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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: (1) better matching between referred customers and the firm and (2) 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 the theory that better matching affects contribution margins, (1) referrer–referral dyads exhibit shared unobservables in customer contribution margins, (2) referrers with more extensive experience bring in higher-margin referrals, and (3) this association between the referrer's experience and margin gap becomes smaller over the referral's lifetime. Consistent with the theory that social enrichment affects retention, 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 recommendation for the managers of the firm studied is to recruit referrers among their customers who have been acquired at least six months ago, exhibit high margins, and are unlikely to churn.

Keywords: customer referral programs, customer relationship marketing, referral marketing, social networks, word-of-mouth marketing

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How Customer Referral Programs Turn Social Capital into Economic Capital

Marketers are increasingly keen on leveraging customer-to-customer connections. As a result, the topic of social influence among customers and the question of how to leverage it to acquire and retain customers 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 (1) do not require any data on connections among customers, (2) do not require sizable up-front expenditure, (3) are simple to administer, and (4) allow for a certain degree of targeting. A study by Schmitt, Skiera, and Van den Bulte (2011; SSV hereinafter) has documented significant economic post-acquisition benefits as well. Referred customers had a higher contribution margin, though this difference eroded over time, and a higher retention rate, and this difference persisted over time. Higher margins and higher retention combined into a customer lifetime value (CLV) that was 16%–25% higher.

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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 nonreferred customers in contribution margin, retention, and customer value, without identifying or testing the intervening mechanisms. The present study, in contrast, uses data not only on referred and nonreferred 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 who exhibit higher margins and lower churn, the present study provides the first evidence on the mechanisms at work, that is, 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 people 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, Setren, and Topa 2016; Burks et al. 2015; Castilla 2005; Fernandez, Castilla, and Moore 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 nonreferred 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 noncustomers 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 (1) buy more offerings at given prices, (2) have a higher willingness to pay for given offerings, and (3) require lower service costs (e.g., explaining how the existing offerings can be used to address his or her wants, adapting the basic product to his or her wants). As a result, better matches expectedly result in higher contribution margins. Better matches expectedly also result in greater satisfaction and, thus, lower churn.[1] However, the information asymmetry between referred and nonreferred 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 nonreferred 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, Castilla, and Moore 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, as Bursztyn et al. (2014) document for financial services, the copresence of a fellow customer may also provide functional benefits, such as education and discussion about the advantages and disadvantages of specific product offerings. As a result of these social and functional consequences of copresence, a referred customer expectedly exhibits higher sales or lower cost to serve (thus, higher margins) and greater satisfaction (thus, lower churn) than a nonreferred 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 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 nonreferred 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

Because it is extremely difficult to directly observe the 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 previously. 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

[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, which 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.

referral programs.[3] For 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 previously, better matching is the phenomenon that referred customers fit the firm's offerings better than nonreferred 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—that is, 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 versus nonreferred customers. These are mere main-effects predictions. We develop hypotheses that are more theoretically discriminating—that is, more informative about the mechanism(s) purportedly at work.

None of the hypotheses we advance were posited by SSV. Because 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 margins and churn.

Unlike SSV, whose emphasis was on customer value and program profitability, we do not make predictions about 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 H_1, our hypotheses cannot be tested using the amalgamation of margin and churn into a single, time-invariant metric such as CLV.

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 and 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. In addition, 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 nonreferred customers—provided that the shared characteristics meet two criteria. First, the shared characteristics 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).

Thus, passive matching implies the following refutable hypothesis:

> H_1: Referrers and their referrals have shared unobservables in their (a) contribution margin and (b) churn rate.

Note that, 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 more difficult 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; these may include 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 toward 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). As a result, the quality of matches produced through both passive, homophily-based matching and active, screening-based matching should be

[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 better 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 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 in which 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.

lower for referrers with little experience as customer with the firm than for referrers with extensive experience. These arguments imply:

H_2: The initial gap in (a) contribution margin and (b) churn of referred vs. nonreferred 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 nonreferred customers will erode over the customers' lifetime. Over time, both referred and nonreferred 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 nonreferred 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 nonreferred 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). 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 H_2 should erode the longer the newly acquired customer remains a customer. Thus, we conjecture:

H_3: The referrer experience–related difference in the gap in (a) contribution margin and (b) churn between referred and nonreferred 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, Castilla, and Moore 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, such as experience and credence products and, more generally, categories in which customers experience high risk or ambiguity (e.g., DiMaggio and Louch 1998; Kilian, Greuling, and Hennigs 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 likely to avoid or overcome temporary frustrations with its offerings. Consequently, a referred customer is less likely to churn than a nonreferred 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 nonreferred customers, then the referrer's churn should annihilate the gap in margin and churn. The reason is simply that social enrichment requires continued copresence: no copresence means no enrichment.

This argument is consistent with contagious churn and contagious repeat documented in several studies (Dierkes, Bichler, and Krishnan 2011; Iyengar, Van den Bulte, and Lee 2015; Nitzan and Libai 2011; Sgourev 2011; Zhang et al. 2012), but goes beyond that evidence in three ways. First, it contrasts referred versus nonreferred 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 customers and, thus, lower the contribution margin of referrals who do not churn after their referrer did. So, we propose:

H_4: Referred customers exhibit (a) a lower contribution margin and (b) a higher churn rate after their referrer has churned.

H_5: The referred customers' gap in (a) contribution margin and (b) churn compared with nonreferred customers disappears after their referrer has churned.

H_5 is a stronger version of H_4: once the referrer is no longer copresent, social enrichment is not simply lower (H_4) but disappears with the referrer (H_5).

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 nonreferred customers, as SSV did, but also 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 account for nearly half (49%) of all referrals acquired in that ten-month period. According to the bank, the selection of referrals included in the data is unrelated to their contribution margin or churn. In addition, as we document in Web Appendix A, our data exhibit the same pattern in contribution margins and churn as those reported by SSV using all referrals acquired in 2006. Thus, 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 nonreferred customers is drawn randomly from all nonreferred 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 suggestions, 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 (e.g., a minimum amount of assets, 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 nonreferred customers (SSV).

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 2006–2008 observation period, divided by the total number of days the customer was with the bank over that period. The per diem scaling enables us to compare the contribution margin of customers with different observed (and often censored) durations and, thus, to investigate separately the variance in each of the two drivers of post-acquisition CLV (setting aside the discount factor): margin per time unit versus 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 such as 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 are 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, and 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 nonreferred 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 as 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 nonreferred 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 than 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 in which the dependent variable is measured daily, CLT is updated daily. For the models of contribution margin in which 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 nonparametric baseline for duration dependency. Consequently, adding year dummies in the churn models is superfluous.

Our control variables in models contrasting referred and nonreferred 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 thus, they allow 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 as 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

Table 1

MEAN VALUES OF CHARACTERISTICS OF CUSTOMERS, BY GROUP

	Referrals	*Referrers*	*Nonreferred All*	*Nonreferred 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 (years)	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		

Notes: Le1MonthExp = referrer's and referral's acquisition are not more than one month apart (dummy); 1–6MonthsExp = referrer's and referral's acquisition are between one and six months apart (dummy).

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 ten 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 DFBETACS diagnostic (Preisser and Qaqish 1996) to identify customers with a disproportionally large influence in the panel models for the gap in DCM(t) between referred and nonreferred customers. 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 nonreferred customers.

We also create a subset of nonreferred customers that closely match the referred customers on the observed demographics. Specifically, for a nonreferred 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 nonreferred customers, 1,788 match at least one referred customer.[4]

Table 1 profiles the four sets of customers—referrals, referrers, nonreferred customers, and matched nonreferred 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 nonreferred customers as those documented by SSV (Web Appendix A).

SHARED UNOBSERVABLES IN MARGIN (H_{1a})

H_1 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.

[4]We use exact matching on the unordered 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 one valid match for each of the 1,799 referred customers. If we do not allow the same nonreferred 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.

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 enables 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, ..., 1,799), 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):

$$(1)\qquad \text{DCM}_{ijt} = \beta_0 + \beta_1\text{Referral}_{ij} + \sum_{k=2}^{22}\beta_k X_{kijt} + d_j + u_{ij} + e_{ijt},$$

where 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 we use empirical standard errors robust to clustering and heteroskedasticity 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 (σ_u = 4.128) or observation-specific (σ_e = 2.86), a significant part of it is dyad-specific (σ_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, Provost, and Volinsky 2006; Iyengar, Van den Bulte, and Lee 2015; Nair et al. 2010). These studies note that correlated behavior can stem not only from shared unobservables but also from peer influence. This ambiguity raises the following question: Is the evidence of shared unobservables in margins between referrals and referrers robust to controlling for the length of time the referral and the referrer were both customers with the bank (and thus 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 clear: customers' DCM is not affected by their peer's churn, and our conclusion of significant shared unobservables in contribution margin continues to hold.[6]

Placebo Tests

We also conduct placebo tests involving fake dyads constructed by keeping the referrer but replacing the referral with a nonreferred customer who matches 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 we report in Web Appendix B, we indeed find that the dyad-specific variation is typically indistinguishable from zero, is always weaker than in the true dyads, and always results in worse model fits.

SHARED UNOBSERVABLES IN CHURN (H_{1b})

Common Random Effects in Churn

Next, we assess the presence of shared unobservables in the churn behavior of referrals and referrers, again by testing for the presence of common random effects. Because we also want to control for ReferGone and RefalGone, which are time-varying, we use a discrete-time model for the churn hazard h_{ijt} of member i (i = 1, 2) in dyad j (j = 1, ..., 1,799) 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:

$$(2)\qquad g\left(h_{ijt}\right) = \alpha_t + \beta_1\text{Referral}_{ij} + \beta_2\text{ReferGone}_{ijt} + \beta_3\text{RefalGone}_{ijt} + \sum_{k=4}^{22}\beta_k X_{kij} + d_j,$$

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 that [s]he was still present on day t − 1 [note that 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 time of acquisition (i.e., customer age and cohort).

[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 approximately €.30 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 approximately −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 €1.20 margin difference between referrals and referrers in Table 1.

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

Table 2

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

	(1)		*(2)*	
	Coefficient	*z*	*Coefficient*	*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
	Estimate	*z*	*Estimate*	*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
Log-likelihood	−30,339.21		−30,338.65	
Pseudo-R^2	.805		.805	
N	10,794		10,794	

*$p < .05$.
**$p < .01$.
***$p < .001$.

Notes: Significance tests for coefficients are based on empirical robust standard errors. Models are 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.

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 nonparametric baseline is very flexible and makes the 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, because 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, (s)he 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 quasicomplete 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.

[7]A minor challenge is that when no customers churn 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, Van den Bulte, and Lee 2015).

[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 neither improved model fit significantly nor affected the substantive findings.

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

	(1)		*(2)*	
	Coefficient	*z*	*Coefficient*	*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
	Estimate	*z*	*Estimate*	*z*
Dyad-specific variation σ_d	1.290***	9.28	.005	.19
Log-likelihood	−2,668.99		−2,658.47	
N	3,598		3,598	

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: The models are complementary log-log hazard models estimated on the churn behavior of 1,799 referrals and 1,799 referrers. They control for duration dependency nonparametrically through a piecewise 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. Because no referral or referrer acquired in February 2006 churned, the coefficients for Acquisition in February and March 2006 are set to be equal.

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, Bichler, and Krishnan 2011; Haenlein 2013; Iyengar, Van den Bulte, and Lee 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, Muchnik, and Sundararajan 2009; Van den Bulte and Lilien 2001). This ambiguity raises the question: Is the evidence of shared unobservables in churn among the 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 ten 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 of 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 ($\sigma_d = .005$, $p > .05$). Our conclusion of significant shared unobservables in churn 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 we report in Web Appendix C, fake dyads do not show evidence of contagious churn or evidence of shared unobservables that vanishes after controlling for contagious churn.

TESTS OF H_{2a}, H_{3a}, H_{4a}, AND H_{5a} ON MARGINS

We presented several hypotheses that should be supported if the margin gap between referred and nonreferred customers stems from better matching. H_{2a} implies a negative association between limited referrer experience and the margin gap. H_{3a} implies that the differences in margin gap related to the referrers' experience erode over the referrals' lifetime with the bank. Because 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 than or exactly one month and between one and six months.

We also hypothesized that if the margin differential stems from social enrichment, then the differential should be lower (H_{4a}) and should even disappear (H_{5a}) after the referrer has churned.

For this analysis, we use data on the 1,799 referred and the 3,663 nonreferred customers and model the DCM of customer i in year t as

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

where the Referral dummy distinguishes between referred and nonreferred customers; the first set of X variables includes the linear, two-way interaction and three-way interaction terms necessary to test H_{2a} and H_{3a}; PropReferGone, used to test H_{4a} and H_{5a}, is defined previously; and the second set of X variables controls 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 ordinary least squares to estimate the fixed effects specification. In both cases, we use empirical standard errors robust to heteroskedasticity and clustering.

Table 4

DAILY CONTRIBUTION MARGIN OF REFERRED VERSUS NONREFERRED CUSTOMERS (RANDOM-EFFECTS MODELS)

	(1)		*(2)*		*(3)*	
	Coefficient	*z*	*Coefficient*	*z*	*Coefficient*	*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 × 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 × CLT	−.559**	−2.79	−.558**	−2.79		
Age × CLT	.002	.37	.002	.37		
Referral × Age × CLT	−.033***	−3.31	−.033***	−3.31		
Le1MonthExp × CLT	.690**	2.99	.692**	2.98		
1–6MonthsExp × CLT	.474	1.83	.475	1.83		
PropReferGone	−.000	−.18			.000	.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
Log-likelihood	−42,178.01		−42,178.01		−42,221.38	
Pseudo-R^2	.456		.455		.462	
N	16,316		16,316		16,316	

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: All tests are based on empirical robust standard errors. All models are estimated on 16,316 customer-year observations from 1,799 referrals and 3,663 nonreferred 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.

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 H_{2a} and H_{3a} (except for age, which is always included as a control). The model in column 3 excludes the PropReferGone variable associated with H_{4a} and H_{5a}. 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 one month of experience with the bank generate referrals exhibiting markedly lower margins than referrers with more than six months of experience do. Referrals generated by such inexperienced referrers not only lack a positive boost in DCM but are even *less* profitable than nonreferred customers (.672 – .821 < 0). Referrers with experience between one and six 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 between one and six 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 H_{2a} and H_{3a}.

The positive coefficient of Referral × Age (.024) indicates that the initial margin gap between referred and nonreferred is greater for older consumers. Customer lifetime (CLT) moderates this referral-by-age association negatively, and the latter turns negative after approximately 730 days (.024/.033 × 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

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

is that older customers have more complex needs and, thus, exhibit more pronounced patterns consistent with better matching.

Support for H_{2a} and H_{3a} reinforces 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 (H_{4a}), let alone disappears (H_{5a}), after the referrer has churned. The continued presence of the referrer shows no clear association with the referral's contribution margin.

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).

TESTS OF H_{2b}, H_{3b}, H_{4b}, AND H_{5b} ON CHURN

We next turn to how customer experience and joint presence relate to the difference in churn between referred and nonreferred customers. Because 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 nonreferred customers as

$$g(h_{it}) = \alpha_t + \beta_1 \text{Referral}_i + \sum_{k=2}^{7} \beta_k X_{kit} + \beta_8 \text{ReferGone}_{it} + \sum_{k=9}^{26} \beta_k X_{ki}, \tag{4}$$

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 nonreferred customers; the first set of X variables includes the linear, two-way interaction, and three-way interaction terms necessary to test H_{2b} and H_{3b}; ReferGone is used to test H_{4b} and H_{5b}; and the second set of X variables controls for gender, marital status, age, and month of acquisition. As in the hazard analysis reported previously, we do not include dummies for 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 nonreferred customers. The model in column 2 excludes CLT and all the variables that we interact with CLT associated with H_{2b} and H_{3b} (except for age, which is always included as a control), and the model in column 3 excludes the ReferGone variable associated with H_{4b} and H_{5b}. 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 were affected by better matching. There is no consistent and significant evidence that referrers with limited experience produce faster-churning referrals (H_{2b}), or that such a gap in churn rate becomes more muted over the referrals' lifetime (H_{3b}).[10] The lack of support for H_{2b} and H_{3b} 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 nonreferred 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 nonreferred customers [exp(–.48 + 1.82) – 1]. So, not only does the positive association between referral and loyalty decrease (H_{4b}) and disappear (H_{5b}), 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 with nonreferred customers. This finding is consistent with the notion that referrals' lower churn stems from social enrichment.

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 enable 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 for which we have contribution data), 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, although we observe a pattern that some kinds of referrers tend to generate more attractive referrals than other referrers, this does not imply that any of the referrals is unprofitable.

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 nonreferred 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 (1) referral

[10]Column 1 of Table 5 reports a significantly positive coefficient for 1–6MonthsExp, but column 3 does not. This result does not amount to consistent support for H_{2b}. Both columns 1 and 3 report a significantly negative coefficient for Age × 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, which we included as a control.

Table 5
CHURN HAZARD OF REFERRED VERSUS NONREFERRED CUSTOMERS

	(1)		(2)		(3)	
	Coefficient	*z*	*Coefficient*	*z*	*Coefficient*	*z*
Referral	−.329	−.52	−.484***	−4.84	−.482	−.77
Age (centered)	.038**	2.68	.010***	3.35	.038**	2.68
Referral × 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 × CLT	−.349	−.37			.068	.07
Age × CLT	−.043*	−2.03			−.043*	−2.03
Referral × Age × CLT	.014	.31			.012	.27
Le1MonthExp × CLT	−.894	−.48			−.412	−.22
1–6MonthsExp × 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
Log-likelihood	−6,230.61		−6,236.38		−6,256.57	
Δ −2log-likelihood versus column 1			11.56 (p = .237)		51.94 (p < .001)	
N	5,462		5,462		5,462	

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: The models are complementary log-log hazard models estimated on the churn behavior of 1,799 referrals and 3,663 nonreferred customers. They control for duration dependency nonparametrically 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.

programs convert social capital into economic capital and (2) firms can take a more selective approach to referral programs to increase their economic benefits.

Because 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, in which the emphasis is turning from investigating *whether* peer influence operates to *how* it operates (e.g., Godes 2011; Iyengar, Van den Bulte, and Valente 2011a). The second is the intersection of 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 difficult-to-profile needs, and firms marketing complex and risky experience products are likely to benefit most from such programs (see also Iyengar, Van den Bulte, and Valente 2011b; 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 such as Dropbox, two-sided market platforms such as Uber and Airbnb, makers of multiplayer games such as World of Warcraft, and professional associations such as 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).

[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/).

Table 6
PREDICTING THE REFERRAL'S DCM AND CHURN FROM THE REFERRER'S CHARACTERISTICS

	DCM (OLS)		Churn (Cox)	
	Coefficient	*t*	*Coefficient*	*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			
Log-likelihood			−1,259.72	
N	1,799		1,799	

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

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 aim to leverage? Strong ties tend to be more homophilous than weak ties, so they are likely to provide better passive, homophily-based matching. Because 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, Petersen, and Leone (2007)? Is it because these customers distrust marketing campaigns but trust peer recommendations? Or is it 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? Both answers are consistent with the results of a field experiment by AT&T (Hill, Provost, and Volinsky 2006), and both suggest that some of the benefits of better matching and social enrichment may materialize at the time of acquisition and need not be limited to the post-acquisition benefits studied here.

Fourth, why and when do customers acquired through referral remain more engaged post-acquisition than customers acquired through firm-to-consumer communication (as observed by Lee, Ofek, and Steenburgh [2013])? Are superior matching and social enrichment part of the answer, rather than merely seeking and maintaining status (Hu and Van den Bulte 2014; Toubia and Stephen 2013)?

Fifth, how does the superior profitability of referrals relate to their usage behavior? (1) Do referred customers use more products than nonreferred 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. (2) Compared with nonreferred customers, does a higher fraction of referred customers use "experience" and "credence" products (e.g., life insurance, investment advice, estate planning) that provide more opportunities for differentiation and high margins than "search" products do (e.g., checking accounts, savings accounts, mortgages) (Armelini, Barrot, and Becker 2015)? Higher use among referred customers of products that are difficult to assess in advance would be consistent with better matching, social enrichment through trust-enhancing social bonding, and social enrichment through education and discussion. (3) Do referred customers rely less on customer support provided by the firm than nonreferred customers do? Reduced reliance on customer support would be consistent with better matching, social enrichment, and the eBay anecdote mentioned previously. 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? In addition, 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 who exhibit lower-than-expected margins and higher-than-expected churn (where expectations are based on observable characteristics)? Are higher referral fees associated with referred customers who exhibit 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 their higher-margin customers who have been with the bank more than a few months and 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 discussed previously. Examples include the following:

- 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 nonreferred customers?
- Are there prospects (e.g., those with complex needs) who 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 customers who are 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 toward 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, Provost, and Volinsky 2006; Hinz et al. 2011; Iyengar, Van den Bulte, and Lee 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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