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How Customer Referral Programs Turn Social Capital into Economic Capital

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Report Summary

Customer referral programs are a popular form of word-of-mouth or network marketing. Customers acquired through such a program have been observed to exhibit higher margins and lower churn than customers acquired through other means. However, the question remains why this is the case. Christophe Van den Bulte, Emanuel Bayer, Bernd Skiera, and Philipp Schmitt use data from a bank's referral program to test two possible mechanisms, suggested by theory, which could explain this phenomenon: *better matching* between referred customers and the firm, and *social enrichment* by the referrer.

Better matching implies the presence of characteristics common to the referrer and his or her referrals but unobserved by the firm. So, to document the presence of shared unobservables in customers' profitability, the authors estimate a panel model with both person-specific and dyad-specific random effects. They also calculate the correlation in residuals from the regression analyses for the profitability of referrers and referrals, respectively. To document the presence of shared unobservables in customers' churn behavior, the authors estimate a Cox proportional hazard model with common random effects.

Social enrichment implies that the benefits of referral diminish or even vanish after the referrer churns. So, to document the presence of social enrichment, the authors compare the referral's churn before and after the referrer churns.

Consistent with better matching affecting profitability, (1) referrer-referral dyads exhibit shared unobservables in customer profitability, and (2) referrers with more extensive experience bring in more profitable referrals. Consistent with social enrichment affecting retention, (3) referrals exhibit lower churn but only as long as their referrer has not churned. These findings support the notion 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.

These findings suggest that referral programs can be made more profitable by recruiting referrers among long-tenured and profitable customers, and by using churn by the referrer as an early warning signal for churn by the referral. Often, word-of-mouth marketing campaigns target opinion leaders and other influential customers likely to generate a high number of referrals. Such social targeting assumes that all referrals are equally valuable. Instead, selectively recruiting loyal and profitable customers to act as referrers is likely to generate new customers who are more loyal and more profitable than average and who, consequently, deliver a higher marketing ROI.

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Marketers are increasingly keen on leveraging customer-to-customer connections to their advantage. As a result, social influence among customers and how it can be leveraged to acquire and retain customers are topics that are attracting growing interest from both practitioners and academics (e.g., Godes 2012; Haenlein 2013; Hinz et al. 2011; Iyengar et al. 2014; Nitzan and Libai 2011). 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., Kumar et al. 2010; Ryu and Feick 2007; Schmitt et al. 2011).

Customer referral programs have long been viewed as an attractive way to acquire customers because (i) they 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 (e.g., Kumar 2008). A recent study by Schmitt, Skiera and Van den Bulte (2011)—henceforth SSV—has documented economic post-acquisition benefits as well. Referred customers (i) had a higher contribution margin, though this difference eroded over time, and (ii) had 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 differential, SSV proposed, might stem from better matching, whereas the churn difference might stem from social enrichment. 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, not on identifying or testing the intervening mechanisms. The present study, in contrast, assesses whether the superior value of referred customers indeed stems 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 gain new customers who are especially valuable in financial terms, 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.

Better matching features prominently in theoretical and empirical research on employee referral programs in sociology and economics (e.g., Beaman and Magruder 2012; Brown et al. 2013; Castilla 2005; Fernandez et al. 2000; Montgomery 1991; Pallais and Sands 2013; Rees 1966; Yakubovich and Lup 2006). Better matching is also central to the theoretical analysis of incentivized customer referrals by Kornish and Li (2012). In essence, the idea is that referred customers are a more suitable match with the firm than non-referred customers are. 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. Better matches between what customers want and what firms offer result in higher sales or lower costs, and hence higher margins. 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, and the gap between referred and non-referred customers erodes.

Social enrichment, the second mechanism of interest, also appears in research on employee referral programs in sociology and economics (Castilla 2005; Fernandez et al. 2000; Pallais and Sands 2013). In essence, the idea is that the relation 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 from joint consumption, such as the opportunity to discuss the pros and cons of specific product offerings (Burszrtyn et al. 2014). As a result of these social and functional benefits of co-presence, the referred customer has a lower tendency to churn than a non-referred one, provided that the referrer remains a customer.

With the participation of the same retail bank studied by SSV, we analyze 1,799 referrer-referral customer dyads for specific patterns in churn and profitability that should occur if better matching and social enrichment are at work. These patterns include (i) the presence of correlated unobservables within referrer-referral dyads, (ii) the initial margin gap between referred and non-referred customers being an increasing function of the referrer's experience with the firm, and (iii) the disappearance of the retention gap once the referrer churns. The findings support the notion that better matching affects the referral profitability gap, whereas social enrichment affects the referral churn gap.

Better understanding *how* marketing programs convert the connections of current customers into new customers with superior lifetime value, 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 emerging intersection among social status, customer valuation, and targeting (e.g., Hinz et al. 2011; Hu and Van den Bulte 2014; Wei et al. 2014). The third is social capital theory (e.g. Bourdieu 1986; Coleman 1988; Latour and Woolgar 1986) and its various applications to marketing (e.g., Gonzalez et al. 2014; Grewal et al. 2006; Wuyts et al. 2004).

We first provide a brief description of customer referral programs and prior research, and then develop 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.

Customer Referral Programs

Customer referral programs provide incentives to existing customers to bring in new customers. The key idea is to use the social connections of existing customers with non-customers to attract and convert the latter. An important requirement for such programs is that individual purchase histories are available so the firm can ascertain whether a referred customer is indeed a new rather than an existing or a former customer.

Customer referral programs are not the only form of stimulated word-of-mouth or network marketing where firms provide incentives to leverage social ties among consumers, professionals or businesses to acquire new customers. However, referral programs have some unique characteristics.

First, unlike most forms of incentivized buzz and viral marketing (including viral-for-hire companies like BzzAgent, providing samples to bloggers, social couponing, and group buying), the activated source of social influence consists only of existing customers. Referrers with considerable experience about what they recommend are expected to have source credibility, which matters especially for complex and risky experience products (Iyengar et al. 2011a; Jing and Xie 2011).

Second, unlike viral-for-hire programs and programs focusing on distributing samples to influential bloggers and reviewers, the referrer is likely to know both the firm’s offerings and the prospective referral well. This familiarity facilitates the transfer of rich knowledge about how the firm’s offering may match the unique needs of the referral.

Finally, unlike multilevel marketing, existing customers are rewarded only for bringing in new customers. Since they do not generate any income or in-kind benefit from subsequent sales or continued membership, referrers have no ulterior incentive to exert any influence after the referral has become a customer. Consequently, referral programs do not carry the stigma of exploiting social ties for mercantile purposes, as multilevel marketing does (Biggart 1989).

Existing studies of customer referral programs have analyzed the impact of rewards and tie strength on referral likelihood and referral acceptance (Jin and Huang 2014; Ryu and Feick 2007; Tuk et al. 2009; Verlegh et al. 2013; Wentzel et al. 2014; Wirtz and Chew 2002; Wirtz et al. 2013), have provided guidance about when and what kinds of rewards should be offered (Biyalogorsky et al. 2001; Jing and Xie 2011; Kornish and Li 2010; Xiao et al. 2011), have documented that making a compensated referral can make existing customer more loyal to the firm they recommend (Garnefeld et al. 2011; Garnefeld et al. 2013), have quantified to what extent customers acquired through referral are more profitable, loyal, and valuable than customer acquired through other means (SSV 2011), and have quantified the monetary value of making a referral (Barrot et al. 2013; Helm 2003; Kumar et al. 2007, 2010; Walsh and Elsner 2012).

Several of these studies rely on specific behavioral assumptions to obtain their analytical results (Jing and Xie 2011; Kornish and Li 2010; Xiao et al. 2011) or explain their empirical observations about post-acquisition outcomes (Garnefeld et al. 2013; SSV 2011). These behavioral premises, however, have typically not been documented empirically in the realm of customer referral programs. Specifically, while the study by SSV has shown *that* customer referral programs turn social network capital into economic capital, there is no empirical evidence yet on *how* this happens.

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 are unlikely to be supported otherwise (e.g., Iyengar et al. 2011; Iyengar et al. 2014). Our hypotheses focus on the two mechanisms put forward by SSV, better matching and social enrichment. They are informed by prior work on employee referral (e.g., Coverdill 1998; Montgomery 1991; Rees 1966), especially the empirical research on employee referral programs by Fernandez, Castilla, and Moore (2000), Neckerman and Fernandez (2003), Castilla (2005), Yakubovich and Lup (2006), Brown, Setren, and Topa (2013) and Pallais and Sands (2013). These studies provide evidence that the benefits of such programs are realized through distinct mechanisms, of which only better matching and social enrichment are likely to be relevant to customer referral programs.[1]

As noted earlier, better matching is the phenomenon that referrals fit the firm's offerings better than non-referrals 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.

Better matching

Matching on shared (correlated) unobservables. For active matching or selective screening by referrers to result in better matches, referrers must have information on their referral's traits that are related to match quality but are not fully observable to the firm before the customer is acquired. Superior matches need not be deliberate but may also stem from homophily, the pervasive tendency for people to interact with others like them. Existing customers 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, existing customers are likely to be similar to the referrals they bring in. Consequently, referrals are more likely to be a good match than customers acquired through other means—provided at least that the intra-dyadic similarity is in characteristics that meet two criteria. First, the shared characteristics are relevant to the enjoyment of the product, the need for additional service, or customer value broadly. Second, the characteristics are not immediately observable to the firm. In short, passive matching is predicated on the presence of *correlated or shared unobservables*: traits related to customer

[1] Favoritism by referrers who help their referrals gain promotions or higher performance reviews after being hired has no equivalent in customer referral programs. Favoritism does not apply to customers who pay the firm as opposed to employees who are being paid. Similarly, monitoring by referrers to safeguard their reputation with the employer in case the referral engages in moral hazard seems applicable only in very special circumstances where moral hazard is a key driver of customer profitability *and* fellow customers can monitor each other. Some business markets with large transaction-specific investments by the seller may be such a setting. Credit card referral by close family members or friends in emerging markets without a sophisticated credit rating infrastructure may be another (Guseva and Rona-Tas 2001).

value that are common within a referral-referrer dyads and that are not fully observable by the firm.

Examples of such traits relevant to banking services include preferences for opening hours, risk aversion, and fiscal responsibility. When matching occurs on such characteristics, lenders 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 is similarly predicated on the idea that the creditworthiness of one's contacts is informative about one's own creditworthiness (Wei et al. 2014).

So, passive matching implies the following refutable hypothesis:

H1. Referrers and their referrals have shared unobservables in their (i) profitability and (ii) churn rate.

Referrals' need complexity and benefit of matching. If the benefits of referral programs indeed stem from better matching in unobservables, then those benefits should be greater for customer groups with more complex needs that are harder for firms to profile a priori, identify and understand quickly, and meet efficiently. For retail banks, older customers can be such a group. As customers grow older, their needs evolve beyond simple savings and checking accounts to include mortgage financing, life insurance, investments, retirement planning, and estate planning. Though the firm may learn complex customer needs over time, it will at first have only a limited understanding of how to best serve such customers. Hence, if one makes the auxiliary assumption that higher age is associated with customer needs that are more complex and harder to identify, understand, and meet, then better matching on unobservables implies the following testable hypothesis:

H2: The initial gap in (i) profitability and (ii) churn between referred and non-referred customers is more pronounced among older customers.

Referrers' experience and quality of matching. Better matching on unobservables implies that the relationship between the referrer and the firm should also affect the value of the referral. A referrer who has been a customer for a long time typically has a relationship with the firm that has survived many occasion 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 expending the effort to deliberately screen 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 be willing to exert greater effort in finding good matches and be less likely to generate referrals opportunistically just to pocket the reward (Jin and Xie 2011; SSV 2011). As a result, the matches produced through both passive, homophily-based matching and active, screening-based matching should be more valuable for referrers who have been with the firm for some time.

H3: The gap in (i) profitability and (ii) churn of referred vs. non-referred customers is greater when the referrer has been a customer with the firm for some time before making the referral.

The same arguments involving occasions for churn, information, and motivation should apply to the strength or duration of the relationship between the referrer and the referral rather than between the referrer and the firm (Kornish and Li 2010). We do not formulate the corresponding hypothesis because we do not have the data on the nature of ties between referrers and 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 profitability or churn between referred and non-referred customers will erode over the customers' lifetime. As non-referred customers accumulate experience with the firm, they become equally well informed about the firm's products 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. The argument, in essence, is that the information asymmetry that is initially resolved through better matching becomes less pronounced over time due to learning. This substitution of "direct learning from experience" for "social learning through matching" as ways to address the initial paucity of information implies that the effects hypothesized in H2 and H3 should erode the longer the newly acquired customer remains a customer. Hence, we propose:

H4: The customer age-related difference in the gap in (i) profitability and (ii) churn between referred and non-referred customers erodes over the customers' lifetime.

H5: The referrer experience-related difference in the gap in (i) profitability and (ii) 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 (Castilla 2005; Fernandez et al. 2000), joint consumption (Bursztyn et al. 2014), or team production (Pallais and Sands 2013). 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 strengthen his or her affective bond with it (Van den Bulte and Wuyts 2007). This social bonding mechanism should be particularly relevant for products for which trust is especially 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).

Being connected to a fellow customer may also provide functional benefits, such as 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, and having an advocate when resolving customer complaints (e.g., Bursztyn et al. 2014; Gargiulo 1993; Reichheld 2006; Wuyts and Van den Bulte 2012).

As a result 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 products. Consequently, a referred customer is less likely to churn than a non-referred customer, provided that the referrer does not churn either. The latter condition is likely to hold: Referrers typically have a greater long-term likelihood of staying, which is why intention to refer is frequently used as an indicator or predictor of loyalty (Gupta and Zeithaml 2006).

However, some referrers do churn. If social enrichment is indeed a reason for why referrals exhibit higher profitability or lower churn than non-referred customers, then the referrer's churn should annihilate the gap in profitability and churn. This argument is consistent with the phenomena of contagious churn and contagious repeat documented in several recent studies (Dierkes et al. 2011; Iyengar et al. 2014; Nitzan and Libai 2011; Sgourev 2011; Zhang et al. 2012). However, the argument goes beyond that prior 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 odds of the referral's churn, 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 of the referrals who remain a customer. So, we propose:

H6: Referred customers exhibit (i) a lower profitability and (ii) a higher churn rate after their referrer has churned.

H7: Referred customers' gap in (i) profitability and (ii) churn compared to non-referred customers disappears after their referrer has churned.

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 referrals and non-referred customers acquired during the same period, as SSV did, but also data on the customers who generated those referrals. The data include 1,800 customers 18 years or older and acquired through the bank's referral program between January 2006 and October 2006, as well as their referrer. The data include only a single referral per referrer, comprises all referral-referrer dyads for which the bank had the required demographic information on both members of the dyad, and 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 profitability or churn. Also, 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 cause for concern that missing data would bias our hypothesis tests.

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

The observation period spans from January 2006 to September 2008 (33 months), and the data on each individual customer include the day of acquisition, the day of leaving the bank (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 referral program was communicated 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 euros 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, and so on) was on average approximately 20 euros lower than that for non-referred customers.

Dependent variables

We have three dependent variables. The first is the customer's daily contribution margin (DCM). It is the total contribution margin the customer generates in the 2006-08 observation period, divided by the total number of days the customer was with the bank over that period. This per diem scaling allows to compare the contribution margin of customers with different observed (and possible censored) durations. The contribution margin equals revenue (interest and fees) less direct costs (e.g., interest expenses, sales commissions, brokerage, trading costs). The acquisition costs are not subtracted from the contribution margin.

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 observed to be with the bank in 2006-08. It is the basis for analyzing retention or churn.

Unlike SSV whose emphasis was on customer value and program profitability, we do not compute customer lifetime values (CLVs). The present research focuses on empirically documenting the social mechanisms underlying the differences in profitability and churn, and these mechanisms cannot be diagnosed sharply by investigating the amalgamation of margin and churn into a single, time-invariant CLV metric.

Independent variables

We have data on three types of customers: 1,800 referrals, i.e., customers acquired through referral, 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 referrals 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 affects the profitability 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 a customer with the bank. For the churn models where the dependent variable is measured daily, CLT is updated daily. For the models of profitability where the dependent variable (contribution margin) 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 cluttering the tables, CLT is expressed in thousands of days.

The time-varying dummies Year2007 and Year2008 capture whether the customer profitability pertains to 2006, 2007 or 2008. The hazard models for churn feature not only dummies for cohort or time of acquisition but also a non-parametric baseline for duration dependency (CLT). Consequently, adding year dummies in the churn models is superfluous.

Finally, we also have four covariates to assess how customers' profitability 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, but switches to 1 once the referrer churns. ReferGone can change any day, and so can be used for assessing changes in the referral's risk of churn. In contrast, ReferGone cannot be used to model 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. The numerator is either the number of days that the referral was a customer or that the referrer was a customer with the bank, whichever is the lower of the two values, in a particular year. The denominator is the number of days that the referral was a customer in that same year. So, the variable represents the fraction of the referral's days as a customer that the referrer was also a customer. The variable ranges between 0 and 1. It equals 0 if the referrer left before January 1 of the focal year; it equals 1 if the referrer remained a customer throughout the period that the referral was a customer during that year, and takes an intermediate value if the referral was a customer after the referrer had churned.

The dummy RefalGone and the ratio PropRefalGone are constructed in a similar fashion, to study how the referrer's profitability and churn changes after the referral's churn.

Data purification and final data set

The data include several customers with an extremely high 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 referral gap in DCM(t) (Preisser and Qaqish 1996). This diagnostic is a generalization of the DFBETAS to identify influence points in linear regression (Belsley, Kuh, and Welsch 1980). This influence analysis led us to delete one referral customer, resulting in a final data set of 1,799 referral-referrer pairs and 3,663 non-referred customers.

Table 1 profiles the three sets of customers—referrals, referrers, and non-referred customers—by reporting the mean values of their common explanatory variables. It also reports mean values of the two dyad-specific variables.

[see Table 1, following References]

Preliminary Analysis

Before testing our hypotheses about mechanisms underlying profitability 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.

As reported in Table 1, referrals 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 euros 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 sizably larger than the €.11 difference in raw means mostly 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 referrals (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 referrals 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 ($p > .05$).

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. Having documented these patterns, we now turn to our main research objective: Assessing to what extent they are consistent with better matching and social enrichment.

Shared Unobservables in Profitability (H1(i))

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

Simple analyses of prediction errors

We start by assessing the presence of shared unobservables in the daily contribution margin over the customer's total observed history across the years 2006, 2007, and 2008. We do so using the correlation in OLS regression residuals after accounting for basic demographics and time of acquisition. We first regress the 1,799 referrals' DCM on their age, gender, 4 dummies for marital status, and 9 dummies for month of acquisition ($R^2 = .036$). Similarly, we regress the referrers' DCM on their age, gender, 4 dummies for marital status, 9 dummies for month of acquisition in 2006, and 5 dummies for acquisition in other years ($R^2 = .051$). The resulting residuals, representing the part of the DCM that is not predicted by the observed covariates, exhibit intra-dyadic correlation (Pearson: .137; Spearman: .126; both $p < .001$).

Common random effects in panel data

Next, we exploit the fact that we observe customer profitability (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 another 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 referrer and referral customers (ij) nested in 1,799 dyads (j):

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

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 Huber-White 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*.

Column 1 in Table 2 reports the results. Though most of the unexplained variance in the annual profitability of referrals and referrers is customer-specific ($\sigma_u = 4.13$) or observation-specific ($\sigma_e = 2.86$), a significant part of it is dyad-specific ($\sigma_d = 1.23$).[2] This last test result is consistent with the presence of shared unobservables in profitability.

Shared unobservables or peer presence?

Several studies have documented the presence of correlated purchase incidence or correlated purchase volume between people who share an organic referral tie or other social tie (e.g., Haenlein and Libai 2013; Hill et al. 2006; Iyengar et al. 2014; Nair et al. 2010). These studies note that correlated behavior can stem not only from shared or correlated unobservables but also from peer influence. This ambiguity raises the question: Is the evidence of shared unobservables in profitability between referrals and referrers robust to controlling for the continued co-presence of the counterpart in the dyad?

We therefore extend the model in equation (1) with variables capturing the presence or absence of the dyadic counterpart, i.e., *PropReferGone* and *PropRefalGone*. These variables

[2] 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. That 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 minus 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.

measure the fraction of the time that a referral (respectively, referrer) was with the bank in a particular year after his or her referrer (respectively, referral) had left. 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 neither is the evidence of significant shared unobservables. The conclusion of significant shared unobservables in contribution margin arrived at earlier continues to hold.

[see Table 2, following References]

Shared Unobservables in Churn (H1(ii))

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. We do so using a Cox proportional hazard model with shared frailty (e.g., Therneau and Grambsch 2000). The standard Cox model allows one to analyze right-censored duration data and to exploit the fine-grained measurement of churn at the daily level without imposing any restriction on how the average churn rate evolves over time. Furthermore, for single units of observations, the non-parametric baseline hazard makes the model robust to unobserved heterogeneity in all but very extreme cases (e.g., Lin and Wei 1989; Schmoor and Schumacher 1997; Struthers and Kalbfleisch 1986). For grouped observations, such as referrals and referrers nested in dyads, the model can be extended with a "shared frailty" or common random group-specific effect. Let t denote the number of days since the customer was acquired (or since January 1, 2006 for referrers acquired before that date), j denote a dyad (j: 1, …, 1799), and i denote whether the customer is a referral or a referrer (i: 1, 2). Let $h_{ij}(t)$ be the hazard of churn, i.e., the rate at which member i of dyad j churns at time t given that the customer has not churned yet. We estimate the following shared frailty Cox model:

$$h_{ij}(t) = \alpha(t)\, \eta_j \, \exp\left(\sum_{k=1}^{20} \beta_k X_{ijk}\right) \tag{2}$$

where $\alpha(t)$ is the non-parametric baseline hazard common across all customers, $\eta_j > 0$ is the dyad-specific random effect following a Gamma distribution with mean 1 and variance θ, and the variables in X include a dummy whether the customer was the referral or the referrer, the customer's age, and dummies for gender, marital status, month of acquisition in 2006, and acquisition in other years. The model reduces to the standard Cox model when $\theta = 0$.

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, that customer 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.[3] 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 results. The variance of the shared frailty effects is significantly different from zero ($\theta = 2.529$, $p < .001$), indicating the presence of common unobservables in churn of both members of the dyad.

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; Iyengar et al. 2014; 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 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*, a dummy that equals 1 for referrals after their referrer has churned and equals 0 otherwise, and its counterpart *RefalGone*, a dummy that equals 1 for referrers after their referral has churned and equals 0 otherwise. 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 on the same day in only 10 cases. When both

[3] 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 not improve model fit significantly and did not affect the substantive findings.

leave and the referrer does first (last), the average inter-event time is 104 (95) days. So, truly coordinated churn is quite unlikely.

Since *ReferGone* and *RefalGone* are time-varying, we use a discrete-time hazard model with shared heterogeneity 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:

$$g(h_{ijt}) = \alpha_t + \beta_1 \mathrm{Refal}_{ij} + \beta_3 \mathrm{ReferGone}_{ijt} + \beta_3 \mathrm{RefalGone}_{ijt} + \sum_{k=4}^{22} \beta_k X_{kij} + d_j \text{, where} \tag{3}$$

$g(h) = \ln(-\ln(1-h))$ is the complementary log-log link function, h_{ijt} is the discrete-time hazard, i.e., the probability of churn on day t given that the customer was still present on day t-1, the α 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 customer lifetime 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 that customers are at risk of churning, 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. Using such piece-wise constant baseline hazard remains more flexible and closer to the Cox model than imposing a parametric functional form on the duration dependency. When not a single customer churns in a 30-day block, the likelihood reaches its true maximum only when that block's α parameter estimate reaches $-\infty$. One simple solution to such "quasi-complete separation" follows from recognizing that we already know the true maximum likelihood value of those baseline parameters in our data ($-\infty$) and that, at that value, the observations provide no information about the other parameters. Hence, we simply delete all the data in those blocks from the data set, delete the corresponding dummy variables from the model, and proceed as usual (Anderson 1987; Iyengar et al. 2014; Lien and Rearden 1990; Oksanen 1986).

Column (2) in Table 3 reports the estimates of this Normal-Complementary log-log hazard model excluding *ReferGone* and *RefalGone*. The results are strikingly similar to those of the Gamma-Cox shared frailty model in column (1). The two specifications produce nearly identical parameter estimates and both show evidence of shared unobservables ($\theta = 2.529$; $\sigma_d = 1.290$; both $p < .001$). However, the results in column (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 may have been a confound between shared unobservables and contagious churn. This contrasts with the evidence of shared unobservables in customer margin, which was robust to controlling for peer churn.

[see Table 3, following References]

Tests of Hypotheses H2(i)-H7(i) on Profitability

We presented several hypotheses which should be supported if the margin gap between referral and non-referred customers stems from better matching: The gap is greater for older customers whose needs are harder to assess a priori (H2), and for customers whose referrer had sufficient experience with the bank (H3). Also, both differences in margin gap should erode over time (H4, H5).

To test the hypotheses, we assess whether the margin gap associated with being referred varies by that customer's age and by the experience of that customer's referrer at the time of referral, and whether those associations erode over the customer's lifetime. H2 implies a positive interaction between referral status and age on DCM. H3 implies a negative association between limited referrer experience and DCM. H4 and H5 imply that those age- and experience-related differences in margin gap erode over the referral's 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: Less or equal to 1 month and between 1 and 6 months of experience with the bank before making the referral.

We also hypothesized that, if the margin differential stems from social enrichment, then the differential should be lower (H6) and even disappear (H7) 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:

$$DCM_{it} = \beta_0 + \beta_1 Referral_i + \sum_{k=2}^{11} \beta_k X_{kit} + \beta_{12} PropReferGone_{it} + \sum_{k=13}^{28} \beta_k X_{ki} + u_i + e_{it}, \text{ where} \quad (4)$$

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 H2-H5, *PropReferGone* used to test H6-H7 is defined as above, and the second set of X variables includes dummies for gender, marital status, month of acquisition, and the year. The person-specific effects u_i can be either random or fixed. We use generalized least squares to estimate the random effects specification, and OLS to estimate the fixed effects specification. In both cases, we use heteroscedasticity-robust Huber-White standard errors.

Column (1) in Table 4 reports the model estimates of equation (4) with random effects. The model in column (2) excludes the *PropReferGone* variable associated with H6-H7. The model in column (3) excludes the variables interacting with customer lifetime (except for age, which is always included) that are associated with H2-H5. The results are robust across specifications, indicating that our conclusions are not affected by some harmful inability to distinguish between the patterns in the data implied by better matching versus social enrichment.

The positive coefficient of *Referral x Age* (.024) indicates that the initial referral gap is greater for older consumers. This is consistent with H2. 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, H4 is supported also.

Referrers with less than 1 month of experience with the bank generate markedly less profitable customers than referrers with more than 6 months of experience. Actually, 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). 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). Also, decreases in the DCM gap associated with limited experience by the referrer erode over time and vanish after about 1,200 days for very inexperienced referrers (.821/.690 x 1,000 days) and about 1,000 days for moderately inexperienced referrers (.500/.474 x 1,000 days). These patterns are consistent with H3 and H5.

Support for H2 through H5 corroborates the claim that the margin gap stems from better matching. In contrast, there is no support whatsoever for the notion that the margin differential is smaller (H6), let alone disappears (H7), after the referrer has churned. The continued presence of the referrer shows no clear association with the referral's profitability.

In short, our findings indicate that the margin differential stems from better matching and not from social enrichment. The models reported in Table 5 show that this conclusion is robust to specifying fixed rather than random effects to control for the presence of multiple observations per individual.

[see Tables 4 and 5, following References]

Tests of Hypotheses H2(ii)-H7(ii) on Churn

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

$$g(h_{it}) = \alpha_t + \beta_1 \text{Referral}_i + \sum_{k=2}^{11} \beta_k X_{kit} + \beta_{12} \text{Refergone}_{it} + \sum_{k=13}^{26} \beta_k X_{ki}\text{, where} \tag{5}$$

$g(h) = \ln(-\ln(1-h))$, 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 H2-H5, *ReferGone* is used to test H6-H7 and equals 1 for referrals after their referrer has churned and equals 0 otherwise, and the second set of X variables includes dummies for gender, marital status, month of acquisition. As in the discrete-time 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 6 reports the estimates of the model in equation (5) estimated on the data comprising 1,799 referrals and 3,663 non-referred customers. The model in column (2) excludes the *ReferGone* variable associated with H6-H7. That in column (3) excludes the variables associated with H2-H5 (except for age, which is always included). The results are robust across specifications, indicating that our conclusions are not affected by some harmful inability to distinguish between the patterns in the data implied by better matching versus social enrichment.

The results in columns (1) and (3) show that the data do not exhibit any of the patterns predicted to hold if churn was affected by better matching. There is no consistent and significant evidence that the churn gap varies by age (H2), that referrers with limited experience produce faster-churning referrals (H3), or that either difference becomes more muted over the referrals' lifetime (H4 and H5).[4] The predictions do not hold, either individually as implied by the lack of significance of coefficients, or collectively as implied by a likelihood ratio test between Models (1) and (2) (Δ -2LL = 11.56, df = 9, $p > .05$).

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 columns (2) indicate that referrals whose referrer is still with the bank have a churn hazard that is only about 60% that of non-referred customers (1-exp(-.48)). This difference changes dramatically once the referrer has churned. Referrals whose referrer has left the bank have a churn hazard that is about 380% that of non-referred customers (1-exp(-.48+1.82)). So, not only does the positive association between referral and loyalty decrease (H6) and disappear (H7), consistent with social enrichment, but the associations turn from markedly positive to markedly negative.

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

[see Table 6, following References]

Predicting Referral Margin and Churn from Referrer Characteristics

Managers want to know whether particular 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 using the same variables. The results in Table 7 show that referrals tend to be more profitable if they

[4] Column (1) reports a significantly positive coefficient for 1-6MonthsExp, but column (3) does not. This does not amount to consistent support for H3 in churn. Both columns (1) and (3) report a significantly negative coefficient for Age x CLT, but that interaction is not relevant to any hypothesis and is included only as a necessary lower-order term for the predicted third-order interaction between Referral, Age, and CLT.

were acquired through a referrer who generates 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 individually significant, the overall pattern suggests that referrals tend be more profitable if acquired through a customer who has been with the bank for more than a few months. In contrast, none of the referrer's characteristics is a significant predictor of the referral's speed of churn. These results suggest that managers may want to focus their invitations to serve as referrers to (i) their more profitable customers who (ii) have been with the bank more than a few months. Conversely, managers may want to avoid engaging less profitable and recently acquired customers to act as referrers.

[see Table 7, following References]

Discussion

We tested, and found support for, 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—especially the change in referrals' churn after their referrer churns—are consistent with *social enrichment.*

Rival explanations

We now discuss possible rival explanations for our findings, i.e., threats to internal validity.

Selectivity. A concern with comparing the behavior of customers acquired through different channels that customers may self-select into different modes of acquisition based on characteristics unobserved by the researcher. Correctly identifying the counter-factual 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. But since 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, we are not aware of any dimension of unobserved heterogeneity that may explain our results for H6 and H7.

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

Post-acquisition differences in marketing mix treatment. According to the bank, the referred and non-referred customers were not treated 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 hypotheses H2-H7, all of which involve moderator effects, i.e., differences in differences (compare Iyengar et al. 2014).

Implications for theory and research

Marketers increasingly recognize the power of connections among customers and adapt their strategies accordingly. In this new approach, Kumar (2008, p. 88) notes, customers are viewed not only as a source of business but also as a resource that can be leveraged to boost marketing effectiveness and, consequently, profits. Consequently, the value of a customer base consists not only of the economic capital derived from the customers' transactions with the firm, but also of the social capital that these customers' connections represent. Two questions of great interest to both practitioners and scholars are whether and how this social capital can be converted into economic benefits by referral programs. Whereas the study by Schmitt et al. (2011) answered the "whether" affirmatively, the present study answers the "how".

Yet, many questions remain unanswered and our findings raise several new ones. First, what kinds of firms and products are most likely to derive post-acquisition benefits from referral programs? Our evidence of better matching implies that firms with rather unsophisticated customer-profiling skills and firms targeting customers with hard-to-profile needs are likely to benefit disproportionately from such programs. 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 of such users are file sharing services like Dropbox, makers of multiplayer games like World of Warcraft, and professional associations like the American Marketing Association or the American College of Physicians. 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? Since strong ties tend to be more homophilous than weak ties, they are likely to provide better passive, homophily-based matching than weak ties. Since strong ties also tend to exhibit greater benevolence, they are also likely to provide better active, screening-based matching and as well as higher social enrichment.

Third, why is it that referral programs can 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 disproportionately distrust marketing campaigns but trust peer recommendations? Or because these customers have needs that marketers do not address well in campaign materials but that their friends do 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 only provide post-acquisition benefits.

Finally, 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)?

Answering these questions pertaining to marketing effectiveness would benefit from research on how, not just whether, customer referral programs turn social capital into economic capital. 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 (e.g., Hill et al. 2006; Hinz et al. 2011; Wei et al. 2014).

Implications for practice

Much of the emphasis in the trade press is on how customer referral programs provide an efficient means to acquire customers with little upfront investment. However, the benefits of matching and social enrichment are realized *after* the customers are acquired in the form of higher margins and lower churn. Better matching, social enrichment, and the eBay anecdote mentioned earlier all imply that reduced service support may be an important benefit of referral programs that has been hitherto ignored. Also, marketers should consider designing customer referral programs aimed at boosting not only participation rates, the focus of most attention to date, but also post-acquisition benefits. For the latter, our results imply, managers may want to focus their referrer recruitment efforts on their more profitable customers who have been with the firm more than a few months. Conversely, managers may want to avoid engaging less profitable and recently acquired customers to act as referrers.

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Table 1
MEAN VALUES OF CHARACTERISTICS OF CUSTOMERS, BY GROUP

<table>
<tr><th></th><th>Referrals</th><th>Referrers</th><th>Non-referred</th></tr>
<tr><td>N</td><td>1,799</td><td>1,799</td><td>3,663</td></tr>
<tr><td>DCM (across 33 months)</td><td>.646</td><td>1.825</td><td>.538</td></tr>
<tr><td>Fraction churned</td><td>.097</td><td>.064</td><td>.145</td></tr>
<tr><td>Age</td><td>39.860</td><td>44.056</td><td>46.712</td></tr>
<tr><td>Female</td><td>.572</td><td>.455</td><td>.513</td></tr>
<tr><td>Single</td><td>.512</td><td>.402</td><td>.355</td></tr>
<tr><td>Married</td><td>.305</td><td>.376</td><td>.451</td></tr>
<tr><td>Divorced</td><td>.086</td><td>.084</td><td>.102</td></tr>
<tr><td>Widowed</td><td>.038</td><td>.041</td><td>.066</td></tr>
<tr><td>Other</td><td>.059</td><td>.097</td><td>.027</td></tr>
<tr><td>Acquired Jan 2006</td><td>.003</td><td>.018</td><td>.074</td></tr>
<tr><td>Acquired Feb 2006</td><td>.003</td><td>.023</td><td>.088</td></tr>
<tr><td>Acquired Mar 2006</td><td>.029</td><td>.032</td><td>.133</td></tr>
<tr><td>Acquired Apr 2006</td><td>.113</td><td>.021</td><td>.063</td></tr>
<tr><td>Acquired May 2006</td><td>.134</td><td>.034</td><td>.078</td></tr>
<tr><td>Acquired June 2006</td><td>.140</td><td>.043</td><td>.110</td></tr>
<tr><td>Acquired July 2006</td><td>.178</td><td>.050</td><td>.129</td></tr>
<tr><td>Acquired Aug 2006</td><td>.201</td><td>.029</td><td>.110</td></tr>
<tr><td>Acquired Sep 2006</td><td>.150</td><td>.011</td><td>.077</td></tr>
<tr><td>Acquired Oct 2006</td><td>.048</td><td>.006</td><td>.139</td></tr>
<tr><td>Acquired 2006</td><td>-</td><td>.268</td><td>-</td></tr>
<tr><td>Acquired 2005</td><td>-</td><td>.141</td><td>-</td></tr>
<tr><td>Acquired 2004</td><td>-</td><td>.054</td><td>-</td></tr>
<tr><td>Acquired 2001-2003</td><td>-</td><td>.116</td><td>-</td></tr>
<tr><td>Acquired 1996-2000</td><td>-</td><td>.168</td><td>-</td></tr>
<tr><td>Acquired before 1996</td><td></td><td>.253</td><td></td></tr>
<tr><td>Le1MonthExp</td><td colspan="2">.126</td><td>-</td></tr>
<tr><td>1-6MonthsExp</td><td colspan="2">.125</td><td>-</td></tr>
</table>

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	2.210***	3.98
Referral	.296**	3.09	.148	.65
PropReferGone			-.189	-1.11
PropRefalGone			.160	.71
Year 2007	-.243***	-4.61	-.209**	-2.83
Year 2008	-.570***	-7.14	-.539***	-7.29
Age (centered)	.028***	4.15	.028***	4.15
Female	-.551***	-3.86	-.551***	-3.86
Married	.202	1.06	.202	1.06
Divorced	.061	.17	.061	.16
Widowed	1.387	1.44	1.387	1.44
Other	.056	.28	.057	.28
Acquired Feb 2006	-.946	-1.68	-.945	-1.68
Acquired Mar 2006	-1.016	-1.74	-1.011	-1.73
Acquired Apr 2006	-1.210*	-2.22	-1.198*	-2.20
Acquired May 2006	-1.181*	-2.22	-1.170*	-2.19
Acquired June 2006	-1.281*	-2.38	-1.269*	-2.36
Acquired July 2006	-1.144*	-2.14	-1.132*	-2.12
Acquired Aug 2006	-1.190*	-2.22	-1.176*	-2.20
Acquired Sep 2006	-1.150*	-2.17	-1.136*	-2.14
Acquired Oct 2006	-.872	-1.49	-.857	-1.47
Acquired in 2005	-.789	-1.48	-.793	-1.49
Acquired in 2004	-.049	-.05	-.052	-.05
Acquired in 2001-2003	.390	.53	.387	.53
Acquired in 1996-2000	1.125	1.39	1.121	1.38
Acquired before 1996	.693	1.17	.687	1.16
	Est.	St. Err.	Est.	St. Err.
Dyad-specific variation (σ_d)	1.234	.163	1.235	.163
Customer-specific variation (σ_u)	4.128	.840	4.128	.840
Observation-specific variation (σ_e)	2.856	.499	2.855	.499
LL	-30,339.21		-30,338.88	
N	10,794		10,794	

* $p < .05$, ** $p < .01$, *** $p < .001$. Significance tests for coefficients based on Huber-White robust standard errors. Models estimated on 10,794 customer-year observations from 1,799 referrals and 1,799 referrers.

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

	(1) Gamma-Cox No contagion		(2) Normal-cloglog No contagion		(3) Normal-cloglog With contagion	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Referral	-.170	-.89	-.179	-.93	-.035	-.19
Refergone					1.329***	5.76
Refalgone					1.397***	6.35
Age (centered)	-.001	-.15	.000	.00	.000	-.07
Female	-.083	-.64	-.083	-.63	-.067	-.55
Married	.082	.44	.059	.32	.065	.39
Divorced	.079	.30	.076	.29	.069	.29
Widowed	.371	.91	.322	.79	.296	.82
Other	-.046	-.15	-.054	-.18	-.059	-.22
Acquired Feb-Mar 2006	-.156	-.24	-.188	-.29	-.233	-.40
Acquired Apr 2006	.813	1.33	.804	1.31	.671	1.22
Acquired May 2006	.110	.17	.078	.12	.013	.02
Acquired June 2006	.716	1.17	.691	1.13	.564	1.03
Acquired July 2006	.662	1.08	.633	1.03	.493	.90
Acquired Aug 2006	1.185	1.93	1.156	1.88	.900	1.64
Acquired Sep 2006	1.457*	2.34	1.399*	2.24	1.100*	1.96
Acquired Oct 2006	2.044**	3.05	2.013**	3.02	1.583**	2.70
Acquired in 2005	-.166	-.27	-.229	-.38	-.200	-.37
Acquired in 2004	-.328	-.48	-.408	-.60	-.345	-.56
Acquired in 2001-2003	-.665	-1.04	-.715	-1.12	-.694	-1.20
Acquired in 1996-2000	-.768	-1.24	-.821	-1.33	-.784	-1.40
Acquired before 1996	-2.280***	-3.26	-2.355***	-3.35	-2.236***	-3.45
	Est.	St. Err.	Est.	St. Err.	Est.	St. Err
Dyad-specific variation θ	2.529***	.638				
Dyad-specific variation σ_d			1.290***	.139	.005	.027
LL	-2,229.05		-2,668.99		-2,658.47	
N	3,598		3,598		3,598	

* $p < .05$, ** $p < .01$, *** $p < .001$.
Since no referral or referrer acquired in February 2006 churns, the coefficients for Acquisition in Feb and March 2006 are set to be equal.
All models control for duration dependency non-parametrically. Models (2) and (3) do so 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 data set prior to estimating Models (2) and (3).

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

	(1)		(2)		(3)	
	Coef.	*z*	Coef.	*z*	Coef.	*z*
Constant	-1.021	-.75	-1.020	-.75	.992***	4.27
Referral	.672***	4.40	.672***	4.40	.302***	4.75
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	5.674	1.44	5.674	1.44		
Referral x CLT	-.559**	-2.78	-.558**	-2.79		
Age x CLT	.002	.37	.002	.37		
Referral x Age x CLT	-.033***	-3.30	-.033***	-3.30		
Le1MonthExp x CLT	.690**	2.98	.692**	2.98		
1-6MonthsExp x CLT	.474	1.82	.475	1.83		
PropReferGone	.000	-.18			-.333	-1.58
Year 2007	-2.122	-1.47	-2.122	-1.47	-.093**	-2.56
Year 2008	-3.696	-1.48	-3.696	-1.48	-.281***	-4.21
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***	3.49
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	.248	.57	.248	.57	-.276	-1.05
Acquired May 2006	.304	.59	.304	.59	-.385	-1.59
Acquired June 2006	.374	.59	.374	.59	-.506*	-2.14
Acquired July 2006	.677	.91	.677	.91	-.366	-1.51
Acquired Aug 2006	.751	.87	.751	.87	-.464	-1.95
Acquired Sep 2006	.987	1.01	.987	1.01	-.384	-1.59
Acquired Oct 2006	1.101	1.01	1.101	1.01	-.469	-1.95
Customer-specific var. σ_u	1.477		1.478		1.490	
Observation-specific var. σ_e	2.919		2.919		2.923	
R^2	.018		.018		.012	
Pseudo- R^2	.455		.455		.461	
N	16,316		16,316		16,316	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on Huber-White 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 actual and predicted values including the random effect.

Table 5
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	.000		.000		.001	
Pseudo- R^2	.481		.481		.479	
N	16,316		16,316		16,316	

* $p < .05$, ** $p < .01$, *** $p < .001$. All tests based on Huber-White 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 actual and predicted values including the fixed effect.

Table 6
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	-6230.61		-6236.38		-6256.57	
Δ -2LL vs (1)			11.56 (p = . 239)		51.94 ($p < .001$)	
N	5,462		5,462		5,462	

* $p < .05$, ** $p < .01$, *** $p < .001$. Coefficients are those of a complementary log-log link function hazard model. All models estimated on 2,757,980 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. 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 data set to avoid quasi-complete separation.

Table 7
PREDICTING REFERRAL'S MARGIN 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 Huber-White robust standard errors. Both models estimated on data for 1,799 referral customers