	0.10	0.09	0.10	-0.01	1.00																
7. Female	0-1	0.54	0.50	0.07	0.01	0.01	0.01	0.01	0.05	1.00															
8. Married	0-1	0.39	0.49	-0.15	-0.02	-0.03	-0.02	-0.03	0.43	0.01	1.00														
9. Single	0-1	0.44	0.50	0.16	-0.05	-0.04	-0.05	0.01	-0.65	-0.10	-0.70	1.00													
10. Divorced	0-1	0.10	0.30	0.00	0.03	0.03	0.03	0.02	0.13	0.06	-0.26	-0.29	1.00												
11. Widowed	0-1	0.05	0.22	-0.05	0.11	0.11	0.10	0.03	0.36	0.14	-0.18	-0.20	-0.07	1.00											
12. Acquired Jan06	0-1	0.03	0.17	-0.17	0.07	0.08	0.03	0.31	0.02	0.00	0.01	-0.03	-0.00	0.04	1.00										
13. Acquired Feb06	0-1	0.03	0.18	-0.18	0.02	0.03	-0.01	0.27	0.05	-0.02	0.04	-0.04	-0.00	0.01	-0.03	1.00									
14. Acquired Mar06	0-1	0.06	0.24	-0.18	0.04	0.04	0.01	0.29	0.07	-0.01	0.05	-0.04	-0.00	0.00	-0.04	-0.05	1.00								
15. Acquired Apr06	0-1	0.06	0.23	0.02	0.04	0.04	0.02	0.24	-0.01	-0.00	-0.03	0.02	0.02	0.01	-0.04	-0.05	-0.06	1.00							
16. Acquired May06	0-1	0.07	0.26	0.03	0.03	0.04	0.01	0.22	-0.02	-0.01	-0.01	0.02	-0.01	-0.02	-0.05	-0.05	-0.07	-0.07	1.00						
17. Acquired Jun06	0-1	0.08	0.28	-0.01	0.02	0.02	0.01	0.14	0.02	0.02	-0.01	-0.01	0.00	0.04	-0.05	-0.06	-0.08	-0.07	-0.08	1.00					
18. Acquired Jul06	0-1	0.10	0.30	0.00	0.01	0.01	0.01	0.08	0.02	-0.00	0.00	-0.02	0.03	-0.00	-0.06	-0.06	-0.09	-0.08	-0.09	-0.10	1.00				
19. Acquired Aug06	0-1	0.11	0.31	0.06	-0.00	-0.00	-0.00	-0.01	-0.08	0.00	-0.06	0.05	0.02	-0.02	-0.06	-0.06	-0.09	-0.08	-0.09	-0.10	-0.12	1.00			
20. Acquired Sep06	0-1	0.08	0.27	0.07	0.00	0.00	0.01	-0.08	-0.06	0.01	-0.03	0.04	-0.00	-0.02	-0.05	-0.06	-0.08	-0.07	-0.08	-0.09	-0.10	-0.10	1.00		
21. Acquired Oct06	0-1	0.12	0.33	0.04	-0.03	-0.04	-0.01	-0.22	0.01	0.01	0.02	-0.00	-0.01	-0.01	-0.07	-0.07	-0.09	-0.09	-0.10	-0.11	-0.13	-0.13	-0.11	1.00	
22. Acquired Nov06	0-1	0.12	0.33	0.04	-0.05	-0.06	-0.02	-0.31	-0.00	-0.03	0.01	-0.01	-0.01	-0.00	-0.07	-0.07	-0.09	-0.09	-0.10	-0.11	-0.13	-0.13	-0.11	-0.14	1.00
23. Non-Retail Customers	0-1	0.12	0.32	-0.03	0.27	0.27	0.27	-0.00	0.03	0.00	0.01	-0.01	-0.03	0.00	0.02	-0.00	0.01	0.01	-0.04	0.00	-0.01	-0.02	-0.02	-0.03	0.00

N = 9,495. All correlations with absolute value of 0.02 or higher are significant at the 5% level.
Note: Differences in observed Duration across customers are strongly affected by differences in the month of acquisition. As a result, the zero-order correlations of Duration with other variables also correlated with month of acquisition can be quite misleading. For instance, the correlation between Duration and Referral Program changes from -0.17 to 0.03 after controlling for month of acquisition.

Table 2: Main Results for Differences in Daily Contribution Margin, Churn (i.e. the converse of retention), Observed Customer Value, and Customer Lifetime Value

	H1a	H1b	H2a	H2b	H3	H3
	Daily Contrib. Margin	Daily Contrib.Margin (time-varying)	Churn	Churn (time-varying)	Observed Cust. Value	Customer Lifetime Value
Referral Program	0.076***	- [a]	-0.198**	0.917	49.157***	39.906***
	(0.010)	-	(0.059)	(1.479)	(7.096)	7.152
Age	0.003***	-	0.011**	0.011***	1.879***	1.626***
	(0.000)	-	(0.002)	(0.002)	(0.283)	(0.285)
Female	-0.009	-	-0.034	-0.034	-4.459	-3.376
	(0.010)	-	(0.056)	(0.056)	(6.902)	(6.958)
Married	-0.078*	-	-0.027	-0.028	-52.798*	-52.258*
	(0.033)	-	(0.166)	(0.166)	(22.427)	(22.563)
Single	-0.040	-	-0.163	-0.163	-27.306	-24.035
	(0.033)	-	(0.167)	(0.167)	(22.573)	(22.706)
Divorced	-0.016	-	-0.176	-0.177	-12.278	-7.656
	(0.037)	-	(0.183)	(0.183)	(24.776)	(24.933)
Widowed	0.111*	-	-0.470*	-0.470*	76.085*	87.249**
	(0.046)	-	(0.212)	(0.212)	(31.128)	(31.355)
Acquired Jan06	0.172***	-	-1.828**	-1.833***	228.228***	247.960***
	(0.039)	-	(0.201)	(0.201)	(31.589)	(31.666)
Acquired Feb06	0.063*	-	-1.365**	-1.369***	127.706***	133.591***
	(0.031)	-	(0.160)	(0.159)	(24.172)	(24.411)
Acquired Mar06	0.089**	-	-1.155**	-1.157***	136.393***	135.755***
	(0.026)	-	(0.126)	(0.126)	(19.103)	(19.280)
Acquired Apr06	0.084**	-	-1.215**	-1.208***	124.793***	123.153***
	(0.027)	-	(0.140)	(0.140)	(18.753)	(18.895)
Acquired May06	0.082**	-	-1.529**	-1.524***	114.302***	119.426***
	(0.025)	-	(0.150)	(0.150)	(16.791)	(16.909)
Acquired Jun06	0.066**	-	-1.016**	-1.013***	91.090***	92.643***
	(0.022)	-	(0.122)	(0.122)	(14.326)	(14.475)
Acquired Jul06	0.062**	-	-1.026**	-1.023***	79.574***	84.200***
	(0.021)	-	(0.122)	(0.122)	(12.717)	(12.839)
Acquired Aug06	0.059**	-	-0.841**	-0.838***	69.213***	73.167***
	(0.020)	-	(0.119)	(0.119)	(12.111)	(12.233)
Acquired Sep06	0.077**	-	-0.679**	-0.676***	72.213***	76.352***
	(0.022)	-	(0.126)	(0.126)	(13.199)	(13.335)
Acquired Oct06	0.037	-	-0.434**	-0.432***	36.602*	39.391***
	(0.020)	-	(0.108)	(0.108)	(11.133)	(11.257)
Acquired Nov06	0.021	-	-0.217*	-0.215*	19,252	20.551
	(0.019)	-	(0.105)	(0.105)	(10.497)	(10.632)
Year 2007 (Dummy)		-1.306				
		(0.732)				
Year 2008 (Dummy)		-2.259				
		(1.258)				
Cumulative Days (in 000s)		3.513				
		(1.994)				
Cumulative Days (in 000s) x RefProgram		-0.231**				
		(0.085)				
LogDuration x RefProgram				-0.176		
				(0.232)		
Constant	0.154***				66.250*	120.949***
	(0.040)				(26.742)	(26.937)
Observations	9,495	28,353	9,495	9,495	9,495	9,495
R^2	0.025	0.350			0.040	0.040
Log pseudolikelihood			-11,715.6	-11,715.4		

Robust standard errors in parentheses.

[a] captured by customer-specific fixed effects.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 3: Results for Difference in Customer Value within Various Segments

	Observed Customer Value (robust standard errors)	Customer Lifetime Value (robust standard errors)	N (N of referred customers)
Retail Customers	48.620***	39.082***	8,384
	(6.574)	(6.633)	(4,473)
Non-Retail Customers	77.309**	69.803*	1,111
	(29.855)	(30.023)	(536)
High Margin Customers	80.421**	69.669*	950
	(27.768)	(28.004)	(533)
Low Margin Customers	-1.146	-13.212***	962
	(1.581)	(2.087)	(247)
Male Customers	51.679***	42.305***	4,371
	(10.600)	(10.669)	(2,150)
Female Customers	47.437***	38.274***	5,124
	(9.604)	(9.690)	(2,859)
≤25 years of age	35.662**	17.701	1,808
	(12.914)	(12.945)	(1,242)
26-35 years of age	101.975***	85.280***	2,170
	(14.908)	(14.822)	(1,298)
36-45 years of age	66.148***	57.401**	1,621
	(17.534)	(17.707)	(835)
46-55 years of age	62.763**	56.834**	1,437
	(19.671)	(19.827)	(617)
56-65 years of age	9.433	5.122	1,153
	(21.189)	(21.195)	(481)
>65 years of age	-1.577	-8.589	1,306
	(21.421)	(21.409)	(536)

Each row displays the coefficient of Referral Program in models with the same control variables as in Table 2, but estimated for specific segments. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 4: Robustness Checks Allowing for Referral Effects to be Moderated

	H1a	H1b	H2a	H2b	H3	H3
	Daily Contrib. Margin	Daily Contrib.Margin (time-varying)	Churn	Churn (time-varying)	Observed Cust. Value	Customer Lifetime Value
Referral Program	0.133***	0.228***	-0.270**	0.791	88.413***	79.695***
	(0.017)	(0.062)	(0.084)	(1.479)	(10.870)	(10.949)
Age (mean-centered) [a]	0.310***	0.529**	1.421***	1.421***	199.247***	164.893***
	(0.060)	(0.191)	(0.361)	(0.362)	(41.286)	(41.647)
Age^2 (mean-centered) [a]	-0.004	-0.779	-0.014	-0.014	-2.276	-2.190
	(0.003)	(0.733)	(0.014)	(0.014)	(1.834)	(1.848)
Female (mean-centered)	-0.008	.035	0.017	0.016	-3.822	-2.828
	(0.013)	(0.041)	(0.076)	(0.076)	(9.393)	(9.487)
Married (mean-centered)	0.050	.828***	-0.445*	-0.445*	34.372	38.493
	(0.039)	(0.126)	(0.201)	(0.202)	(27.838)	(28.187)
Single (mean-centered)	0.080*	0.933***	-0.472*	-0.473*	52.010	59.890*
	(0.040)	(0.128)	(0.211)	(0.211)	(27.774)	(28.119)
Divorced (mean-centered)	0.111*	0.916***	-0.589*	-0.590*	77.122*	86.686**
	(0.044)	(0.139)	(0.231)	(0.231)	(31.289)	(31.696)
Widowed (mean-centered)	0.340***	1.104***	-1.011***	-1.012***	236.446***	254.709***
	(0.058)	(0.154)	(0.272)	(0.273)	(40.821)	(41.259)
Non-Retail Segment	0.440***	0.551***	-0.263*	-0.263*	310.169***	311.262***
(mean-centered)	(0.031)	(0.060)	(0.124)	(0.124)	(21.972)	(22.152)
Age x RefProgram [a,b]	0.151	0.081	-0.531	-0.532	99.676	117.447*
	(0.086)	(0.255)	(0.514)	(0.514)	(57.745)	(58.183)
Age^2 x RefProgram [a, b]	-0.015***	-0.311	0.022	0.022	-10.212***	-10.392***
	(0.004)	(1.018)	(0.020)	(0.020)	(2.539)	(2.556)
Female x RefProgram [b]	-0.005	-0.019	-0.104	-0.104	-2.980	-2.982
	(0.020)	(0.056)	(0.112)	(0.112)	(13.210)	(13.320)
Married x RefProgram [b]	-0.162*	-0.974***	0.953**	0.951**	-108.801*	-114.852*
	(0.068)	(0.174)	(0.362)	(0.362)	(45.824)	(46.049)
Single x RefProgram [b]	-0.097	-0.972***	0.743*	0.743*	-62.859	-70.679
	(0.068)	(0.175)	(0.366)	(0.366)	(45.988)	(46.207)
Divorced x RefProgram [b]	-0.147*	-0.982***	0.916*	0.917*	-103.598*	-112.706*
	(0.074)	(0.190)	(0.394)	(0.394)	(50.159)	(50.458)
Widowed x RefProgram [b]	-0.270**	-1.181***	1.246**	1.248**	-197.134**	-211.207**
	(0.091)	(0.222)	(0.456)	(0.456)	(60.695)	(61.046)
Non-Retail x RefProgram [b]	-0.025	-0.084	0.014	0.013	-49.754	-49.193
	(0.046)	(0.084)	(0.188)	(0.188)	(30.805)	(31.001)
Year 2007 (Dummy)		-1.487***				
		(0.143)				
Year 2008 (Dummy)		-2.562***				
		(0.236)				
Cumulative Days (in 000s)		4.004***				
		(0.387)				
Cumulative Days (in 000s)		-0.220*				
x RefProgram		(0.101)				
LogDuration x RefProgram				-0.167		
				(0.232)		
Constant	0.211***	0.244***			100.219***	147.265***
	(0.016)	(0.056)			(9.809)	(9.921)
Observations	9,495	28,353	9,495	9,495	9,495	9,495
R^2	0.107	0.099[c]			0.123	0.122
Log pseudolikelihood			-11,705.8	-11,705.6		

Robust standard errors in parentheses. All models include dummies for month of acquisition.

[a] Age is divided by 100 for better readability; [b] Interaction effects are with the first variable mean-centered; [c] Since the model is a random coefficients model estimated with Residual Maximum Likelihood (REML), this value is a pseudo-R^2 calculated as the squared correlation between predicted and actual values.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Figure 1: Average Values of Daily Contribution Margin (€) for Referred and Non-Referred Customers by Year

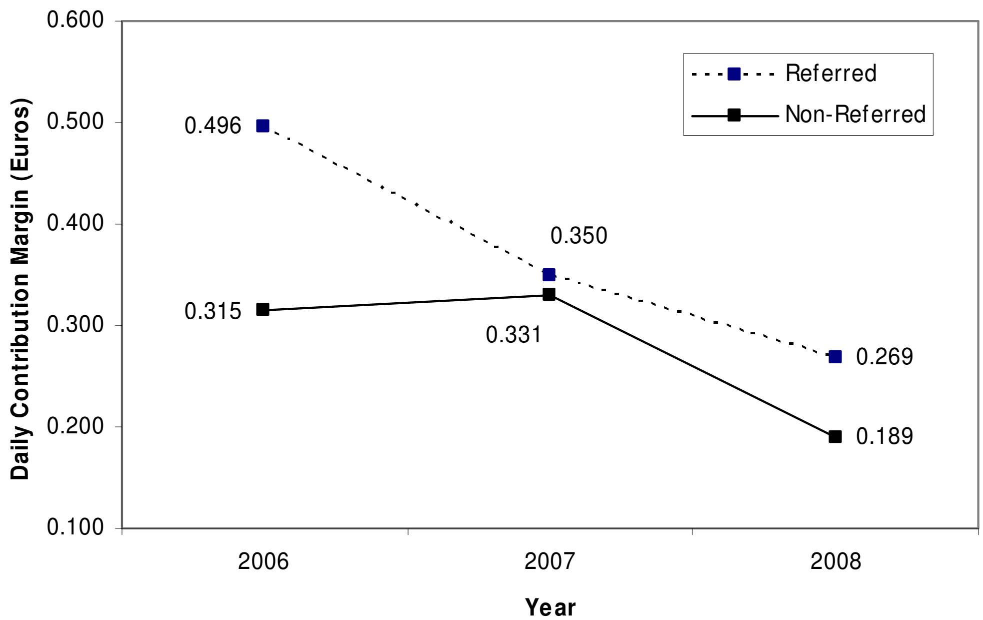
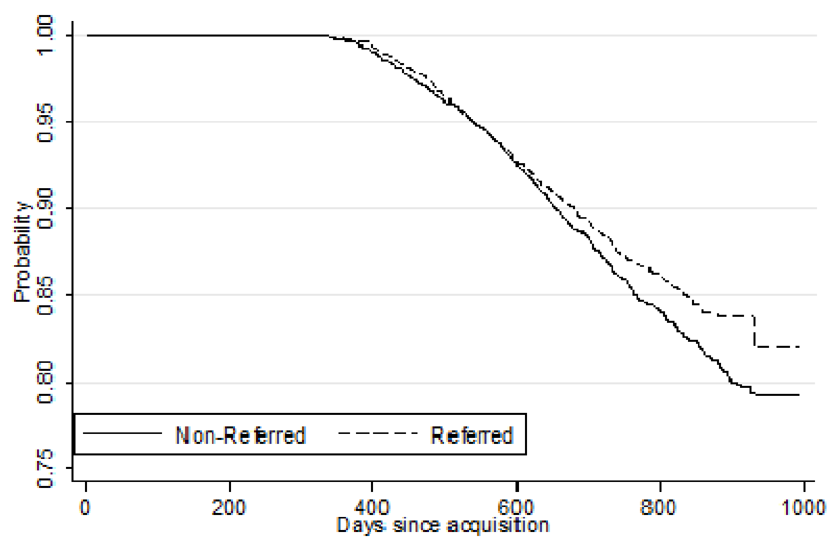


Figure 2. Probability that Referred and Non-Referred Customers Have Remained with the Firm (Kaplan-Meier Estimates of Survivor Functions)



Note: Customers were able to leave immediately after joining, but only a handful did so. The earliest defection took place after 64 days, and only 27 customers left within the first year of joining.