How Customer Referral Programs Turn Social Capital into Economic Capital

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July 10, 2017

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Abstract

Customers acquired through a referral program have been observed to exhibit higher margins and lower churn than customers acquired through other means. Theory suggests two likely mechanisms for this phenomenon: *better matching* between referred customers and the firm, and *social enrichment* by the referrer. The present study is the first to provide evidence of these two mechanisms in a customer referral program. Consistent with better matching affecting contribution margins, (i) referrer-referral dyads exhibit shared unobservables in customer contribution margins, (ii) referrers with more extensive experience bring in higher-margin referrals, and (iii) this association between the referrer's experience and margin gap becomes smaller over the referral's lifetime. Consistent with social enrichment affecting retention, (iv) referrals exhibit lower churn only as long as their referrer has not churned. These findings indicate that better matching and social enrichment are two mechanisms through which firms can leverage their customers' networks to gain new customers with higher customer lifetime value, and convert social capital into economic capital. One implication for the managers of the firm studied is to preferably recruit referrers among their customers who have been acquired at least six months ago, exhibit high margins, and are unlikely to churn.

Key words: Customer referral programs, Customer relationship marketing, Referral marketing, Social networks, Word-of-mouth marketing.

Marketers are increasingly keen on leveraging customer-to-customer connections. As a result, social influence among customers and how to leverage it for acquiring and retaining customers are topics that are attracting growing interest from both practitioners and academics. One specific marketing practice that is gaining renewed prominence are referral programs in which the firm rewards existing customers for bringing in new customers (e.g., Berman 2015).

Customer referral programs have long been viewed as an attractive way to acquire customers because they (i) do not require any data on connections among customers, (ii) do not require sizable up-front expenditure, (iii) are simple to administer, and (iv) allow for a certain degree of targeting. A study by Schmitt, Skiera and Van den Bulte (2011)—henceforth SSV—has documented significant economic post-acquisition benefits as well. Referred customers had (i) a higher contribution margin, though this difference eroded over time, and (ii) a higher retention rate, and this difference persisted over time. Higher margins and higher retention combined into a customer lifetime value that was 16%-25% higher.

The temporary margin gap, SSV proposed, might stem from better matching, whereas the churn difference might stem from social enrichment. However, SSV merely invoked better matching and social enrichment as possible mechanisms, without testing these explanations. Their analysis focused on documenting differences between referred and non-referred customers in contribution margin, retention, and customer value. It did not identify or test the intervening mechanisms. The present study, in contrast, uses data not only on referred and non-referred customers but also on the referrers, i.e., the customers who generated the referrals, to assess whether the superior margins and retention of referred customers indeed stem from better matching and social enrichment. So, whereas SSV documented *that* referral programs are a means through which firms can leverage their existing customers' networks to acquire new customers exhibiting higher margins and lower churn, the present study provides the first evidence on the mechanisms at work, i.e., on *how* this conversion from social capital into economic capital operates.

Two features of customer referral programs are of particular relevance to better matching and social enrichment. First, the referrers usually know both the firm's offerings and the persons they refer. Second, referrers often remain customers for some time after making the referral.

Better matching features prominently in theoretical and empirical research on employee referral in sociology and economics (e.g., Beaman and Magruder 2012; Brown et al. 2016; Burks et al. 2015; Castilla 2005; Fernandez et al. 2000; Montgomery 1991; Pallais and Sands 2016; Pieper 2015; Rees 1966; Yakubovich and Lup 2006). Better matching is also central to the theoretical analysis of incentivized customer referrals by Kornish and Li (2010). In essence, the idea is that referred customers match with the firm better than non-referred customers do.

The formation of such superior matches can be active or passive. Active matching involves deliberate screening and occurs when current customers know their friends and acquaintances better than the firm's marketers do, know the firm's offerings better than non-customers do, and selectively match some of their peers to the firm. Passive matching, in contrast, stems from homophily, the tendency of people to connect with people like them.

A customer whose wants match better with the firms' offerings than those of another customer will expectedly (i) buy more offerings at given prices, (ii) have a higher willingness to pay for given offerings, and (iii) require lower service costs (e.g., explaining how the existing offerings can be used to address his wants; adapting the basic product to his wants). As a result, better matches expectedly result in higher contribution margins. Better matches expectedly also result in greater satisfaction and hence lower churn.[1] However, the information asymmetry between referred and non-referred customers vanishes over time. As customers accumulate experience with the firm, the two get to better know one another, so that the gap between referred and non-referred customers erodes.

Social enrichment, the second mechanism of interest, also appears in research on employee referral in sociology and economics (e.g., Castilla 2005; Fernandez et al. 2000; Neckerman and Fernandez 2003; Pallais and Sands 2016; Pieper 2015). In essence, the idea is that the social bond between a customer and the firm is strengthened by the presence of a third party who is connected to both and so embeds the dyad into a closed triad. In addition, the co-presence of a fellow customer may also provide functional benefits, such as education and discussion about the advantages and disadvantages of specific product offerings, as documented by Bursztyn et al. (2014) for financial services. As a result of these social and functional consequences of co-presence, a referred customer expectedly exhibits higher sales or lower cost to serve (hence higher margins) and greater satisfaction (hence lower churn) than a non-referred customer, as long as the referrer remains a customer.[2]

With the participation of the same retail bank studied by SSV, we analyze 1,799 dyads of referring and referred customers for specific patterns in churn and contribution margins that should occur if better matching and social enrichment are at work. These patterns include the

[1] These statements imply boundary conditions for the effectiveness of matching. For active (screening-based) matching to be effective, referrers must have a more informed assessment of the match between prospect and firm than either of them do. Yet, the prospect's characteristics that are correlated with high margins or low churn and unobserved by the firm do not need to be shared between the prospect and the referrer. In contrast, for passive (homophily-based) matching to be effective, the unobservables correlated with high margins or low churn must be shared between the referrer and the person referred but they do not need to be known to the referrer.

[2] Conceivably, the referrer might also educate the new prospect or the firm *before* making the referral. Such education creates or enhances good matches, in contrast to screening-based matching that simply finds and refers good pre-existing matches. The consequences for post-acquisition margins and churn of such pre-acquisition education are identical to those of screening-based matching, but distinct from those of post-acquisition social enrichment.

presence of correlated unobservables within these dyads of referring and referred customers, the initial margin gap being larger for referred customers acquired through referrers with more extensive customer experience, the narrowing of this experience-related margin gap over the referred customer's lifetime, and the narrowing or even disappearance of the retention gap once the referrer churns. The findings indicate that better matching affects the margin gap and social enrichment affects the churn gap between referred and non-referred customers.

We continue by developing refutable hypotheses consistent with better matching and social enrichment. Next, we describe our data, analyses, and findings. We conclude with implications for theory, research, and practice.

THEORY AND HYPOTHESES

Since it is extremely difficult to directly observe social, psychological or physical mechanisms driving a particular outcome, we use the standard approach of specifying refutable hypotheses that should be supported if a purported process is indeed at work and that are unlikely to be supported otherwise (e.g., Craver and Darden 2013). We build on prior work on employee referral (e.g., Coverdill 1998; Montgomery 1991; Rees 1966), especially the empirical research on employee referral programs cited earlier. These studies provide evidence that the benefits of employee programs are realized through distinct mechanisms, of which better matching and social enrichment are by far the most amply documented in employee referral programs and the only two likely to explain the margin and churn benefits of customer referral programs.[3] For

[3] Research on employee referral programs has advanced two additional mechanisms as potential explanations for the lower churn and higher productivity, remuneration, or rate of promotion of employees hired through referral. The first is *favoritism* by referrers who help their referrals gain promotions or higher performance reviews after being hired. Something similar might be at work in customer referral if firms extend preferential treatment (e.g., a lower mortgage rate) to referrals as a favor to their referrer. Such a functional benefit from joint consumption (Bursztyn et al. 2014) is just a special form of social enrichment. It can explain referrals' lower churn, but not their higher margins. If anything, favoritism should result in *lower* contribution margins. The second additional mechanism is

brevity, and consistently with the prior literature, we use the term "referral" to denote not only the event in which a customer brings in another customer, but also the referred customer.

As noted earlier, better matching is the phenomenon that referred customers fit the firm's offerings better than non-referred customers do, which can happen because of mere homophily (passive matching) or deliberate screening by the referrer (active matching). Social enrichment is the phenomenon that the relationship between the referral and the firm is enriched by the presence of a common third party, i.e., the referrer who is a customer of the firm and has some social relationship with the referral. Both mechanisms predict higher margins and lower churn of referred vs. non-referred customers. These are mere main effects predictions. We develop hypotheses that are more theoretically discriminating, i.e., more informative about the mechanism(s) purportedly at work.

None of the hypotheses we advance were posited by SSV. Since we test rather than take for granted the *ex post* one-to-one mapping by SSV of matching into higher margins and social enrichment into lower churn, we formulate each hypothesis for both (a) margins and (b) churn.

Unlike SSV whose emphasis was on customer value and program profitability, we do not make predictions about customer lifetime values (CLVs). The reason is that we focus on identifying the social mechanisms underlying the differences in margins and churn feeding into CLV. With the exception of the first, our hypotheses cannot be tested using the amalgamation of margin and churn into a single, time-invariant metric like CLV.

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monitoring by referrers who want to safeguard their reputation with the employer and prevent the referral from engaging in moral hazard. There are a few scenarios imaginable where moral hazard is a key driver of profitability *and* fellow customers can monitor each other. Some business markets with large transaction-specific investments by the seller may represent such a scenario. Credit card referrals by close family members or friends in emerging markets without a sophisticated credit rating infrastructure may be another (Guseva and Rona-Tas 2001). Monitoring might explain the higher margins, but not the lower churn of referred customers. If anything, restrictions on the ability to engage in moral hazard would *increase* voluntary churn rather than decrease it.

Better Matching

Matching on shared unobservables. Passive matching is based on the presence of shared unobservables. These are characteristics that are common to the referrer and the referral, are related to the quality of the match, but are not fully observed by the firm before acquiring the customer. Referrers have an above-average chance of being a good match with the firm's offerings. Otherwise, they would not be customers. Also, because of homophily, referrers are likely to be similar to the person they refer. Consequently, referred customers are likely to be a better match than non-referred customers are—provided that the shared characteristics meet two criteria. First, they are relevant to the enjoyment of the product, the need for additional services, or customer value and customer satisfaction broadly, and, consequently, they are associated with higher margins or lower churn. Second, the firm does not fully observe these characteristics prior to acquisition. Passive matching on such shared characteristics implies the presence of correlated unobservables in the margins or the churn behaviors of referrers and their referrals.

Examples of such characteristics relevant to banking services include preferences for opening hours, risk aversion, interest in financial advice, and fiscal responsibility. When matching occurs on such characteristics, lenders can infer from the observed behavior of the referrers which products the referred customers will be most interested in (Guseva 2008). The emerging practice of social credit scoring in the financial industry also relies on the idea that the creditworthiness of one's contacts is informative about one's own creditworthiness (Wei et al. 2016).

So, passive matching implies the following refutable hypothesis:

H1: Referrers and their referrals have shared unobservables in their (a) contribution margin and (b) churn rate.

Note, unlike passive matching based on homophily, active matching based on screening does *not* imply shared unobservables. Both mechanisms require characteristics that are related to the quality of the match and that are not fully observed by the firm before acquiring the customer, but screening-based matching does not require that those unobservables are shared by the referrer and the referral.

Complexity of referrals' needs and benefit of matching. If the benefits of referral programs stem from better matching on unobservables, then those benefits should be greater for customers with complex needs that are harder for firms to profile a priori, identify and understand quickly, and meet efficiently. For retail banks, such customers likely have needs that require more than savings and checking accounts and mortgage financing, and also involve life insurance, investment advice, retirement planning, or estate planning. We do not formulate the corresponding hypothesis because we do not have the data on customers' need complexity or service portfolio that a direct test of such a hypothesis requires. Yet, we return to need complexity when discussing our findings and suggestions for future research.

Referrers' experience and quality of matching. Better matching on unobservables implies that the relationship between the referrer and the firm affects the quality of the match. A referrer who has been a customer for a long time typically has a relationship with the firm that has survived many occasions for potential churn. Such referrers are likely to match up especially well with the firm's offerings (e.g., Fader and Hardie 2010). In addition, they tend to have a better understanding of these offerings and will be able to produce better matches when deliberately screening potential referrals. Finally, to the extent that customers with a longer relationship with a firm also feel more satisfaction, positive affect and benevolence towards that firm, they will also exert greater effort in finding good matches and be less likely to generate referrals opportunistically just to pocket the reward (Jing and Xie 2011; SSV 2011). As a result, the quality of matches produced through both passive, homophily-based matching and active, screening-based matching should be lower for referrers with little experience as customer with the firm than for referrers with extensive experience. These arguments imply:

H2: The initial gap in (a) contribution margin and (b) churn of referred vs. non-referred customers is greater for referrals made by referrers with extensive rather than limited experience with the firm when making the referral.

The same arguments that involve occasions for churn, information, and motivation apply to the strength or duration of the relationship between the referrer and the person referred ("the referral" for short) rather than between the referrer and the firm (Kornish and Li 2010). We do not formulate the corresponding hypothesis because we do not have data on the nature of ties between referrers and their referrals required to test such a hypothesis.

*Initial matching vs. learning over time***.** Assuming learning by firms or customers, both active and passive matching imply that the gaps in margin or churn between referred and non-referred customers will erode over the customers' lifetime. Over time, both referred and non-referred customers learn about the firm's offerings and procedures, and the firm learns about both types of customers. However, matching implies that the learning rate differs. As non-referred customers accumulate experience with the firm, they become as informed about the firm's offerings and procedures as referred customers are. Likewise, the firm is increasingly able to use the purchase and service history of the non-referred customers to serve them better.

In essence, learning over time reduces the information asymmetry that is initially resolved through better matching (e.g., Dustmann et al. 2016; SSV 2011). This substitution of direct learning from experience for social learning through matching as a way to address the firm's initial paucity of information implies that the effects hypothesized in H2 should erode the longer the newly acquired customer remains a customer. Hence, we conjecture:

H3: The referrer experience-related difference in the gap in (a) contribution margin and (b) churn between referred and non-referred customers erodes over the customers' lifetime.

Social Enrichment

Referrals may also provide the firm with advantages because of another mechanism known as social enrichment (e.g., Fernandez et al. 2000), joint consumption (Bursztyn et al. 2014), or team production (Pallais and Sands 2016). The argument is that the relationship with the firm is enriched when a family member, friend or acquaintance is a customer as well.

Both balance theory and social closure theory imply that being connected to a fellow customer increases the referral's trust in the firm and strengthens the affective bond with the firm (Van den Bulte and Wuyts 2007). This social bonding mechanism should be particularly relevant for products for which trust is important, like experience and credence products and, more generally, categories in which customers experience high risk or ambiguity (e.g., DiMaggio and Louch 1998; Kilian et al. 2013). Examples include financial planning, investment advice, and life insurance—all services sold by European retail banks, including the bank studied here.

Being connected to a fellow customer may also provide functional benefits. Examples include help with understanding the pros and cons of various offerings, help with navigating particular procedures without having to rely on the firm's customer support, receiving preferential treatment as a favor to an especially valuable referrer, or having an advocate when resolving customer complaints (e.g., Bursztyn et al. 2014; Reichheld 2006).

Because of social enrichment, referred customers are likely to have a stronger commitment and attachment to the firm, and to avoid or overcome temporary frustrations with its offerings.

Consequently, a referred customer is less likely to churn than a non-referred customer, provided that the referrer has not churned. The latter is likely: referrers often exhibit below-average churn, which is why intention to refer is a popular indicator of loyalty (Gupta and Zeithaml 2006).

However, some referrers do churn. If social enrichment is indeed a reason for why referrals exhibit higher margins or lower churn than non-referred customers, then the referrer's churn should annihilate the gap in margin and churn. The reason is simply that social enrichment requires continued co-presence: *No co-presence means no enrichment*.

This argument is consistent with contagious churn and contagious repeat documented in several studies (Dierkes et al. 2011; Iyengar et al. 2015; Nitzan and Libai 2011; Sgourev 2011; Zhang et al. 2012), but goes beyond that evidence in three ways. First, it contrasts referred vs. non-referred customers. Second, the claim is not only that a referrer's churn boosts the referral's churn probability, but also that the referrer's churn will annihilate the initial boost in the referral's loyalty. Third, the withdrawal of social enrichment, and the concomitant decrease in commitment in the referrals' relation with the firm, may also decrease the amount of business or increase the cost to serve the referrals who remain a customer, and hence lower the contribution margin of referrals who do not churn after their referrer did. So, we propose:

H4: Referred customers exhibit (a) a lower contribution margin and (b) a higher churn rate after their referrer has churned.

H5: The referred customers' gap in (a) contribution margin and (b) churn compared to non-referred customers disappears after their referrer has churned.

H5 is a stronger version of H4: once the referrer is no longer co-present, social enrichment is not simply lower (H4) but disappears with the referrer (H5).

DATA

Research Setting

We use data from the referral program at a German bank studied previously by SSV. The key difference is that we have data not only on referred and non-referred customers, as SSV did, but also data on the customers who generated those referrals. The data include 1,800 customers 18 years or older who were acquired through the bank's referral program between January 2006 and October 2006, as well as their referrer. The data comprise all referral-referrer dyads for which the bank had demographic information on both members of the dyad and the referrer generated only a single referral. The latter restriction avoids major statistical problems in analyzing two-way peer influence within dyads (Lyons 2011). The data accounts for nearly half (49%) of all referrals acquired in that 10-month period. According to the bank, the selection of referrals included in the data is unrelated to their contribution margin or churn. Also, as documented in the "Preliminary Analysis" section below, our data exhibit the same pattern in contribution margins and churn as those reported by SSV using all referrals acquired in 2006. Hence, there is no reason to expect that missing data would bias our hypothesis tests.

We also have data on 3,663 customers 18 years or older who were acquired over the same period through means other than the referral program. That sample of non-referred customers is drawn randomly from all non-referred customers.

The observation period covers the 33 months from January 2006 to September 2008. For each customer, we observe the day of acquisition, the month of churn (if applicable), the contribution margin in each year, and some demographics. We have the date of acquisition of the referrers even if it occurred before January 2006. Because the referral program was used only in a business-to-consumer context, all customers are individual people.

The bank communicated the referral program to existing customers through direct mail, staff, and flyers in the branches. The procedure was straightforward: Every existing customer who brought in a new customer received a reward of €25 in the form of a voucher that could be used at several well-known retailers. Except for opening an account, the referred customer did not have to meet any conditions like a minimum amount of assets or a minimum stay for the referrer to receive the reward. The total acquisition cost for referred customers (including the referral fee and the additional administrative costs of record keeping, paying out, etc.) was, according to the bank, on average approximately €20 lower than that for non-referred customers (SSV 2011).

Dependent Variables

We have three dependent variables. The first is the customer's average daily contribution margin (DCM). It is the total direct contribution margin that the customer generated in the 2006-08 observation period, divided by the total number of days the customer was with the bank over that period. The per diem scaling allows us to compare the contribution margin of customers with different observed (and often censored) durations, and so to investigate separately the variance in each of the two drivers of post-acquisition CLV (setting aside the discount factor): margin per time unit vs. customer lifetime. The direct customer contribution margin equals direct revenue (interest and fees) less direct costs (e.g., interest expenses, sales commissions, brokerage, trading costs). Indirect benefits like the difference between the interest paid on deposits and the bank's financial returns on how it deploys that capital are not added to the margin. The direct acquisition costs is not subtracted.

The second dependent variable is a time-varying version of daily contribution margin. It is obtained 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.

The third dependent variable is duration, the total number of days the customer was with the bank in 2006-08. It is the basis for analyzing retention or churn.

Independent Variables

We have data on three types of customers: 1,800 referrals (i.e., referred customers), their 1,800 referrers, and 3,663 non-referred customers. To distinguish referrals from the other types, we create a binary indicator, *Referral,* which takes the value 1 for referrals and the value 0 for other customers.

We have some demographic data. *Age* is the customer's age in January 2006. In the statistical models, we center age at 40 (the mean age of referrals). *Female* is a dummy coded 1 for women and 0 for men. We also have dummies for marital status, with the categories being married, divorced/separated, widowed, and other, and with single as the base category. We also control for the customer's time of acquisition. For the referred and non-referred customers, all of which are acquired between January and October 2006, we have dummies for each month between February and October and use January as the baseline. So, in a model with all demographics, the intercept or baseline refers to a 40-year old single male customer acquired in January 2006. Most referrers were acquired before 2006. Therefore, we create additional dummies for being acquired in 2005, in 2004, in 2001-03, in 1996-2000, and before 1996.

To investigate how the referrer's experience prior to making the referral relates to the margin or churn of the referred customer, we use two dummies indicating whether the difference in the acquisition dates of the two customers is less or equal to 30 days (*Le1MonthExp*), between 31 and 180 days (*1-6MonthsExp*), or more than 6 months (baseline).

The variable *CLT* (customer lifetime) is the cumulative number of days the customer has been with the bank. For the churn models where the dependent variable is measured daily, *CLT* is updated daily. For the models of contribution margin where the dependent variable is computed only annually, *CLT* is observed on the last day that the customer was with the bank in that year (i.e., December 31 or the day of churn). To avoid very small coefficients, *CLT* is expressed in thousands of days.

The time-varying dummies *Year2007* and *Year2008* capture whether the contribution margin pertains to 2006, 2007 or 2008. The hazard models for churn feature dummies for time of acquisition as well as a non-parametric baseline for duration dependency. Consequently, adding year dummies in the churn models is superfluous.

Our control variables in models contrasting referred and non-referred customers also include *Referral* × *Age* and *Referral* × *Age* × *CLT*. These interaction terms allow referral gaps in margin and churn to vary by age. They also allow for the possibility that younger customers exhibit simpler financial needs than older customers do, and hence for the possibility that matching benefits increase with age.

Finally, we create four covariates to assess how customers' contribution margin and risk of churn change after their counterpart in the same referrer-referral dyad has churned. *ReferGone* is a dummy that is coded 0 as long as the referrer remains with the bank, and switches to 1 once the referrer has churned. *ReferGone* can change any day, and so can be used for assessing changes in the referral's churn risk. In contrast, it cannot be used to assess changes in the referral's daily contribution margin, because the latter dependent variable is observed only annually.

We therefore create a second variable, *PropReferGone*, as a ratio that can vary annually. It is the answer to the following question: of all the days that the referral was a customer in a particular year, what fraction occurred after the referrer churned? The variable ranges between 0 and 1. It equals 1 if the referrer left before January 1 of the focal year; it equals 0 if the referrer remained a customer throughout the period that the referral was a customer during that year; it takes an intermediate value otherwise.

We constructed the dummy *RefalGone* and the ratio *PropRefalGone* in a similar fashion to study how the referrer's contribution margin and churn changes after the referral's churn.

Data Purification and Final Data Set

The data include some customers with a daily contribution margin that is up to 10 standard deviations above the mean. Though skewed customer profitability distributions are common, the risk of genuinely erratic outliers may be acute for the per-diem scaled annual DCM(t) measure of customers who were with the bank for only a short amount of time in a particular year. Because such erratic outliers can influence comparisons of means and regression, we purify the data using the DBETACS diagnostic to identify customers with a disproportionally large influence in the panel models for the gap in DCM(t) (Preisser and Qaqish 1996) between referred and non-referred customer. This diagnostic is a generalization of the DFBETAS to identify influence points in linear regression. This influence analysis led us to delete one referred customer, resulting in a final data set of 1,799 referral-referrer pairs and 3,663 non-referred customers.

We also create a sub-set of non-referred customers that closely match the referred customers on the observed demographics. Specifically, for a non-referred customer to be a match with a referred customer, we require them to be of the same gender and marital status, and to have a similar age and month of acquisition. Of the 3,663 non-referred customers, 1,788 match at least one referred customer.[4]

[4] We use exact matching on the un-ordered categorical variables gender and marital status and use nearest-neighbor matching based on Mahalanobis distance on age and month of acquisition. We use the "teffects nnmatch" procedure in Stata 13.1 and apply its default settings. Because our hypotheses involve interactions, and given the arguments by King and Nielsen (2016), we use nearest-neighbor matching rather than propensity score matching. We identify at least only one valid match for each of the 1,799 referred customers. If we do not allow the same non-referred

Table 1 profiles the four sets of customers—referrals, referrers, non-referred customers, and matched non-referred customers—by reporting the mean values of their common independent variables. It also reports mean values of the two dyad-specific variables. The data exhibit the same patterns of differences between referred and non-referred customers as those documented by SSV (Web Appendix A).

[Insert Table 1 About Here]

SHARED UNOBSERVABLES IN MARGIN (H1A)

Our first hypothesis posits that referrers and referrals have shared (or correlated) unobservables in their margins and churn rate. In this section, we assess the presence of shared unobservables in the daily contribution margin.

Common Random Effects in Panel Data

We exploit the fact that we observe customer margins (DCM) over each of three years by estimating a panel model with both person-specific and dyad-specific random effects. This analysis allows us to test for the presence of common random effects as an instantiation of shared unobservables. Let t denote the calendar year 2006, 2007 or 2008 (t = 1, 2, 3), j denote a dyad (j: 1, …, 1799), and i denote whether the customer is a referral or a referrer (i: 1, 2). We estimate the following model for the DCM in year t of the 3,598 referrers and referrals (ij) nested in 1,799 dyads (j):

(1) $$DCM_{ijt} = \beta_0 + \beta_1 Referral_{ij} + \sum_{k=2}^{22} \beta_k X_{kijt} + d_j + u_{ij} + e_{ijt}\text{, where}$$

customer to serve as a match for multiple referred customers, then we can uniquely match 1,276 referred customers. This reduction in the number of unique matches affects only how we conduct the robustness checks (placebo tests) detailed in the Web Appendices B and C. It does not affect the main analyses.

the *Referral* dummy distinguishes between referrals and referrers, and the control variables *X* include age, and dummies for gender, marital status, month of acquisition in 2006, acquisition in other years, and the current year. The random effect *d* is dyad-specific and the random effect *u* is person-specific. As always, random effects are assumed to be orthogonal to the included covariates and to the observation-specific random shock *e*.

We estimate the model assuming that all random terms are normally distributed, and use empirical standard errors robust to clustering and heteroscedasticity for inference. We make the panel data set balanced within dyads with three annual observations for each customer by setting $DCM_{ijt} = 0$ for customers who churned before year *t*. This balancing affects only 20 of the 10,794 customer-year observations in the analysis.

Column 1 in Table 2 reports the results. Though most of the unexplained variation in the annual contribution margin of referrals and referrers is customer-specific ($\sigma_u = 4.128$) or observation-specific ($\sigma_e = 2.86$), a significant part of it is dyad-specific ($\sigma_d = 1.234$).[5] The latter is consistent with the presence of shared unobservables in contribution margins.

Shared Unobservables or Peer Presence?

Several studies have documented the presence of correlated purchase incidence or correlated purchase volume between people who share a referral tie or other social tie (e.g., Haenlein and Libai 2013; Hill et al. 2006; Iyengar et al. 2015; Nair et al. 2010). These studies note that correlated behavior can stem not only from shared unobservables but also from peer influence.

[5] The coefficient of *Referral* in Table 2 pertains to a 40-year old single male referral customer acquired in January 2006. Such a customer's DCM is about 30 euro cent higher than that of a similar referrer. This result seems to conflict with the average DCM values for referrals and referrers reported in Table 1. There are two explanations for this apparent conflict. First, the coefficients associated with being acquired in other months in 2006, which apply to almost all referrals and only few referrers, are all about -1.2. Second, profitability increases with age, and referrers are on average four years older than referrals. Taking these two elements into account makes the results in Table 2 consistent with the €1.2 margin difference between referrals and referrers in Table 1.

This ambiguity raises the question: Is the evidence of shared unobservables in margins between referrals and referrers robust to controlling for how long the referral and the referrer were both customers with the bank and hence may have influenced each other?

We therefore extend the model in equation (1) with variables capturing the presence or absence of the dyadic counterpart, i.e., *PropReferGone* and *PropRefalGone*. Model (2) in Table 2 reports the estimates of this extended model. The results are quite clear: Customers' DCM is not affected by their peer's churn, and the conclusion of significant shared unobservables in contribution margin arrived at earlier continues to hold.[6]

Placebo Tests

We also conduct placebo tests involving fake dyads constructed by keeping the referrer but replacing the referral by a non-referred customer matching the referral on gender, marital status, age and time of acquisition. Such fake dyads should exhibit much weaker evidence of dyad-specific shared unobservables than true dyads do. As reported in the Web Appendix B, we indeed find that the dyad-specific variation is typically indistinguishable from zero, always weaker than in the true dyads, and always resulting in worse model fits.

[Insert Table 2 About Here]

SHARED UNOBSERVABLES IN CHURN (H1B)

Common Random Effects in Churn

We now turn to assessing the presence of shared unobservables in the churn behavior of referrals and referrers, again by testing for the presence of common random effects. Since we also want to control for *ReferGone* and *RefalGone* which are time-varying, we use a discrete-

[6] Replacing the dyad-level and customer-level random effects in equation (1) by 3,598 customer-specific fixed effects, one for each referrer and one for each referral, and computing their intra-dyadic correlation leads to the same conclusion (Model 1: Pearson .158, Spearman .317; Model 2: Pearson .158, Spearman .319; all $p < .001$).

time model for the churn hazard h_{ijt} of member i (i: 1, 2) in dyad j (j: 1, .., 1799) on day t. We specify a complementary log-log link function. This setup results in the exact discrete-time version of the continuous-time Cox proportional hazard model (Allison 1982; Prentice and Gloeckler 1978), but allows for time-varying covariates. We add a normally distributed dyad-specific random effect. So, our specification is:

(2) $$g(h_{ijt}) = \alpha_t + \beta_1 Referral_{ij} + \beta_2 ReferGone_{ijt} + \beta_3 RefalGone_{ijt} + \sum_{k=4}^{22} \beta_k X_{kij} + d_j$$, where

$g(h) = \ln(-\ln(1-h))$ is the complementary log-log link function, h_{ijt} is the discrete-time hazard, i.e., the probability that customer i of referrer-referral dyad j churns on day t given he or she was still present on day t-1 (note, t captures the time elapsed since acquisition, not calendar time), the α_t coefficients are 30-day fixed effects capturing duration dependency in a piece-wise constant manner, the X control variables include age and dummies for gender, marital status, month of acquisition in 2006, and year of acquisition other than 2006, and d_j is a normally distributed dyad-specific random effect. We do not include dummies for the years 2007 and 2008, because Period = Age + Cohort and the hazard model already contains dummies for duration and for month of acquisition, i.e., customer age and cohort.

To avoid having to include a separate α dummy for each of the 966 days in our data, we organize the baseline hazard into 30-day intervals. That is, though we model the hazard at the daily level, we define the α coefficients such that they can vary freely between 30-day blocks but remain constant within each block.[7] This non-parametric baseline is very flexible and makes the

[7] A minor challenge is that, when not a single customer churns in a 30-day block, the likelihood reaches its true maximum only when that block's baseline α parameter estimate reaches $-\infty$. As a simple solution to such "quasi-complete separation," we delete all the observations in those blocks from the data set, delete the corresponding dummy variables from the model, and proceed as usual (compare Iyengar et al. 2015).

model robust to customer-specific unobserved heterogeneity in all but very extreme cases (e.g., Lin and Wei 1989; Schmoor and Schumacher 1997; Struthers and Kalbfleisch 1986).

Two technical points may be worth noting explicitly. First, since we observe the date of acquisition of both referrals and referrers, there is no left-censoring in our data. However, even if a referrer was acquired before 2006, he or she must have survived until the time the referral took place in 2006. So, in our study, these referrers were *not* observationally at risk prior to 2006. Consequently, we let such referrers enter the risk set only on January 1, 2006.[8] Second, none of the referrals or referrers acquired in February 2006 churned in our data. As a result, the coefficient of the dummy "Acquisition in Feb 2006" has no finite maximum likelihood estimate. To prevent this quasi-complete separation to produce estimation and inference problems, we force the coefficients for acquisition in February and March 2006 to be equal.

Column (1) in Table 3 reports the estimates of the hazard model excluding *ReferGone* and *RefalGone*. The variation of the dyad-specific random effect is significantly different from zero ($\sigma_d = 1.290$; $p < .001$), indicating the presence of shared unobservables in churn.

Shared Unobservables or Peer Presence?

Several studies have documented the presence of correlated disadoption or repeat behavior between people who share an organic referral tie or other social tie (Dierkes et al. 2011; Haenlein 2013; Iyengar et al. 2015; Nitzan and Libai 2011; Sgourev 2011; Zhang et al. 2012). However, correlated timing behavior can stem from both shared unobservables and social contagion, and one is easily confounded with the other (e.g., Aral et al. 2009; Van den Bulte and Lilien 2001). This ambiguity raises the question: Is the evidence of shared unobservables in churn among the

[8] As a robustness check, we added the natural log of the number of days that a referrer had been with the bank on January 1, 2006 as an additional control variable. This extension did neither improve model fit significantly nor affect the substantive findings.

two members of a referral dyad robust to controlling for the churn of the counterpart in the dyad?

We therefore extend the analysis of shared unobservables in churn by controlling for *ReferGone* and its counterpart *RefalGone*. Of the 1,799 dyads, we observe 85 in which only the referrer churns by the end of our data window, 144 in which only the referral churns, and 31 in which both churn. The referral and referrer churn in the same month in only 10 cases, so coordinated action is quite unlikely. When both leave and the referrer does first (last), the average inter-event time is 104 (95) days. So, again, coordinated churn is quite unlikely.

The results in column (2) in Table 3 indicate that a peer's prior churn predicts one's own churn and that the evidence of shared unobservables vanishes after accounting for peer churn ($\sigma_d = .005$; $p > .05$). The conclusion of significant shared unobservables in churn arrived at earlier does not continue to hold, and is likely to have been a confound between shared unobservables and contagious churn. This result contrasts with the evidence of shared unobservables in customer margin, which was robust to controlling for peer churn.

Placebo Tests

We conduct placebo tests for shared unobservables and contagion in churn by estimating the models reported in Table 3 on the fake dyads already used in the DCM placebo tests. As reported in the Web Appendix C, fake dyads do not show evidence of contagious churn, nor evidence of shared unobservables that vanishes after controlling for contagious churn.

[Insert Table 3 About Here]

TESTS OF HYPOTHESES H2A-H5A ON MARGINS

We presented several hypotheses which should be supported if the margin gap between referred and non-referred customers stems from better matching. H2a implies a negative association between limited referrer experience and the margin gap. H3a implies that the differences in margin gap related to the referrers' experience erode over the referrals' lifetime with the bank. Since we do not have a direct measure of what constitutes sufficient experience for a referrer to make an informed match, we use two different levels of experience with the bank before making the referral: Less or equal to 1 month and between 1 and 6 months.

We also hypothesized that, if the margin differential stems from social enrichment, then the differential should be lower (H4a) and even disappear (H5a) after the referrer has churned.

For this analysis, we use data on the 1,799 referred and the 3,663 non-referred customers, and model the Daily Contribution Margin of customer *i* in year *t* as:

(3) $$DCM_{it} = \beta_0 + \beta_1 Referral_i + \sum_{k=2}^{7} \beta_k X_{kit} + \beta_8 PropReferGone_{it} + \sum_{k=9}^{28} \beta_k X_{ki} + u_i + e_{it}$$, where

the *Referral* dummy distinguishes between referred and non-referred customers, the first set of *X* variables include the linear, 2-way interaction and 3-way interaction terms necessary to test H2a-H3a, *PropReferGone* used to test H4a-H5a is defined as above, and the second set of *X* variables controlling for gender, marital status, age, month of acquisition, and the year. The person-specific effects u_i can be either random or fixed. We use maximum likelihood to estimate the random effects specification, and OLS to estimate the fixed effects specification. In both cases, we use empirical standard errors robust to heteroscedasticity and clustering.

Column (1) in Table 4 reports the estimates of equation (3) with random effects. The model in column (2) excludes *CLT* as well as all the variables that we interact with *CLT* associated with H2a-H3a (except for age, which is always included as a control). The model in column (3) excludes the *PropReferGone* variable associated with H4a-H5a. The results are robust across specifications, indicating that our conclusions are not affected by some inability to distinguish between the patterns in the data implied by better matching versus social enrichment.

Referrers with less than 1 month of experience with the bank generate referrals exhibiting markedly lower margins than referrers with more than 6 months of experience do. Referrals generated by such inexperienced referrers not only lack a positive boost in DCM but are even *less* profitable than non-referred customers (.672 – .821 < 0). Referrers with experience between 1 and 6 months exhibit similar but more muted patterns: The decrease in DCM associated with that level of inexperience is significant, both statistically and economically. Referrals generated by customers with only between 1 and 6 months of experience have a margin gap that is only about 25% of that generated by more experienced referrers ([.672 – .500]/.672). These findings are consistent with H2a and H3a.

The positive coefficient of *Referral* × *Age* (.024) indicates that the initial margin gap between referred and non-referred is greater for older consumers. Customer lifetime (*CLT*) moderates this referral-by-age association negatively, and the latter turns negative after about 730 days (.024/.033 x 1,000 days). So, the initial margin gap is greater for older than younger customers, but the gap closes faster for older than younger customers.[9] One possible explanation for this pattern is that older customers have more complex needs, and hence exhibit more pronounced patterns consistent with better matching.

Support for H2a and H3a supports the notion that the margin gap stems from better matching. In contrast, there is no support whatsoever for the notion that the margin gap is smaller (H4a), let alone disappears (H5a), after the referrer has churned. The continued presence of the referrer shows no clear association with the referral's contribution margin.

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[9] SSV tested for the presence of a linear or quadratic interaction between *Age* and *Referral* on DCM(*t*), and found no such pattern (SSV 2011; Table 4, column 2). Their analysis did not include a third-order interaction with *CLT*. Our results in Table 4 of a positive *Referra*l × *Age* coefficient (evaluated at *CLT* = 0) but a negative *Referra*l × *Age* × *CLT* coefficient for DCM(*t*) is consistent with the absence of a significant interaction between *Age* and *Referral* averaged over the values of *CLT*, which is what SSV documented.

In short, our findings indicate that the margin gap stems from better matching and not from social enrichment. This conclusion is robust to specifying fixed rather than random effects (Web Appendix D).

[Insert Table 4 About Here]

TESTS OF HYPOTHESES H2B-H5B ON CHURN

We now turn to how customer experience and joint presence relate to the difference in churn between referred and non-referred customers. Since this analysis requires including a time-varying covariate, *ReferGone*, we again use a discrete-time hazard model with a complementary log-log link function. We model the hazard of churn by referred and non-referred customers as:

(4) $$g(h_{it}) = \alpha_t + \beta_1 Referral_i + \sum_{k=2}^{7} \beta_k X_{kit} + \beta_8 Refergone_{it} + \sum_{k=9}^{26} \beta_k X_{ki}$$, where

$g(h)$ = ln(-ln(1-h)), the α coefficients are fixed effects capturing duration dependency, i.e., how the baseline hazard varies over the customers' lifetime, the *Referral* dummy distinguishes between referrals and non-referred customers, the first set of X variables includes the linear, 2-way interaction and 3-way interaction terms necessary to test H2b-H3b, *ReferGone* is used to test H4b-H5b, and the second set of X variables controls for gender, marital status, age, and month of acquisition. As in the hazard analysis reported earlier, we do not include dummies for the years 2007 and 2008 and organize the baseline hazard into 30-day intervals.

Column (1) in Table 5 reports the estimates of the model in equation (4) from the data comprising 1,799 referred and 3,663 non-referred customers. The model in column (2) excludes *CLT* and all the variables that we interact with *CLT* associated with H2b-H3b (except for age, which is always included as a control), and that in column (3) excludes the *ReferGone* variable associated with H4b-H5b. The key results are robust across specifications, indicating that our conclusions are not affected by some inability to distinguish between the patterns in the data implied by better matching versus social enrichment.

The results in columns (1) and (3) do not exhibit the patterns predicted to hold if churn was affected by better matching. There is no consistent and significant evidence that referrers with limited experience produce faster-churning referrals (H2b), or that such a gap in churn rate becomes more muted over the referrals' lifetime (H3b).[10] The lack of support for H2b and H3b is robust to changing the hazard model specification from a complementary log-log to a linear probability model (Web Appendix E).

In contrast to the lack of patterns consistent with better matching, the large and significant coefficients of *ReferGone* in both columns (1) and (2) provide evidence of social enrichment. The estimates in column (2) indicate that referred customers whose referrer is still with the bank have a churn hazard that is about 40% lower than that of non-referred customers [exp(-.48)-1]. This difference changes dramatically once the referrer has churned. Referred customers whose referrer has left the bank have a churn hazard that is about 280% higher than that of non-referred customers [exp(-.48+1.82)-1]. So, not only does the positive association between referral and loyalty decrease (H4b) and disappear (H5b), consistent with social enrichment, but the associations with loyalty turn from positive to markedly negative.

In short, the data provide strong evidence that the presence of the referrer is critical to the referred customers' higher loyalty compared to non-referred customers. This finding is consistent with the notion that referrals' lower churn stems from social enrichment.

[Insert Table 5 About Here]

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[10] Column (1) reports a significantly positive coefficient for *1-6MonthsExp*, but column (3) does not. This result does not amount to consistent support for H2b. Both columns (1) and (3) report a significantly negative coefficient for *Age x CLT*, but that interaction is not relevant to any hypothesis. It is included only as a necessary lower-order term for the third-order interaction between *Referral*, *Age*, and *CLT* included as a control.

PREDICTING REFERRAL MARGIN AND CHURN FROM REFERRER CHARACTERISTICS

Managers want to know whether some referrers are more likely to generate attractive referrals than others. Our data allow us to shed some light on this question by regressing referrals' DCM on their referrers' characteristics, and by estimating a Cox hazard model of referrals' churn using the same variables. The results in Table 6 show that referrals tend to have higher margins if they were acquired through a referrer who generates a higher daily contribution in 2006 (the earliest year we have contribution data on), is older, and is not divorced. Though only one of the acquisition time coefficients is significant, the overall pattern suggests that referrals tend to exhibit higher margins if their referrer has been with the bank for more than a few months. In contrast, none of the referrer's characteristics predicts the referral's speed of churn. These results suggest that managers may want to focus their invitations to serve as referrers on their higher-margin customers who have been with the bank more than a few months. Note, the pattern that some kinds of referrers tend to generate more attractive referrals than other referrers does not imply that any of the referrals is unprofitable.

[Insert Table 6 About Here]

RIVAL EXPLANATIONS

In Web Appendix F, we discuss and falsify various possible rival explanations for our findings. These include favoritism, monitoring, selectivity, confounding correlated unobservables with peer influence, post-acquisition differences in treatment, and lack of balance in observables between referred and non-referred customers.

CONCLUSION

We investigated two explanations why customers acquired through a referral program exhibit higher margins and lower churn than customers acquired through other means. Patterns in the margin gap across referrals, referrers, and time are consistent with *better matching*, whereas patterns in the churn gap over time—specifically the change in referrals' churn after their referrer churns—are consistent with *social enrichment.* These findings shed new light on how (i) referral programs convert social capital into economic capital and (ii) firms can take a more selective approach to referral programs to increase their economic benefits.

Since better matching and social enrichment are mechanisms that cannot be observed directly, we specified hypotheses that can be tested using observable behaviors and outcomes, that should be supported if a purported process is indeed at work, and that are unlikely to be supported otherwise. This is the standard approach in research (e.g., Craver and Darden 2013).

Better understanding how marketing converts the connections of current customers into valuable new customers, and more broadly social capital into economic capital, is important to three research areas. The first is word-of-mouth marketing, where the emphasis is turning from investigating *whether* to *how* peer influence operates (e.g., Godes 2011; Iyengar et al. 2011b). The second is the intersection among social status, customer valuation, and targeting (e.g., Hinz et al. 2011; Hu and Van den Bulte 2014; Wei et al. 2016). The third is social capital theory and its various applications to marketing (e.g., Gonzalez et al. 2014; Wuyts et al. 2004).

Our findings also raise several new questions about customer referral programs. First, what kinds of firms and products are most likely to derive post-acquisition benefits from referral programs? Our evidence of better matching suggests that firms with unsophisticated customer-profiling skills, firms targeting customers with hard-to-profile needs, and firms marketing complex and risky experience products are likely to benefit most from such programs (see also

Iyengar et al. 2011a; Jing and Xie 2011). Our evidence of social enrichment suggests that firms with products that are sometimes challenging to use or that feature network externalities may also benefit more than average from referral programs. Examples are file sharing services like Dropbox, two-sided market platforms like Uber and Airbnb, makers of multiplayer games like World of Warcraft, and professional associations like the American Marketing Association or the American College of Physicians.[11] Another is eBay, whose referred merchant-customers cost less to serve because they have already been coached by their referrer on how the platform works and because they can rely on friends rather than on eBay service employees to help them solve their problems (Reichheld 2006, p. 12).

Second, what kinds of social ties are likely to convey the greatest *post*-acquisition benefits in referral programs? What kinds of ties should referral programs try to leverage? Since strong ties tend to be more homophilous than weak ties, they are likely to provide better passive, homophily-based matching. Since strong ties also tend to exhibit greater benevolence, they are also likely to provide better active, screening-based matching and higher social enrichment.

Third, why is it that referral programs bring in some customers who are not likely to join through traditional advertising and promotions, as documented by Kumar et al. (2007)? Is it because these customers distrust marketing campaigns but trust peer recommendations? Or because these customers have needs that marketers do not address well in their campaign materials but that their friends recognize, such that referrers form better matches than marketers can? The second possibility is consistent with the results of a field experiment by AT&T (Hill et al. 2006), and suggests that better matching and social enrichment may also operate at the time of acquisition, rather than provide only benefits post-acquisition.

[11] Dropbox, Uber, Airbnb and World of Warcraft are often mentioned as exemplary illustrations of the power of referral programs. See, e.g., http://www.referralcandy.com/blog/47-referral-programs/.

Fourth, why and when do customers acquired through referral remain more engaged post-acquisition than customer acquired through firm-to-consumer communication, as observed by Lee et al. (2013)? Are superior matching and social enrichment part of the answer, rather than merely seeking and maintaining status which some recent research points to (Hu and Van den Bulte 2014; Toubia and Stephen 2013)?

Fifth, how does the superior profitability of referrals relate to their usage behavior? (i) Do referred customers use more products than non-referred customers do? Greater use intensity or greater share of category requirements would be consistent with better matching and with social enrichment through either joint consumption or social bonding enhancing trust. (ii) Compared to non-referred customers, does a higher fraction of referred customers use "experience" and "credence" products like life insurance, investment advice, and estate planning that provide more opportunities for differentiation and generating higher margins for the firm than "search" products like checking accounts, savings accounts, and mortgages (Armelini et al. 2015)? A higher use among referred customers of products that are hard to assess in advance would be consistent with better matching, social enrichment through trust-enhancing social bonding, and social enrichment through education and discussion. (iii) Do referred customers rely less on customer support provided by the firm than non-referred customers do? Reduced reliance on customer support would be consistent with better matching, social enrichment, and the eBay anecdote mentioned earlier. Documenting how differences in referral status map into differences in use intensity, share of wallet, customers' product mix and product margins, and reliance on customer support would be valuable for both theory and practice.

Sixth, how can marketers design customer referral programs that not only motivate their existing customers to make referrals but also generate referrals that exhibit high margins and low churn? Should managers focus their referrer recruitment efforts on their more profitable customers who have been with the firm more than a few months and, given the evidence of contagious churn, have a low risk of defection? More generally, should marketers avoid designing programs that appeal disproportionally to low-value customers who bring in similarly poor matches? Also, what can marketers designing referral programs and customer communities do to strengthen social enrichment?

Seventh, is providing higher referral fees associated with worse matches and lower social enrichment? Managers are often concerned that generous referral fees result in adverse selection, and our work suggests that this selection, if it exists, is likely to depress CLV by means of poorer matching and lower social enrichment. This argument raises several testable questions, such as: Are higher referral fees associated with a greater fraction of referrals being made by existing customers exhibiting lower-than-expected margins and higher-than-expected churn (where expectations are based on observable characteristics)? Are higher referral fees associated with referred customers exhibiting not only lower-than-expected margins and higher-than-expected churn, but also lower-than-expected contagion?

Our work also has practical implications. The findings suggest that managers focus their invitations to serve as referrers to (i) their higher-margin customers who (ii) have been with the bank more than a few months and who (iii) are less likely to churn. There is also practical value in knowing the mechanisms at work, as this helps managers ask more incisive and more nuanced questions about their practice (e.g., Christensen and Raynor 2003; Lafley et al. 2012). These questions of managerial interest are mostly reworked versions of the seven research questions we noted above: Examples include:

- Are better matching and social enrichment likely to be at work in our business? If not, do we have any other reasons to expect that referred customers will be more valuable than non-referred customers?
- Are there prospects, e.g., those with complex needs, which we expect to exhibit greater matching or enrichment benefits? If so, how do we design our program to target them?
- Do our high-margin customers, heavy users, and customers with some minimal level of experience generate referrals who are more profitable or more loyal than average?
- Do our customers acquired through strong-tie referral tend to exhibit higher margins and lower churn than those acquired through weak-tie referral? If so, how can we nudge potential referrers towards activating strong rather than weak ties?
- Are higher referral fees associated with referrals exhibiting lower margins and higher churn? Is the pattern stronger than can be explained by referrer characteristics, margins, and churn?
- Can we develop diagnostic tools and community support tools to help our customers produce better matches and enrich the experience of their referrals?

Direct empirical evidence on each of the seven questions raised by our work pertaining to marketing effectiveness would be valuable for both theory and practice. So would more research on how, not just whether, customer referral programs turn social capital into economic capital. As suggested or illustrated by several studies (e.g., Benoit and Van den Poel 2012; Goel and Goldstein 2013; Hill et al. 2006; Hinz et al. 2011; Iyengar et al. 2015; Wei et al. 2016), a greater sensitivity to mechanisms at work in customer referral, both organic and incentivized, is also likely to generate new insights about customer valuation and targeting.

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Table 1
MEAN VALUES OF CHARACTERISTICS OF CUSTOMERS, BY GROUP

	Referrals	**Referrers**	**Non-referred All**	**Non-referred Matching**
N	1,799	1,799	3,663	1,788
DCM (across 33 months)	.646	1.825	.538	.476
Fraction churned	.097	.064	.145	.134
Age	39.860	44.056	46.712	41.886
Female	.572	.455	.513	.563
Single	.512	.402	.355	.461
Married	.305	.376	.451	.387
Divorced	.086	.084	.102	.084
Widowed	.038	.041	.066	.039
Other	.059	.097	.027	.028
Acquired Jan 2006	.003	.018	.074	.005
Acquired Feb 2006	.003	.023	.088	.006
Acquired Mar 2006	.029	.032	.133	.061
Acquired Apr 2006	.113	.021	.063	.096
Acquired May 2006	.134	.034	.078	.114
Acquired June 2006	.140	.043	.110	.135
Acquired July 2006	.178	.050	.129	.191
Acquired Aug 2006	.201	.029	.110	.180
Acquired Sep 2006	.150	.011	.077	.121
Acquired Oct 2006	.048	.006	.139	.091
Acquired 2005	-	.141	-	-
Acquired 2004	-	.054	-	-
Acquired 2001-2003	-	.116	-	-
Acquired 1996-2000	-	.168	-	-
Acquired before 1996	-	.253	-	-
Le1MonthExp	.126			
1-6MonthsExp	.125			

DCM = Daily contribution margin
Le1MonthExp = Referrer's and referral's acquisition are not more than 1 month apart (dummy)
1-6MonthsExp = Referrer's and referral's acquisition are between 1 and 6 months apart (dummy)

Table 2
DYAD-SPECIFIC SHARED UNOBSERVABLES BETWEEN REFERRALS AND REFERRERS: DAILY CONTRIBUTION MARGIN

	(1)		(2)	
	Coef.	*z*	Coef.	*z*
Constant	2.067***	3.90	2.308***	4.11
Referral	.296**	3.09	.218	1.66
PropReferGone			-.201	-1.17
PropRefalGone			.120	1.05
Year 2007	-.243***	-4.61	-.304***	-4.13
Year 2008	-.570***	-7.14	-.632***	-5.61
Age (centered)	.028***	4.15	.028***	4.15
Female	-.551***	-3.86	-.551***	-3.86
Married	.202	1.06	.203	1.06
Divorced	.061	.17	.062	.17
Widowed	1.387	1.44	1.388	1.44
Other	.056	.28	.057	.28
Acquired Feb 2006	-.946	-1.68	-.946	-1.68
Acquired Mar 2006	-1.016	-1.74	-1.019	-1.74
Acquired Apr 2006	-1.210*	-2.22	-1.210*	-2.22
Acquired May 2006	-1.181*	-2.22	-1.183*	-2.22
Acquired June 2006	-1.281*	-2.38	-1.282*	-2.39
Acquired July 2006	-1.144*	-2.14	-1.145*	-2.14
Acquired Aug 2006	-1.190*	-2.22	-1.190*	-2.23
Acquired Sep 2006	-1.150*	-2.17	-1.150*	-2.17
Acquired Oct 2006	-.872	-1.49	-.872	-1.49
Acquired in 2005	-.789	-1.48	-.789	-1.48
Acquired in 2004	-.049	-.05	-.049	-.05
Acquired in 2001-2003	.390	.53	.390	.54
Acquired in 1996-2000	1.125	1.39	1.125	1.39
Acquired before 1996	.693	1.17	.692	1.17
	Est.	*z*	Est.	*z*
Dyad-specific variation (σ_d)	1.234***	7.57	1.235***	7.59
Customer-specific variation (σ_u)	4.128***	4.91	4.128***	4.91
Observation-specific variation (σ_e)	2.856***	5.72	2.855***	5.73
LL	-30,339.21		-30,338.65	
Pseudo-R^2	.805		.805	
N	10,794		10,794	

* $p < .05$, ** $p < .01$, *** $p < .001$. Significance tests for coefficients based on empirical robust standard errors.
Models estimated on 10,794 customer-year observations from 1,799 referrals and 1,799 referrers.
Pseudo-R^2 is the squared Pearson correlation between observed and predicted values including the random effect.

Table 3
DYAD-SPECIFIC SHARED UNOBSERVABLES BETWEEN REFERRALS AND REFERRERS: CHURN

	(1)		(2)	
	Coef.	*z*	Coef.	*z*
Referral	-.179	-.93	-.035	-.19
Refergone			1.329***	5.76
Refalgone			1.397***	6.35
Age (centered)	.000	.00	.000	-.07
Female	-.083	-.63	-.067	-.55
Married	.059	.32	.065	.39
Divorced	.076	.29	.069	.29
Widowed	.322	.79	.296	.82
Other	-.054	-.18	-.059	-.22
Acquired Feb-Mar 2006	-.188	-.29	-.233	-.40
Acquired Apr 2006	.804	1.31	.671	1.22
Acquired May 2006	.078	.12	.013	.02
Acquired June 2006	.691	1.13	.564	1.03
Acquired July 2006	.633	1.03	.493	.90
Acquired Aug 2006	1.156	1.88	.900	1.64
Acquired Sep 2006	1.399*	2.24	1.100*	1.96
Acquired Oct 2006	2.013**	3.02	1.583**	2.70
Acquired in 2005	-.229	-.38	-.200	-.37
Acquired in 2004	-.408	-.60	-.345	-.56
Acquired in 2001-2003	-.715	-1.12	-.694	-1.20
Acquired in 1996-2000	-.821	-1.33	-.784	-1.40
Acquired before 1996	-2.355***	-3.35	-2.236***	-3.45
	Est.	*z*	Est.	*z*
Dyad-specific variation σ_d	1.290***	9.28	.005	.19
LL	-2,668.99		-2,658.47	
N	3,598		3,598	

* $p < .05$, ** $p < .01$, *** $p < .001$.
The models are complementary log-log hazard models estimated on the churn behavior of 1,799 referrals and 1,799 referrers controlling for duration dependency non-parametrically through a piece-wise constant baseline hazard by including an intercept and separate dummies for every 30-day period since acquisition in which any customer churned. Customer-day observations from 30-day periods since acquisition in which no customer churned do not affect the model likelihood, and are excluded from the estimation.
Since no referral or referrer acquired in February 2006 churns, the coefficients for Acquisition in Feb and March 2006 are set to be equal.

Table 4
DAILY CONTRIBUTION MARGIN OF REFERRED VS. NON-REFERRED CUSTOMERS
(RANDOM EFFECTS MODELS)

	(1)		(2)		(3)	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Constant	-1.019	-.75	-1.019	-.75	.992***	4.28
Referral	.672***	4.41	.672***	4.41	.302***	4.76
Age (centered)	.009**	2.88	.009**	2.88	.011***	3.95
Referral x Age	.024**	3.15	.024**	3.15		
Le1MonthExp	-.821***	-4.71	-.822***	-4.71		
1-6MonthsExp	-.500*	-2.47	-.501*	-2.47		
CLT	5.669	1.44	5.674	1.44		
Referral x CLT	-.559**	-2.79	-.558**	-2.79		
Age x CLT	.002	.37	.002	.37		
Referral x Age x CLT	-.033***	-3.31	-.033***	-3.31		
Le1MonthExp x CLT	.690**	2.99	.692**	2.98		
1-6MonthsExp x CLT	.474	1.83	.475	1.83		
PropReferGone	-.000	-.18			.000	0.34
Year 2007	-2.120	-1.47	-2.122	-1.47	-.093**	-2.56
Year 2008	-3.693	-1.48	-3.696	-1.48	-.281***	-4.18
Female	-.096	-1.55	-.096	-1.55	-.089	-1.42
Married	-.053	-.66	-.053	-.66	-.047	-.58
Divorced	-.053	-.58	-.053	-.58	-.030	-.33
Widowed	.747***	3.25	.747***	3.25	.785***	3.50
Other	-.394	-.74	-.394	-.74	-.379	-.71
Acquired Feb 2006	-.059	-.21	-.059	-.21	-.250	-.96
Acquired Mar 2006	-.122	-.49	-.122	-.49	-.491	-1.56
Acquired Apr 2006	.247	.57	.248	.57	-.276	-1.05
Acquired May 2006	.304	.59	.304	.59	-.385	-1.59
Acquired June 2006	.373	.59	.374	.59	-.506*	-2.14
Acquired July 2006	.676	.91	.677	.91	-.366	-1.51
Acquired Aug 2006	.750	.87	.751	.87	-.464	-1.95
Acquired Sep 2006	.985	1.01	.987	1.01	-.384	-1.59
Acquired Oct 2006	1.100	1.01	1.101	1.01	-.469	-1.95
Customer-specific var. σ_u	1.485***	7.69	1.485***	7.70	1.497***	7.79
Observation-specific var. σ_e	2.916**	3.05	2.916**	3.05	2.921**	3.02
LL	-42,178.01		-42,178.01		-42,221.38	
Pseudo-R^2	.456		.455		.462	
N	16,316		16,316		16,316	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on empirical robust standard errors.
All models estimated on 16,316 customer-year observations from 1,799 referrals and 3,663 non-referred customers.
Pseudo-R^2 is the squared Pearson correlation between observed and predicted values including the random effect.
To avoid very small coefficients, CLT is expressed in thousands of days.

Table 5
CHURN HAZARD OF REFERRED VS. NON-REFERRED CUSTOMERS

	(1)		(2)		(3)	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Referral	-.329	-.52	-.484***	-4.84	-.482	-.77
Age (centered)	.038**	2.68	.010***	3.35	.038**	2.68
Referral x Age	-.010	-.34			-.010	-.34
Le1MonthExp	.876	.72			.779	.65
1-6MonthsExp	2.443*	2.03			2.300	1.90
CLT	2.480	.57			2.504	.57
Referral x CLT	-.349	-.37			.068	.07
Age x CLT	-.043*	-2.03			-.043*	-2.03
Referral x Age x CLT	.014	.31			.012	.27
Le1MonthExp x CLT	-.894	-.48			-.412	-.22
1-6MonthsExp x CLT	-3.564	-1.86			-3.267	-1.70
ReferGone	1.800***	8.61	1.824***	9.03		
Female	-.071	-.92	-.072	-.93	-.084	-1.10
Married	.064	.60	.066	.62	.069	.64
Divorced	-.037	-.25	-.039	-.26	-.030	-.20
Widowed	-.353	-1.62	-.361	-1.66	-.357	-1.64
Other	.264	1.35	.259	1.32	.276	1.41
Acquired Feb 2006	.463	1.90	.451	1.85	.463	1.90
Acquired Mar 2006	.728***	3.27	.712***	3.20	.726***	3.26
Acquired Apr 2006	.554*	2.26	.529*	2.17	.538*	2.20
Acquired May 2006	.359	1.44	.340	1.37	.339	1.36
Acquired June 2006	.778***	3.37	.762***	3.30	.776***	3.36
Acquired July 2006	.804***	3.51	.791***	3.46	.802***	3.50
Acquired Aug 2006	.965***	4.17	.949***	4.11	.986***	4.26
Acquired Sep 2006	1.164***	4.86	1.147***	4.80	1.166***	4.87
Acquired Oct 2006	1.457***	6.35	1.441***	6.31	1.469***	6.40
LL	-6,230.61		-6,236.38		-6,256.57	
Δ -2LL vs (1)			11.56 (*p* = .237)		51.94 (*p* < .001)	
N	5,462		5,462		5,462	

* *p* < .05, ** *p* < .01, *** *p* < .001.
The models are complementary log-log hazard models estimated on the churn behavior of 1,799 referrals and 3,663 non-referred customers, controlling for duration dependency non-parametrically through a piece-wise constant baseline hazard by including an intercept and separate dummies for every 30-day period since acquisition in which any customer churned. Customer-day observations from 30-day periods since acquisition in which no customer churned do not affect the model likelihood, and are therefore excluded from the estimation.
To avoid very small coefficients, CLT is expressed in thousands of days.

Table 6
PREDICTING REFERRAL'S DAILY CONTRIBUTION MARGIN (DCM) AND CHURN FROM REFERRER'S CHARACTERISTICS

	DCM (OLS)		Churn (Cox)	
	Coef.	*t*	Coef.	*z*
Constant	.654**	2.80		
DCM in 2006	.034**	3.02	-.012	-.72
Age (centered)	.012***	3.20	.010	1.59
Female	.013	.18	-.100	-.63
Married	-.084	-.75	-.192	-.92
Divorced	-.263*	-2.20	.008	.03
Widowed	.116	.39	-.312	-.68
Other	.095	.47	-.238	-.79
Acquired Feb 2006	.150	.41	.211	.23
Acquired Mar 2006	-.123	-.41	.358	.43
Acquired Apr 2006	-.403	-1.66	.773	.92
Acquired May 2006	-.173	-.68	-.592	-.59
Acquired June 2006	-.443	-1.84	1.319	1.74
Acquired July 2006	-.393	-1.61	1.343	1.79
Acquired Aug 2006	-.167	-.62	.429	.49
Acquired Sep 2006	-.190	-.71	1.978*	2.35
Acquired Oct 2006	-.517*	-2.06	.723	.59
Acquired in 2005	-.201	-.84	.496	.67
Acquired in 2004	.025	.09	.584	.75
Acquired in 2001-2003	-.003	-.01	.291	.39
Acquired in 1996-2000	.114	.42	.232	.31
Acquired before 1996	.011	.04	.523	.72
R^2	.053			
LL			-1,259.72	
N	1,799		1,799	

* $p < .05$, ** $p < .01$, *** $p < .001$. For DCM, significance tests for coefficients based on empirical robust standard errors. Both models are estimated on data for 1,799 referred customers

WEB APPENDICES

A. CURRENT DATA VS. SSV DATA

Before testing our hypotheses about mechanisms underlying margin and loyalty benefits from referral, we first document that our data exhibit the same patterns of differences between referred and non-referred customers as those documented by SSV who used a larger number of referred and non-referred customers.

As reported in Table 1, referred customers are on average 11 euro cents per day more profitable than non-referred customers. The difference in their average DCM, €.65 vs. €.54, is statistically significant (Mann-Whitney U test, $z = -10.31$, $p < .001$). The difference in DCM amounts to €40 annually or about 20% on a relative basis (.11/.54), which is financially significant.

The margin gap remains positive after controlling, through linear regression, for differences in customer demographics and time of acquisition, variables on which referrals and non-referred customers do not match perfectly. For a single male 40-year old customer acquired in January 2006, the expected DCM is €1.11 if referred and €.88 if non-referred. This gap of €.23 ($t = 4.81$, $p < .001$) is larger than the €.11 gap in raw means, in part because younger customers are less profitable than older ones, and referrals tend to be younger than non-referred customers (Table 1). The gap, however, narrows over a customer's lifetime with the bank ($p < .05$) and is expected to vanish after about 1,350 days or 45 months.

We now turn to customer churn. Table 1 reports that, by the end of the data window (September 2008), 14.5% of the non-referred customers had churned as opposed to only 9.7% of the referrals ($\chi^2_{(1)} = 24.35$, $p < .001$). This comparison, however, does not account for the fact that the average acquisition date in 2006 was later for the referred customers (Table 1). The difference in churn narrows by about a quarter but remains highly significant ($z = 3.52$, $p < .001$) after controlling for age, gender, marital status and month of acquisition in a binary logit model.

The difference in churn between referred and non-referred customers is corroborated by the Kaplan-Meier estimator of the survivor functions and a Cox proportional hazard model. The non-parametric Kaplan-Meier survivor functions and the log-rank test confirm that the referrals are less likely to churn ($p < .001$). The daily churn rate of referred customers is about 30% lower than that of non-referred customers ($p < .001$) after controlling for differences in age, gender, marital status and time of acquisition in a Cox model. This difference does not change significantly over time ($p > .05$).

In short, our data on 1,799 referred and 3,663 non-referred customers acquired between January and October 2006 exhibit the same basic patterns as those reported by SSV for all 5,181 referred and a random of sample of 4,633 non-referred customers acquired between January and December 2006. Referred customers exhibit a higher daily contribution margin and lower churn, and do so both before and after controlling for differences in age, gender, marital status, and month of acquisition. Also, the gap in contribution margin erodes over time but that in churn rate does not.

All these patterns are present also when contrasting the 1,799 referred customers to the 1,788 matched non-referred customers rather than all 3,663 non-referred customers.

As reported in Table 1, referrals are on average 17 euro cents per day more profitable than non-referred customers. The difference in their average DCM, €.65 vs. €.48, is statistically significant (Mann-Whitney U test, $z = -9.70$, $p < .001$). The difference in DCM amounts to €62 annually or about 35% on a relative basis (.17/.48), which is financially significant.

The margin gap remains positive after controlling, through linear regression, for differences in customer demographics and time of acquisition, variables on which referrals and non-referred customers do not match perfectly. For a single male 40-year old customer acquired in January 2006, the expected DCM is €.74 if referred and €.50 if non-referred. This gap of €.23 (t = 4.70, p < .001) is €.06 larger than the €.17 difference in raw means. So, even after matching, the difference between the differences in regression-based and raw means remains sizable and significant. The gap between referred and matched non-referred customers narrows over a customer's lifetime with the bank (t = -1.84; p < .07) and is expected to vanish after about 730 days or 24 months.

We now turn to customer churn. Table 1 reports that, by the end of the data window (September 2008), 13.4% of the matched non-referred customers had churned as opposed to only 9.7% of the referred customers ($\chi^2_{(1)}$ = 11.97, p < .001). The difference in churn remains about the same in size and remains highly significant (z = 3.21, p < .001) after controlling for age, gender, marital status and month of acquisition in a binary logit model.

The difference in churn between referred and non-referred customers is corroborated by the Kaplan-Meier estimator of the survivor functions and a Cox proportional hazard model. The non-parametric Kaplan-Meier survivor functions and the log-rank test confirm that the referrals are less likely to churn (p < .001). The daily churn rate of referred customers is about 30% lower than that of non-referred customers (p < .001) after controlling for differences in age, gender, marital status and time of acquisition in a Cox model with non-parametric duration dependency. This difference does not change significantly over time (z = .10; p > .10).

In short, our data on 1,799 referred and 1,788 matched non-referred customers acquired between January and October 2006 exhibit the same basic patterns as those reported by SSV for all 5,181 referred and a random of sample of 4,633 non-referred customers acquired between January and December 2006. Referred customers exhibit a higher daily contribution margin and lower churn, and do so both before and after controlling for differences in age, gender, marital status, and month of acquisition. Also, the gap in contribution margin erodes over time but that in churn rate does not.

B. PLACEBO TESTS FOR SHARED UNOBSERVABLES IN DCM (H1A)

We conduct placebo tests involving fake dyads constructed by keeping the referrer of each dyad but replacing his or her referral by a non-referred customer matching the referral on gender, marital status, age and time of acquisition. Such fake dyads should exhibit evidence of dyad-specific shared unobservables that is markedly weaker than true dyads do.

To ensure that the error terms are independent, we cannot use the same non-referred customers in more than one fake dyad. Since only 1,276 referred customers can be given a *unique* match among the 1,788 matching non-referred customers, we build 10 data sets featuring 1,276 fake referrer-referral dyads by varying how we allocate shared matches to each referrer. For each of those 10 data sets, we estimate the models in Table 2 on both the fake dyads and the true dyads.

As reported in Table A-1, the dyad-specific variation in the DCM exhibited by such fake dyads is indistinguishable from zero in 8 of the 10 data sets, is markedly smaller than the variation in the true dyads in 10 of the 10 data sets, and results in worse model fits for fake vs. true dyads in 10 of the 10 data sets.

C. PLACEBO TESTS FOR SHARED UNOBSERVABLES AND CONTAGION IN CHURN (H1B)

We also conduct placebo tests for shared unobservables and contagion in churn. We do so by estimating the models reported in Table 3, but now using the 10 data sets of 1,276 fake and true dyads used in the DCM placebo tests.

As reported in Table A-2, Model (1), which does not feature intra-dyadic contagion, never exhibits evidence of shared unobservables in fake dyads but always in true dyads. Model (2), which does feature the intra-dyadic contagion regressors *ReferGone* and *RefalGone*, exhibits evidence of shared unobservables in fake dyads for 2 of the 10 data sets but never in true dyads. More importantly, the coefficients of *ReferGone* and *RefalGone* are never significantly positive with fake dyads, but always are with true dyads. In short, only true dyads consistently show evidence of spurious shared unobservables stemming from intra-dyadic contagion. Fake dyads do not. If anything, the co-occurrence of significant shared variation and large *negative* coefficients of *ReferGone* in data sets 2 and 8 suggests that trying to identify both shared unobservables and contagion in fake dyads, neither of which should be present in such dyads, can lead to poor model identification and estimation artefacts.

D. TESTING H3A-H5A USING FIXED EFFECTS

The models reported in Table 4 include random effects to control for unobserved heterogeneity across customers. These analyses support H2a-H5a. The models reported in Table A-3 show that the substantive conclusions about H3a-H5a are robust to specifying fixed effects rather than random effects. Because H2a involves variables that do not vary over time, it cannot be tested using fixed effects specifications.

E. TESTING H2B-H5B USING LINEAR PROBABILITY MODELS

Since complementary log-log hazard models are not linear, there may be a concern that the failure to find support for the interaction hypotheses H2b and H3b in the realm of churn may stem from the functional form, more specifically from the notion that the non-linear hazard specification already has interactions built into it. To assuage this concern, we repeated the analyses reported in Table 5 using linear regression. Table A-4 shows the results of linear probability models estimated using OLS and robust Huber-White errors to account for heteroscedasticity. The substantive conclusions and hypothesis tests for the full model, Model 1, are strikingly robust.

We also estimated linear models with customer-specific random effects, using both "subject-specific" effects models estimated with GLS and "population-averaged" effects models estimated with generalized estimation equations (GEE). The GLS models found no evidence of customer-specific unobserved heterogeneity: the estimated variance of the random effects was 0. This finding is consistent with the notion that the flexible baseline hazard already captures the very great majority of the unobserved heterogeneity in a hazard models for non-repeated events. Similarly, the GEE models yield a within-subject correlation coefficient of less than .0002. In short, both types of random effects models reduced to the OLS models presented in Table A-4.

F. RIVAL EXPLANATIONS

F.1. Favoritism and monitoring

As discussed in footnote 3, favoritism by referrers is a viable explanation for lower churn by employee referrals but not customer referrals. Favoritism where the bank extends preferential treatment to referrals as a favor to their referrer and the bank withdraws that treatment when the referrer churned, is a form of social enrichment. In short, as explanation, favoritism is either not viable or not a rival. As to monitoring by parent-referrers, it quite unlikely matters much in our setting because all the customers studied were 18 years or older, and the gap in margin between referred and non-referred customer increased rather than decreased with age (so did the gap in CLV between ages 18 to 40 reported by SSV, Table 4).

F.2. Selectivity

A concern with comparing the behavior of customers acquired through different channels is that customers may self-select into different modes of acquisition based on characteristics unobserved by the researcher. Correctly identifying the causal effects of the mode of acquisition on subsequent behavior often requires controlling for such selectivity (e.g., Gensler et al. 2013). However, better matching does *not* involve any causal claim about the acquisition mode ("how would this specific customer have behaved if (not) acquired through referral?"). Rather, at its very core, better matching is predicated on selectivity. Hence, attempting to control for selectivity not only is superfluous but even results in an invalid test of the mechanism.

Social enrichment, in contrast, does involve a counterfactual, causal claim. It is conceivable that some types of consumers, e.g., those who are little informed or tend to value social relations, are both more likely to be recruited through referral and less likely to churn. If so, then direct association between referral status and churn need not be causal. But since (i) the hypotheses we use to test the mechanism involve within-person variation (what happens with the referral before vs. after the referrer churns?) rather than cross-person variation, and (ii) the non-parametric baseline is an effective control for unobserved heterogeneity (Lin and Wei 1989; Schmoor and Schumacher 1997; Struthers and Kalbfleisch 1986), we are not aware of any dimension of unobserved time-invariant heterogeneity that may explain our results for H4 and H5.

F.3. Correlated unobservables vs. peer influence

Whereas homophily-based matching is predicated on correlated unobservables, social enrichment is predicated on peer influence. So, to distinguish between better matching and social enrichment, we must distinguish between correlated unobservables and peer influence. We did so, and found that the evidence of time-invariant correlated unobservables in margin was robust to controlling for the dyadic peer's co-presence, whereas the evidence of time-invariant correlated unobservables in churn was not. Conversely, we found evidence of peer influence in churn but not in margin after controlling for time-invariant correlated unobservables.

In contrast, the possibility of *time-varying* correlated unobservables or common shocks, like the withdrawal of a service attractive to both the referral and the referrer, is impossible to rule out entirely. Adding a fixed effect for every dyad-month combination is not a viable solution in a hazard model. Since 85.5% of the dyads show no churn by either member, adding fixed effects would result in massive truncation biases (Van den Bulte and Iyengar 2011). Yet, adding controls for lagged churn by others who are similar in observed characteristics increases the confidence that evidence of within-dyad contagion is genuine (Hu and Van den Bulte 2014; Iyengar et al. 2015; Nair et al. 2010). The reason is that if time-varying correlated unobservables are at work, then they should be correlated with the lagged churn (periodic or cumulative) of people like oneself. Analyses reported below show that our results are robust to including such controls for time-varying shared unobservables or common shocks.

It is impossible to rule out entirely the possibility of time-varying correlated unobservables in the referrers' and referrals' churn, like the withdrawal of a service attractive to both the referral and the referrer. Yet, adding controls for lagged churn by others similar in observed characteristics increases the confidence that evidence of within-dyad contagion is genuine (Hu and Van den Bulte 2014; Iyengar et al. 2015; Nair et al. 2010). The reason is that if time-varying correlated unobservables u_{it} are at work, then they should be correlated with the lagged churn (periodic or cumulative) of people like oneself z_{it}.

We do not observe all relevant dimensions of similarity and hence do not observe the true z_{it}, but we approximate it as the lagged churn (periodic or cumulative) of people like oneself on observed covariates, q_{it}. The effect of prior time-varying unobservables that is not specifically unique to the dyad but is common across people with similar observed characteristics will be absorbed into q_{it}. E.g., this procedure cannot control for the unobserved withdrawal of a service that is *uniquely* attractive to the referral and the referrer, but it can control for the unobserved withdrawal of a service that is *similarly attractive to everyone similar* to the referral and the referrer with regard to age, neighborhood, income category, and other observed dimensions.

For this analysis, we capture the similarity between referrer and referral along six dimensions. For all 1,799 dyads we have data on (i) daily contribution margin in 2006, (ii) gender, (iii) marital status, and (iv) age. For a subset of 1,317 dyads, we also have data on (v) the purchasing power classification and (vi) the residential area classification.

We operationalize similarity with regard to the six variables in a binary fashion. For gender and marital status, people are considered similar if and only if they are in the same category. For age, we treat people as being similar if their ages differ by at most 5 years. For daily contribution margin, we treat people as being similar if their DCMs in 2006 differ by at most €0.10. For purchasing power, we use 30 groups of equal size, and for the residential area we use the 43 categories pre-specified by the bank.

For each of these 6 dimensions, we create 4 time-varying variables:

(1) The cumulative fraction of customers similar to the referral who churned prior to *t*;

(2) The cumulative fraction of customers similar to both the referral and the referrer who churned prior to *t*;

(3) The empirical hazard of churning at *t*-1 by customers similar to the referral;

(4) The empirical hazard of churning at *t*-1 by customers similar to both the referral and referrer,

where the empirical hazard at *t*-1 is defined as usual: the number of customers churning at *t*-1 divided by the number of customers who have not churned yet prior to *t*-1. We use lagged values to avoid endogeneity (e.g., Nair et al. 2010).

We call variables of type (1) based on a particular dimension, "*dimension*_lagcumulprop"; those of type (2) "*dimension*_BOTHlagcumulprop"; those of type (3), "*dimension*_laghazard"; and those of type (4) "*dimension*_BOTHlaghazard".

Table A-5 extends the two discrete-time hazard models reported in Table 3 with the 4 time-varying variables based on the 4 dimensions observed for all 1,799 dyads. Adding those 16 control variables significantly improves model fit, both of the model without *ReferGone* and *RefalGone* (Δ-2LL = 30.32, df = 16, $p < .05$) and that including *ReferGone* and *RefalGone* (Δ-2LL = 29.62, df = 16, $p < .05$). Yet, because of collinearity, only two coefficients are significant. More importantly, adding those 16 control variables does not affect the results of substantive interest: We continue to find that the referrals become much more likely to churn after their referrer has churned, and that the evidence of time-invariant shared unobservables vanishes after accounting for peer churn. Table A-6 shows that the results of substantive interest are supported also in the sub-set of 1,317 dyads after adding all 24 control variables.

F.4. Post-acquisition differences in marketing mix treatment

According to the bank, it did not treat referred and non-referred customers systematically differently. Also, while differences in marketing treatment might explain main-effect differences between referred and non-referred customers, they do not provide a compelling alternative account for our tests of H2-H5 which involve moderator effects and within-person variation.

F.5. Unobservables on what, to whom and when?

The theory involving better matching invokes customer characteristics that are unobservable to the firm at the time of customer acquisition, whereas our tests of H1 are about any customer-specific variables that are unobservable to us based on a post-acquisition data-base. Hence, our tests of H1 are not a very incisive assessment of the matching mechanism. The same concern does not apply to our tests of H2-H3, which are more elaborate hypotheses that should also hold if better matching on unobservables is a mechanism at work (for a brief discussion of theoretical elaboration as a means to strengthen causal identification in observational studies, first proposed by R.A. Fisher, see Iyengar et al. 2015).

F.6. Balance in observables between referred and non-referred customers.

The 3,663 non-referred customers do not exhibit very tight balance or common support in the observables with the 1,799 referred customers (Table 1). Some might be concerned that this feature of the data somehow affects our conclusions based on contrasting referred and non-referred customers. It does not. Limiting the analyses reported in Tables 4 and 5 to only the matching referred and non-referred customers does not affect the conclusions about H2-H5.

The tests for H2-H5 involve contrasting patterns in DCM and churn between referred and non-referred customers. Conceivably, the outcome of these tests may be affected by the lack of very tight balance or common support in the observables between the 1,799 referred customers and the 3,663 non-referred customers (Table 1). We therefore re-estimate all models that we report in Tables 4, 5 and A-3 and that we use to test H2-H5, but we now include only the matching 1,799 referred customers and 1,788 non-referred customers.

Table A-7 exhibits the same key patterns as Table 4. A referral's DCM is positively associated with the referrer's experience, and that margin gap associated with referrer experience narrows over the customer's lifetime. Hence, the hypotheses H2a and H3a predicated on better matching are supported. The extent to which the referrer remained with the bank while the referral was a customer is not associated with the latter's DCM. Hence, there is no support for the hypotheses predicated on social enrichment affecting DCM (H4a, H5a).

Table A-8 exhibits the same key patterns as Table A-3. The evidence in support of H3a and the lack of support for H4a or H5a is robust to whether we use random or fixed effects, and to whether we use all non-referred customers or only those who match the referrals.

Table A-9 exhibits the same strong support of H4b and H5b as does Table 5. Hence, the support for the hypotheses consistent with social enrichment affecting referrals' churn is robust. In contrast, there is less than perfect consistency with respect to H2b and H3b about better matching affecting referrals' churn. In Table 5, there was no compelling support for H2b (only 1 of 4 coefficients for referrer experience at $CLT = 0$ being significant) and no support whatsoever for H3b (none of the 4 interactions between referrer experience and *CLT* were significant). In Table A-9, the evidence is somewhat more mixed but still far less than compelling, with only 2 of 4 coefficients of experience at $CLT = 0$ being significant, and only 1 of the 4 interactions between referrer experience and *CLT* being significant. Hence, applying a conservative mindset in refuting conjectures leads to the conclusion that, when using only matching referred and non-referred customers, there still is no compelling evidence of better matching affecting churn but there remains strong evidence of social enrichment affecting referrals' churn.

REFERENCES INCLUDED IN APPENDICES BUT NOT IN MAIN TEXT

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TABLE A-1.
PLACEBO ANALYSIS OF DYAD-SPECIFIC SHARED UNOBSERVABLES
BETWEEN REFERRALS AND REFERRERS:
DAILY CONTRIBUTION MARGIN

Data	**Placebo dyads**					**True dyads**					**Difference: True – Placebo**		
#	σ_{d1}	z	σ_{d2}	z	R^2	σ_{d1}	z	σ_{d2}	z	R^2	σ_{d1}	σ_{d2}	R^2
1	.202	.69	.214	1.19	.539	.911	7.42	.911	7.43	.690	.709*	.698	.151
2	.000	.18	.000	.16	.555	.953	7.31	.954	7.32	.708	.953	.954	.154
3	.000	.17	.002	.02	.692	1.162	5.84	1.163	5.85	.864	1.161	1.161	.172
4	.000	.25	.000	.28	.655	1.120	6.60	1.120	6.60	.829	1.120	1.120	.174
5	.389	2.65	.393	2.67	.617	1.050	7.85	1.051	7.86	.824	.661	.658	.207
6	.000	.16	.000	.18	.716	1.297	6.82	1.298	6.83	.874	1.297	1.298	.158
7	.002	.12	.001	6.67	.578	1.021	5.89	1.022	5.90	.714	1.020	1.021	.136
8	.000	.20	.000	.20	.546	.973	7.62	.974	7.63	.700	.973	.974	.154
9	.141	30.71	.160	17.99	.673	1.137	5.67	1.138	5.67	.801	.995	.978	.128
10	.000	.13	.000	.13	.550	.932	7.37	.933	7.38	.702	.932	.933	.152

* $p < .05$; all other differences between σ_{d1} in true vs. fake dyads, and all differences between σ_{d2} in true vs. fake dyads: $p < .001$.
Data # = Each of 10 data sets consists of 1,276 referrers, their referral, and a matched non-referred customer serving as placebo referral.
A true dyad consists of a referrer and a referral. The placebo consists of a referrer and a placebo referral, i.e., a non-referred customer matching the referrer's true referral.
σ_{d1} = Standard deviation of the dyad-specific random effect in Model (1), excl. PropReferGone and PropRefalGone.
σ_{d2} = Standard deviation of the dyad-specific random effect in Model (2), incl. PropReferGone and PropRefalGone.
R^2 = Pseudo-R^2 is the squared Pearson correlation between observed and predicted values including the random effect.
Models (1) and (2) correspond to the model specifications reported in Table 2.

TABLE A-2.
PLACEBO ANALYSIS OF DYAD-SPECIFIC SHARED UNOBSERVABLES
BETWEEN REFERRALS AND REFERRERS:
CHURN

Data	**Placebo dyads**								**True dyads**							
	Model 1		**Model 2**						**Model 1**		**Model 2**					
#	**sd**	***z***	**sd**	***z***	**ReferGone**	***z***	**RefalGone**	***z***	**sd**	***z***	**sd**	***z***	**ReferGone**	***z***	**RefalGone**	***z***
1	.015	.15	.383	.88	-.498	-.87	.138	.39	1.176	7.74	.003	.14	1.321	5.35	1.266	5.28
2	.443	1.28	.728	2.73	-.945	-1.37	.010	.02	1.156	6.52	.006	.20	1.218	3.91	1.162	3.86
3	.410	1.14	.039	.20	.364	.93	.039	.09	1.118	6.39	.003	.16	1.265	4.23	1.084	3.61
4	.009	.18	.182	.16	-.708	-.85	.189	.44	1.134	6.18	.002	.07	1.390	4.47	1.167	3.57
5	.013	.20	.012	.19	-.075	-.16	.383	1.02	1.153	6.68	.005	.15	1.318	4.57	1.162#	3.99
6	.024	.11	.020	.17	.030	.06	.548	1.35	1.101	5.73	.005	.11	1.095	3.11	1.044#	3.10
7	.023	.26	.024	.20	-.006	-.01	.399	1.06	1.203	7.24	.004	.14	1.509	5.83	1.337	4.79
8	.540	1.89	.875	3.81	-1.557	-1.94	.211	.51	1.174	6.51	.005	.15	1.386	4.62	1.203	3.95
9	.513	1.85	.517	1.36	-.028	-.05	.434	1.20	1.161	6.98	.004	.21	1.393	5.24	1.208	4.38
10	.025	.26	.463	1.16	-.987	-1.22	.348	.85	1.096	6.08	.005	.14	1.433	4.94	1.116#	3.57

difference between RefalGone in true vs. fake dyads $p > .05$; all other differences between RefalGone in true and fake dyads, and all differences between ReferGone in true and fake dyads: $p < .05$.

Data # = Each of 10 data sets consisting of 1,276 referrers, their referral, and a matched non-referred customer serving as placebo referral.
A true dyad consists of a referrer and a referral. The placebo consists of a referrer and a placebo referral, i.e., a non-referred customer matching the referrer's true referral.

Models (1) and (2) correspond to the model specifications reported in Table 3.

Table A-3
DAILY CONTRIBUTION MARGIN OF REFERRED VS. NON-REFERRED CUSTOMERS
(FIXED EFFECTS MODELS)

	(1)		(2)		(3)	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
CLT	4.286	.99	4.286	.99		
Referral x CLT	-.564**	-2.81	-.554**	-2.78		
Age x CLT	-.002	-.45	-.002	-.45		
Referral x Age x CLT	-.032**	-3.06	-.032**	-3.07		
Le1MonthExp x CLT	.697**	3.00	.712**	3.04		
1-6MonthsExp x CLT	.463	1.70	.471	1.73		
PropReferGone	-.000	-1.66			-.000	-1.51
Year 2007	-1.612	-1.02	-1.614	-1.02	-.093**	-2.57
Year 2008	-2.842	-1.04	-2.842	-1.04	-.287***	-4.26
Customer-specific var. σ_u	2.315		2.315		2.278	
Observation-specific var. σ_e	2.919		2.919		2.923	
R^2	.481		.481		.479	
N	16,316		16,316		16,316	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on empirical robust standard errors.
All models estimated on 16,316 customer-year observations from 1,799 referrals and 3,663 non-referred customers.
R^2 is the squared Pearson correlation between observed and predicted values including the fixed effect.
To avoid very small coefficients, CLT is expressed in thousands of days.

Table A-4
LINEAR PROBABILITY MODELS FOR
CHURN HAZARD OF REFERRED VS. NON-REFERRED CUSTOMERS

	(1)		(2)		(3)	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
Referral	.492**	3.19	-.652***	-5	.454**	2.93
Age (centered)	.000	.02	.017**	3.33	.000	-.05
Referral x Age	.001	.10			.000	.02
Le1MonthExp	-.412	-1.2			-.659	-1.91
1-6MonthsExp	.178	.57			.030	.10
CLT	3.162	.47			3.131	.46
Referral x CLT	-3.115***	-5.03			-2.667***	-4.24
Age x CLT	.044*	2.13			.044*	2.13
Referral x Age x CLT	-.011	-.31			-.015	-.43
Le1MonthExp x CLT	2.271	1.39			3.491*	2.14
1-6MonthsExp x CLT	.291	.21			.650	.47
ReferGone	11.976***	4.51	11.700***	4.42		
Female	-.121	-.98	-.124	-1.00	-.136	-1.09
Married	.075	.43	.075	.43	.103	.59
Divorced	-.126	-.55	-.130	-.56	-.079	-.34
Widowed	-.635	-1.94	-.628	-1.93	-.622	-1.91
Other	.415	1.18	.402	1.14	.428	1.22
Acquired Feb 2006	.554	1.82	.564	1.85	.554	1.82
Acquired Mar 2006	1.037***	3.64	1.027***	3.61	1.035***	3.63
Acquired Apr 2006	.750**	2.72	.690**	2.49	.758**	2.74
Acquired May 2006	.543*	2.11	.499	1.95	.512*	1.99
Acquired June 2006	1.037***	3.91	1.010***	3.82	1.066***	4.02
Acquired July 2006	1.104***	4.31	1.084***	4.24	1.091***	4.26
Acquired Aug 2006	1.317***	5.04	1.319***	5.05	1.340***	5.13
Acquired Sep 2006	1.571***	5.41	1.571***	5.41	1.597***	5.49
Acquired Oct 2006	2.201***	7.13	2.146***	6.97	2.215***	7.18
F-Test			F(9; 4,396,711) = 5.03, p <.001		F(1; 4,396,711) = 178.21, p <.001	
N	5,462		5,462		5,462	

* $p < .05$, ** $p < .01$, *** $p < .001$. Coefficients are those of an ordinary least squares regression. Coefficients were multiplied by 10,000 for better readability. Significance tests for coefficients are based on Huber-White robust standard errors.
All models estimated on 4,396,770 customer-day observations from 1,799 referrals and 3,663 non-referred customers. All models control for duration dependency non-parametrically through a piece-wise constant baseline hazard by including an intercept and separate dummies for every 30-day period since acquisition in which any customer churned. F-Tests assume homoscedasticity of residuals.

Table A-5
ANALYSIS OF CONTAGIOUS CHURN WITHIN DYADS, CONTROLLING FOR TIME-VARYING SHARED UNOBSERVABLES (I)

	Normal-cloglog No contagion			Normal-cloglog With contagion		
	Coef.		*z*	Coef.		*z*
Referral	-.158		-.82	-.025		-.13
Refergone				1.327	***	5.72
Refalgone				1.363	***	6.16
Age (centered)	.000		.03	.000		-.06
Female	-.186		-1.21	-.172		-1.19
Married	.367		1.76	.381	*	2.01
Divorced	.756	*	2.25	.778	*	2.49
Widowed	.891	*	2.01	.884	*	2.21
Other	-.787	*	-2.07	-.809	*	-2.27
Acquired Feb-Mar 2006	-.277		-.43	-.302		-.51
Acquired Apr 2006	.712		1.17	.603		1.1
Acquired May 2006	-.031		-.05	-.082		-.14
Acquired June 2006	.595		.97	.492		.89
Acquired July 2006	.529		.87	.415		.75
Acquired Aug 2006	1.043		1.71	.811		1.47
Acquired Sep 2006	1.296	*	2.09	1.022		1.82
Acquired Oct 2006	1.886	**	2.85	1.488	*	2.54
Acquired in 2005	-.332		-.55	-.279		-.51
Acquired in 2004	-.516		-.76	-.452		-.73
Acquired 2001-2003	-.751		-1.18	-.718		-1.24
Acquired in 1996-2000	-.839		-1.36	-.792		-1.41
Acquired before 1996	-2.415	***	-3.45	-2.292	***	-3.53
Gender_laghazard	40.132		.63	39.436		.63
Gender_lagcumulprop	-92.348		-1.53	-88.731		-1.49
Gender_BOTHlaghazard	.533		.02	-4.595		-.17
Gender_BOTHlagcumulprop	.342		.09	.324		.09
Marital_laghazard	10.807		.42	11.237		.44
Marital_lagcumulprop	-62.068	**	-3.11	-64.065	**	-3.25
Marital_BOTHlaghazard	-19.271		-.8	-18.547		-.79
Marital_BOTHlagcumulprop	-1.200		-.3	-.883		-.23
Age_laghazard	-3.357		-.22	-4.032		-.27
Age_lagcumulprop	-3.146		-.48	-2.899		-.47
Age_BOTHlaghazard	14.592		1.37	14.285		1.39
Age_BOTHlagcumulprop	.936		.29	.751		.26
DCM06_laghazard	-23.991	*	-2.08	-21.463		-1.96
DCM06_lagcumulprop	5.195	*	2.52	4.380	**	2.65
DCM06_BOTHlaghazard	3.811		.32	2.990		.26
DCM06_BOTHlagcumulprop	4.079		1.51	3.114		1.29
	Est.		St. Err.	Est.		St. Err.
Dyad-specific variation	1.275	***	.139	.005		.027
LL	-2,653.83			-2,643.66		
N	3,598			3,598		

* $p < .05$, ** $p < .01$, *** $p < .001$.
As in Table 3, the coefficients for Acquisition in Feb and March 2006 are set to be equal and duration dependency is controlled for non-parametrically through a piece-wise constant baseline hazard.

Table A-6
ANALYSIS OF CONTAGIOUS CHURN WITHIN DYADS,
CONTROLLING FOR TIME-VARYING SHARED UNOBSERVABLES (II)

	Normal-cloglog No contagion			Normal-cloglog With contagion		
	Coef.		*z*	Coef.		*z*
Referral	.118		.29	.288		.78
Refergone				1.367	***	4.48
Refalgone				1.639	***	5.95
Age (centered)	-.005		-.57	-.004		-.63
Female	-.107		-.56	-.116		-.66
Married	.101		.36	.195		.78
Divorced	.756		1.64	.791		1.84
Widowed	1.047		1.74	1.000		1.86
Other	-1.163	*	-2.24	-1.124	*	-2.32
Acquired Feb-Mar 2006	-.458		-.58	-.462		-.66
Acquired Apr 2006	.590		.78	.465		.7
Acquired May 2006	-.144		-.18	-.197		-.28
Acquired June 2006	.213		.27	.080		.12
Acquired July 2006	.146		.18	.042		.06
Acquired Aug 2006	.736		.93	.507		.73
Acquired Sep 2006	1.109		1.4	.854		1.22
Acquired Oct 2006	3.752	*	2.39	2.752	*	2.28
Acquired in 2005	-.218		-.31	-.108		-.17
Acquired in 2004	-.314		-.4	-.276		-.4
Acquired 2001-2003	-.543		-.73	-.466		-.71
Acquired in 1996-2000	-.549		-.77	-.457		-.72
Acquired before 1996	-2.044	*	-2.57	-1.857	**	-2.6
Gender_laghazard	10.180		.13	11.577		.14
Gender_lagcumulprop	-124.738		-1.49	-129.271		-1.56
Gender_BOTHlaghazard	1.499		.04	-1.001		-.03
Gender_BOTHlagcumulprop	.931		.21	.286		.07
Marital_laghazard	8.986		.25	7.687		.22
Marital_lagcumulprop	-83.422	**	-3.13	-82.067	**	-3.12
Marital_BOTHlaghazard	18.979		.73	18.777		.75
Marital_BOTHlagcumulprop	-2.192		-.46	-2.438		-.56
Age_laghazard	21.059		1.14	19.876		1.09
Age_lagcumulprop	-7.243		-.85	-6.858		-.87
Age_BOTHlaghazard	-6.868		-.38	-6.780		-.38
Age_BOTHlagcumulprop	1.846		.47	1.676		.47
PurchasePower_laghazard	-7.370		-.15	-9.172		-.19
PurchasePower_lagcumulprop	8.550		.58	7.980		.61
PurchasePower_BOTHlaghazard	10.080		.17	8.679		.15
PurchasePower_BOTHlagcumulprop	3.864		.42	4.110		.47
ResidentialArea_laghazard	-4.298		-.37	-3.863		-.33
ResidentialArea_lagcumulprop	2.260		.6	1.980		.62
ResidentialArea_BOTHlaghazard	10.818		1.15	9.576		1.05
ResidentialArea_BOTHlagcumulprop	-.804		-.23	-1.228		-.41
DCM06_laghazard	-12.415		-.96	-9.566		-.81
DCM06_lagcumulprop	6.139	**	2.7	4.819	**	2.83
DCM06_BOTHlaghazard	8.799		.36	7.336		.31
DCM06_BOTHlagcumulprop	5.833		1.62	4.422		1.35
	Est.		St. Err.	Est.		St. Err.
Dyad-specific variation	1.427	***	.186	.004		.031
LL	-1,651.91			-1,633.38		
N	2,634			2,634		

* $p < .05$, ** $p < .01$, *** $p < .001$.
As in Table 3, the coefficients for Acquisition in Feb and March 2006 are set to be equal, and duration dependency is controlled for non-parametrically through a piece-wise constant baseline hazard.

Table A-7
DAILY CONTRIBUTION MARGIN OF MATCHING REFERRED VS. NON-REFERRED CUSTOMERS (RANDOM EFFECTS MODELS)

	(1)		(2)		(3)	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Constant	-2.676	-1.08	-2.676	-1.08	.565*	2.43
Referral	.682***	4.34	.682***	4.35	.330***	4.06
Age (centered)	.016***	3.80	.016***	3.80	.017***	4.41
Referral x Age	.021**	2.60	.021**	2.60		
Le1MonthExp	-.842***	-4.76	-.842***	-4.75		
1-6MonthsExp	-.499*	-2.44	-.499*	-2.43		
CLT	9.031	1.30	9.031	1.30		
Referral x CLT	-.514*	-2.32	-.516*	-2.33		
Age x CLT	-.002	-.27	-.002	-.27		
Referral x Age x CLT	-.029*	-2.56	-.029*	-2.55		
Le1MonthExp x CLT	.701**	2.98	.698**	2.96		
1-6MonthsExp x CLT	.481	1.86	.480	1.86		
PropReferGone	.000	.34			.000	.55
Year 2007	-3.400	-1.33	-3.399	-1.33	-.161***	-3.71
Year 2008	-5.804	-1.32	-5.804	-1.32	-.332***	-3.40
Female	-.024	-.27	-.024	-.27	-.020	-.23
Married	-.213*	-2.15	-.213*	-2.15	-.213*	-2.19
Divorced	-.196	-1.38	-.196	-1.38	-.187	-1.29
Widowed	.327	.93	.327	.93	.375	1.08
Other	-.526	-.76	-.526	-.76	-.512	-.75
Acquired Feb 2006	.519	1.45	.519	1.45	.277	.94
Acquired Mar 2006	.243	.82	.243	.82	-.366	-.59
Acquired Apr 2006	1.047	1.39	1.047	1.39	.181	.66
Acquired May 2006	1.262	1.36	1.262	1.36	.142	.58
Acquired June 2006	1.450	1.25	1.450	1.25	.026	.11
Acquired July 2006	1.804	1.33	1.804	1.33	.116	.47
Acquired Aug 2006	2.023	1.29	2.023	1.29	.060	.25
Acquired Sep 2006	2.358	1.33	2.358	1.33	.141	.59
Acquired Oct 2006	2.606	1.33	2.606	1.33	.122	.49
Customer-specific var. σ_u	1.259***	7.54	1.259***	7.54	1.271***	7.65
Observation-specific var. σ_e	3.326**	2.63	3.326**	2.63	3.337**	2.61
LL	-28,753.49		-28,753.49		-28,798.39	
Pseudo- R^2	.359		.359		.379	
N	10,728		10,728		10,728	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on empirical robust standard errors.
All models estimated on 10,728 customer-year observations from 1,799 referrals and 1,788 matching non-referred customers.
Pseudo-R^2 is the squared Pearson correlation between observed and predicted values including the random effect.
To avoid very small coefficients, CLT is expressed in thousands of days.

Table A-8
DAILY CONTRIBUTION MARGIN OF MATCHING REFERRED VS. NON-REFERRED CUSTOMERS (FIXED EFFECTS MODELS)

	(1)		(2)		(3)	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
CLT	8.271	1.06	8.271	1.06		
Referral x CLT	-.549**	-2.58	-.540*	-2.54		
Age x CLT	-.006	-1.03	-.006	-1.03		
Referral x Age x CLT	-.027*	-2.47	-.027*	-2.48		
Le1MonthExp x CLT	.733**	3.06	.747**	3.09		
1-6MonthsExp x CLT	.475	1.74	.482	1.76		
PropReferGone	-.000	-1.44			-.000	-1.44
Year 2007	-3.118	-1.09	-3.119	-1.09	-.161***	-3.71
Year 2008	-5.333	-1.08	-5.332	-1.08	-.340***	-3.45
Customer-specific var. σ_u	2.415		2.415		2.333	
Observation-specific var. σ_e	3.329		3.329		3.340	
R^2	.429		.429		.425	
N	10,728		10,728		10,728	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on empirical robust standard errors.
All models estimated on 10,728 customer-year observations from 1,799 referrals and 1,788 matching non-referred customers.
R^2 is the squared Pearson correlation between observed and predicted values including the fixed effect.
To avoid very small coefficients, CLT is expressed in thousands of days.

Table A-9
CHURN HAZARD OF MATCHING REFERRED VS. NON-REFERRED CUSTOMERS

	(1)		(2)		(3)	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Referral	-.748	-1.04	-.480***	-4.51	-.492	-1.24
Age (centered)	.015	.81	.008	1.92	.016	.85
Referral x Age	.009	.62			.008	.51
Le1MonthExp	.961	.73			.865	.68
1-6MonthsExp	2.912*	2.16			2.695*	2.00
CLT	7.923***	3.23			7.810***	3.18
Referral x CLT	.295	.27			.697	.64
Age x CLT	-.012	-.45			-.013	-.48
Referral x Age x CLT	-.042	-.52			-.041	-.52
Le1MonthExp x CLT	-1.017	-.51			-.527	-.27
1-6MonthsExp x CLT	-4.297*	-1.99			-3.879	-1.80
ReferGone	1.829***	8.72	1.864***	9.18		
Female	-.053	-.52	-.055	-.55	-.079	-.78
Married	-.018	-.12	-.013	-.09	-.010	-.07
Divorced	-.010	.05	-.007	-.03	.002	.01
Widowed	-.059	-.19	-.078	-.25	-.084	-.27
Other	.242	1.02	.238	1.01	.265	1.12
Acquired Feb-Mar 2006	-.051	-.19	-.152	-.21	-.039	-.05
Acquired Apr 2006	.175	.24	.060	.08	.178	.24
Acquired May 2006	-.171	-.23	-.284	-.39	-.175	-.23
Acquired June 2006	.231	.31	.119	.16	.249	.33
Acquired July 2006	.345	.46	.236	.33	.367	.49
Acquired Aug 2006	.379	.51	.268	.37	.424	.57
Acquired Sep 2006	.647	.87	.529	.73	.674	.90
Acquired Oct 2006	.929	1.23	.827	1.13	.988	1.31
LL	-3670.24		-3677.29		-3696.81	
Δ -2LL vs (1)			7.05 (p = .632)		26.57 (p < .001)	
N	3,587		3,587		3,587	

* p < .05, ** p < .01, *** p < .001.
The models are complementary log-log hazard models estimated on the churn behavior of 1,799 referrals and 1,788 matched non-referred customers controlling for duration dependency non-parametrically through a piece-wise constant baseline hazard by including an intercept and separate dummies for every 30-day period since acquisition in which any customer churned. Customer-day observations from 30-day periods since acquisition in which no customer churned do not affect the model likelihood, and are therefore excluded from the estimation.
To avoid very small coefficients, CLT is expressed in thousands of days. Since no referral or referrer acquired in February 2006 churns, the coefficients for Acquisition in Feb and March 2006 are set to be equal.