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Referral Contagion: Downstream Benefits of Customer Referrals

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Abstract

Companies often invest in referral reward programs to incentivize their current customers to spread word-of-mouth. Previous work has documented that referred customers tend to be more valuable than non-referred customers through their purchases or engagement with the company. We propose a previously overlooked benefit of encouraging referrals – referred customers are also more valuable because they make more referrals. Using a large-scale field dataset, we show that referred customers make 31-57% more referrals than non-referred customers conditional on purchase activities. Using preregistered lab experiments, we replicate the main effect and propose one underlying mechanism: referred customers perceive referring to be more socially appropriate than non-referred customers. In a field experiment, we build on previous work on norm salience and show that reminding referred customers that they joined through a referral further boosts their referral likelihood by 21%. These results advance our understanding of the social motives that contribute to referral decisions and illustrate that promoting referrals is substantially more valuable than previously estimated.

Keywords: Referrals, Word-of-Mouth, Customer Value, Social Motives

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Introduction

Word-of-mouth (WOM) has proven a valuable marketing tool for acquiring new customers, in part because people consider their friends and family to be trusted sources of information (Brown and Reingen 1987, Tuk et al. 2009). Referral campaigns that incentivize the spread of WOM are attractive because they are found to be more effective than other acquisition methods for bringing in new customers (Trusov, Bucklin, and Pauwels 2009). Furthermore, customers who joined through a referral are more valuable than customers who joined through other means because referred customers tend to have higher margins and greater loyalty than non-referred customers (Villanueva, Yoo, and Hanssens 2008, Schmitt, Skiera, and Van den Bulte 2011, Armelini, Barrot, and Becker 2015). These studies focus on the customers' behavior through their purchases or activities with the focal company and suggest that firms should invest in referral programs to gain new customers with higher lifetime values. Referring can also be beneficial because the act of providing a recommendation increases current customers' attitudinal and behavioral loyalty (Garnefeld et al. 2013).

In this paper, we document a previously overlooked benefit of referral contagion – referred customers *make more referrals* compared to non-referred customers. By doing so, we broaden the view of the overall value of referred customers by considering not only their purchases or activities but also the new customers that they successfully recruit. Consistent with the idea that the total value of customers includes not only their profitability with the firm but also their social value (Kumar, Petersen, and Leone 2007, Ho et al. 2012, Libai, Muller, and Peres 2013, Ascarza et al. 2017), we show that generating more referrals constitutes a substantial portion of the total value of referred customers. Understanding this downstream effect of referrals will provide important managerial insights into the value of motivating customer referrals, such as determining whether and how much to invest in referral reward programs.

We answer three research questions. First, do customers who join through referrals (vs. other marketing tactics) make more referrals? We find that referred customers make 31-57% more referrals than non-referred customers, even after conditioning on purchase activities. What drives referral contagion? Prior literature has found several systematic differences between referred and non-referred customers. In addition to these factors, we propose the underlying role of social appropriateness beliefs: customers who joined through a referral believe that referring a friend is more socially appropriate than those who joined through other means. Leveraging this mechanism, can we encourage even more referrals from referred customers? We demonstrate the effectiveness of a simple intervention using a field experiment.

We address the first question using field data from a large mobile technology company that provides cashback rebates to users for shopping at their partnering stores. Leveraging data from 41.2 million customers over 10 years, we find that, in addition to more purchases, referred customers also brought in more new customers through referrals compared to non-referred customers. The higher number of referrals can potentially be explained by better matching between referred and non-referred customers, which is reflected by higher purchase activities (Kornish and Li 2010, Schmitt, Skiera, and Van den Bulte 2011, Van den Bulte et al. 2018). We employ two modeling approaches to show that referred customers still make more referrals after controlling for their purchase activities. The first is logistic regression with random effects with monthly panel data, and the second uses double machine learning to account for the entire monthly purchase history (Chernozhukov et al. 2018). Both approaches show that referred customers have more successful referrals even after conditioning on purchase activities. To the extent that referred and non-referred customers may differ in ways not captured through observables, we complement the field data analysis with randomized experiments and show converging results.

The difference in referrals is economically meaningful. We quantify the difference in value for referred versus non-referred customers in terms of both their purchases and the value from referrals, which is represented by purchases made by their referral recipients. We find that not accounting for the higher number of referrals will underestimate about 20−36% of the total difference in value for referred customers.

Beyond this particular field setting, we empirically evaluate the generalizability of referral contagion across a broader spectrum of companies using data from SaaSquatch by impact.com.[1] SaaSquatch offers a platform that builds referral reward programs and tracks customer behavior for a wide variety of businesses offering diverse referral reward sizes and structures. Prior to the acquisition, SaaSquatch provided us with referral data from a random sample of firms across various industries. Among the 20 companies, 19 show higher referrals among referred customers compared to non-referred customers.

The higher number of successful referrals can arise from more referral invitations or a higher acceptance rate. Using another field dataset from My Yoga Teacher, where we observe both referral invitation and acceptance stages, we show that the higher number of successful referrals arises in large part from referred customers sending more referral invitations.

Why are referred customers more likely to refer? We propose that referred customers find referring to be more *socially appropriate* which contributes to referral contagion. It is well accepted that peer influence or social contagion can affect product adoption (Manchanda, Xie, and Youn 2008, Iyengar, Van den Bulte, and Lee 2015). Previous work suggests that such contagion stems in part from normative influence (Van den Bulte and Lilien 2001), or the desire to conform

[1] SaaSquatch was acquired by impact.com in 2023.

to our peers' expectations about proper or appropriate behavior in social contexts (Cialdini and Trost 1998). Using hypothetical scenario experiments, we find that customers who joined through a referral believe that referring is more socially appropriate than those who joined through other means. This mechanism is consistent with prior literature, which finds that customers are concerned with being perceived negatively when making referrals, which reduces referral rates (Ryu and Feick 2007, Tuk et al. 2009, Jin and Huang 2014). We propose that the experience of being referred (i.e., observing a peer's referral behavior) sets a norm that referring in this setting is socially appropriate. This should help overcome psychological barriers to referring as individuals use norms as a guide to avoid social disapproval or gain approval (Cialdini, Reno, and Kallgren 1990). People typically exhibit greater norm influence based on their level of identification with the reference group and the extent to which the group is salient in the given context (Hornsey et al. 2003, Rabb et al. 2022). We would therefore predict that consumers will be more likely to refer a friend if they joined through a referral from their social network (e.g., friends) than if they joined through an affiliate (i.e., "influencer") referral. We find evidence consistent with such prediction in both the field data and in a randomized controlled experiment.

There are several alternative explanations for our findings, including the level of matching with the firm, social enrichment or validation from the presence of a third party (Schmitt, Skiera, and Van den Bulte 2011), the impact of social status, social network effects, and homophily. Using both field data and randomized controlled experiments, we show that referred customers remain more likely to refer after accounting for these alternative explanations. Therefore, the perception of social appropriateness drives referral contagion beyond these alternative explanations. In practice, we believe that referral contagion is multiply determined, and all of these explanations jointly lead to the overall difference in referral behaviors between referred and non-referred customers.

Leveraging our proposed mechanism of social appropriateness, how can we encourage even more referrals from referred customers? We aimed to increase norm salience (Reno, Cialdini, and Kallgren 1993) to highlight that referring others in this context is appropriate. We demonstrate the effectiveness of a simple messaging intervention in a field experiment with more than 10 million referred customers. Reminding customers that they initially joined through a referral ("You were referred in - now refer your friends!") increases their referral rate by more than 20% compared to the control message ("Refer your friends!"). Such a reminder makes it more salient for referred customers that they initially joined through a referral. Consequently, this leads them to perceive referring as more appropriate than those who do not see such a reminder.

Our paper makes two primary contributions. First, we identify a previously overlooked advantage of referrals: referred customers are more likely to bring in new customers via referrals. This paper, therefore, offers important managerial implications to companies aiming to invest in referral reward programs and understand the value of referred customers. Not accounting for referral contagion will significantly underestimate the total value of referrals. Second, our research demonstrates the effectiveness of a simple intervention that companies can employ to further increase referrals. This intervention is driven by the insight that referred customers believe referring others in this context is more socially appropriate. This social norm is made more salient by reminding referred customers that they joined through a referral, which further increases their referral likelihood.

Literature Review

Our paper provides insights in three streams of literature. First, this work contributes to the large literature documenting the value of referral programs. WOM has long been understood as an important source of influence in consumers' purchase decisions, leading to higher compliance, and thus is effective in attracting new customers (Brown and Reingen 1987, Tuk et al. 2009, Trusov, Bucklin, and Pauwels 2009). Referrals also tend to recruit customers that are more valuable than customers gained through other marketing tactics (Villanueva, Yoo, and Hanssens 2008, Schmitt, Skiera, and Van den Bulte 2011). Moreover, participating in referral programs can increase the loyalty of current customers (Garnefeld et al. 2013). We contribute to this literature by proposing another important source of value for referred customers, namely referred customers are more likely to refer.

This paper is also related to the literature on social barriers to referral. Given the low effort cost (Gershon, Cryder, and John 2020) and the potential for rewards (Biyalogorsky, Gerstner, and Libai 2001), why don't more customers choose to refer? Previous research proposes that customer motivation for referring is not limited to financial or time costs and often includes social motives (Xiao, Tang, and Wirtz 2011). That is, consumers are motivated to shape how others perceive them through what they say, share, and recommend (Chung and Darke 2006, Berger and Milkman 2012). When offered a referral incentive, individuals may worry about social costs, such as being perceived as having ulterior motives beyond helping their friend make good product decisions (Jin and Huang 2014). Even without a reward, consumers report discomfort when making recommendations to a friend due to concerns that their friend may have a negative experience and attribute their dissatisfaction to the recommendation (Ryu and Feick 2007). Given these well-established social concerns for referring, marketers would benefit from interventions that persuade customers that referring is socially appropriate. We contribute to this literature by documenting that being referred makes customers perceive referring as more socially appropriate, which contributes to more referrals among referred customers.

Lastly, our paper contributes to the literature on interventions to encourage successful referrals. Some recommend incentivizing existing customers to refer, which appears especially effective for weaker social ties and weaker brands (Ryu and Feick 2007). Others find that offering in-kind referral rewards instead of monetary incentives may reduce expected social costs and increase referrals (Jin and Huang 2014). Disclosing incentives may make the act of referring appear more honest, cooperative, and communal, which also increases referral likelihood (Xu, Yu, and Tu 2023). Referral messaging that mentions the existence of referral rewards or the sender's purchase status prior to referral also influences follow-through for referred customers (Sun, Viswanathan, and Zheleva 2021). Additional work concerns the design of referral reward programs (Biyalogorsky, Gerstner, and Libai 2001). For example, offering a shared reward for both the referrer and recipient or only rewarding the referral recipient reduces social signaling concerns and increases referral likelihood (Gershon, Cryder, and John 2020). The size of rewards also matters for not only the number of referred customers, but also profitability (Wolters, Schulze, and Gedenk 2020). We contribute to this literature by proposing an effective and costless intervention: reminding referred customers that they joined through a referral.

Referred Customers Make More Referrals

Field Data Description

We obtained anonymized individual-level field data from a large mobile technology company that offers cashback incentives to users for shopping at partnering stores. After creating an account, users can earn cashback incentives across a wide range of partnering stores from a variety of categories, such as clothing, health and beauty, and grocery delivery. Consumers can use either the website or its app to interact with the company. The dataset covers all registered customers over a decade, from May 2012 to May 2022. The company runs a referral program where existing customers can refer their friends. Importantly for our research question, we track whether each customer joined via a referral and, for those who did, we know the referring customer. This means that we have data on successful referrals that lead to a new account registration but not on unsuccessful referral invitations.[2]

We observe each customer's purchase activities on a monthly basis. Each purchase activity corresponds to a shopping occasion through the company's cashback website or app. While we observe the number of these shopping occasions, we do not have data on the amount spent or the quantity of products purchased. Therefore, we rely on the number of purchase occasions to represent the purchase activities a consumer has with the firm.

As is common in practice, referrals are incentivized for both the referring customer and the referral recipient upon successful referrals.[3] Because of the incentives, the company encounters fraudulent referral activities, with approximately 3.8% of the accounts flagged as fraudulent in the data provided to us. We conduct further cleaning by leveraging a feature indicating whether the referred customer uses the same device as the referrer or not. This distinction is valuable as customers who refer themselves for the bonus are more likely to use the same device, unlike authentic referrals where customers refer their friends. In our analysis, we focus on referrals not identified as fraudulent and where the referred customer uses a different device from the referrer.

[2]In the following section, we will introduce another dataset where we observe both successful and unsuccessful referral invitations.

[3]When the referral recipient has registered an account and made at least one purchase through the platform, both parties receive a bonus. The referral recipient gets $10. The bonus amount for referring has changed over time, but is most recently at $10 as well.

After removing potentially fraudulent accounts, there are 41.2 million registered customers.[4] Table 1 column (1) shows that among these customers, 12.2 million (close to 30%) joined through a referral, while the rest joined through other channels such as advertising or other organic means (e.g., search engines). Column (2) reports the average tenure of the customers is 48.5 months for referred customers, slightly lower than 51.1 months for non-referred customers. Column (3) shows that referred customers have a higher average number of successful referrals (0.30) compared to non-referred customers (0.18). In column (4), we look at the probability of referrals, with referred customers having a higher likelihood (11.9%) of making at least one successful referral compared to non-referred customers (7.6%). Column (5) shows refereed customers have a higher number of purchase occasions compared to non-referred customers.

Table 1: Summary Statistics

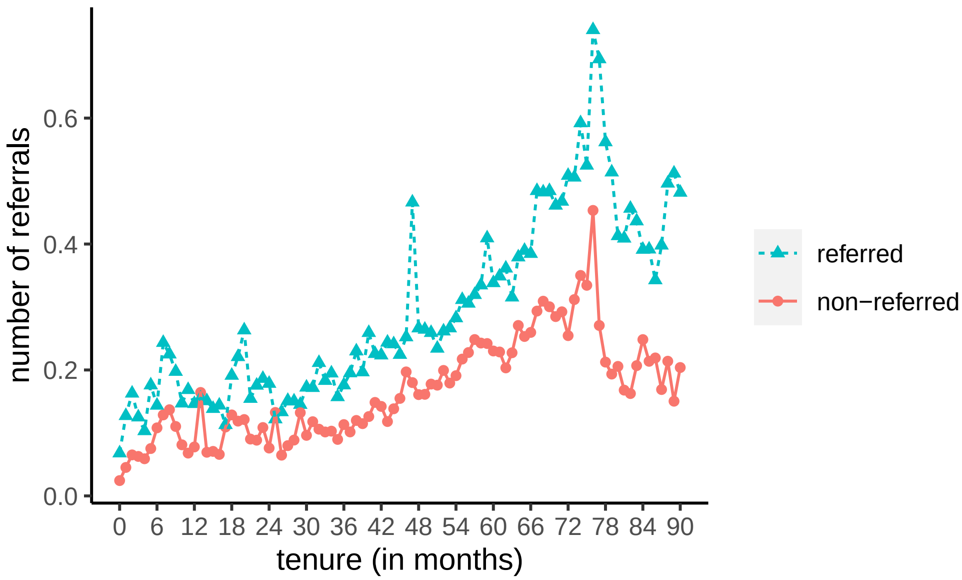
	Total number of customers (million) (1)	Average tenure (in months) (2)	Number of successful referrals (3)	Percentage of customers making a successful referral (4)	Number of purchase occasions (5)
Total	41.2	50.4	0.22	8.8%	25.1
Referred	12.2	48.5	0.30	11.9%	31.1
Non-referred	29.0	51.1	0.18	7.6%	22.5

Figure 1 plots the number of referrals made by customers based on their tenure. This is taken from a cross-sectional analysis. For example, at 12 months tenure, the plot reflects the behavior of customers who joined 12 months before the end of the data observation period. Overall, the data pattern suggests that referred customers make more referrals than non-referred customers conditional on tenure. Note that customers who joined at different times were subject to different

[4]For the main analysis, we also exclude approximately 3% of customers who registered through affiliate (i.e., influencer) accounts. Affiliates use their own channels, blogs or other forms of social media to refer their followers to use the service. Affiliates receive incentives from the company upon successful referrals. We discuss these affiliate referrals in a later section.

promotional activities which can impact their referral propensity (e.g., customers with 76 months tenure have a large number of referrals). Importantly, despite the cohort differences, we see a consistent main effect that refereed customers make more referrals than non-referred customers.

Figure 1: Referrals Made by Referred vs. Non-referred Customers



Both Table 1 (columns 3−4) and Figure 1 provide descriptive evidence indicating that referred customers tend to make more referrals compared to non-referred customers. However, it is important to note that referred customers differ from non-referred customers in other aspects as well. Notably, Table 1 column 5 shows that referred customers also engage in a higher number of purchase occasions. Consequently, it is plausible that referred customers may be more inclined to refer simply because they like the service more or have more opportunities to refer. In the rest of this section, we quantify the difference in referral behavior after controlling for customers' purchase activities with the company. Employing two empirical methods, we demonstrate that the higher number of referrals among referred customers persists after controlling for observable attributes.

Before we present the empirical models, it is useful to note that we can only interpret the increase in referrals as "causal" if we are willing to assume that, conditional on observable attributes, being referred is independent of the outcome. In a later section, we discuss several potential reasons why this assumption may be violated. Ultimately, this unconfoundedness assumption is untestable in a field data setting and motivates us to conduct randomized controlled experiments, which we also describe in a later section.

Logistic Regression with Random Effects for Referrals

Our first empirical strategy uses logistic regression to quantify the difference in referral propensity between referred and non-referred customers with monthly panel data. We do so both with and without considering the level of activity on the platform (proxied by the number of purchase occasions). We now describe how we model referrals while accounting for purchases as well as some individual-level heterogeneity in the baseline tendency to refer.

The utility to refer for customer i in month t is specified as follows:

$$u_{it} = \delta_i + \alpha \cdot referred_i + \beta \cdot X_{it} + \epsilon_{it}. \tag{1}$$

For each consumer i, δ_i represents their baseline propensity to make referrals. We assume that this referral propensity varies across consumers and follows a normal distribution $\delta_i \sim \mathcal{N}(\mu_\delta, \sigma_\delta^2)$. If customer i joined through a referral, $referred_i = 1$, and 0 if not. X_{it} represent control variables for consumer i in month t that can influence their propensity to refer, which includes consumer tenure in the baseline model. In the main model, we also consider the number of purchase occasions in month t. ϵ_{it} is an idiosyncratic error term that follows a Type 1 extreme value distribution. Consumer i chooses to refer in month t, $y_{it} = 1$, when the utility to refer is larger than the outside option. The parameters set to estimate is $\Theta = (\mu_\delta, \sigma_\delta, \alpha, \beta)$.

The key parameter of interest α captures the difference in referral propensity for referred customers after controlling for observables in X_{it}. The model is estimated via simulated maximum likelihood on a random sample of 500,000 consumers for ease of computation. The estimation results are reported in Table 2, with columns (1) and (2) considering only tenure in X_{it}, and columns (3) and (4) also incorporating monthly purchase activities. For both models, we estimate a version assuming δ_i is the same for all consumers ($\sigma_\delta = 0$), simplifying it to a standard logistic regression. Columns (1) and (3) report results for this standard logistic regression, whereas columns (2) and (4) allow for individual-level random effects on δ.

Table 2: Referral Probability

	Dependent Variable:			
	Referral		Referral (control for purchases)	
	(1)	(2)	(3)	(4)
δ	-4.8839^{***}		-5.0211^{***}	
	(0.0064)		(0.0066)	
μ_δ		-6.2927^{***}		-6.2063^{***}
		(0.0126)		(0.0119)
σ_δ		0.6540^{***}		0.4929^{***}
		(0.0045)		(0.0048)
α: Referred customers	0.4739^{***}	0.5546^{***}	0.4228^{***}	0.4636^{***}
	(0.0077)	(0.0109)	(0.0080)	(0.0105)
β^p: Number of purchase occasions			0.0765^{***}	0.0876^{***}
			(0.0002)	(0.0003)
β^t: Tenure (in months)	-0.0498^{***}	-0.0519^{***}	-0.0529^{***}	-0.0546^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	25,245,302	25,245,302	25,245,302	25,245,302
Log-likelihood	-463,004.6	-433,581.4	-420,836.7	-397,210.2
AIC	926,015.2	867,170.8	841,681.4	794,430.4
BIC	926,060.3	867,231.0	841,741.6	794,505.6
pseudo R^2	0.0564	0.1163	0.1423	0.1905

*** indicates significance at p = 0.01.

We find that α is positive and significant across all model specifications, which suggests a higher referral propensity among referred versus non-referred consumers. For columns (2) and (4), the dispersion parameters of δ are significant, indicating a heterogeneous baseline tendency to refer. Model comparison metrics, AIC and BIC, show that models with random effects have a better fit with data than their counterparts without. Therefore, we focus on interpreting the parameters in columns (2) and (4) to understand differences in referral propensity among referred customers.

To interpret the economic magnitude, we use the estimates to calculate referral probabilities for both referred and non-referred customers, keeping other variables at their sample mean. We repeat this process 100 times by sampling δ_i from the distribution $\mathcal{N}(\hat{\mu}_\delta, \hat{\sigma}_\delta^2)$. We find that the referral probability is 74% higher for referred customers than non-referred customers on average. After factoring in the difference in purchases, the referral probability from referred customers remains 58% higher than that of non-referred customers. Therefore, referred customers have a higher referral propensity beyond what could be explained by their activity levels on the platform.

Double Machine Learning Estimator to Control for Purchase History

The logistic regression model assumes that the referral propensity is only affected by purchases made within the same month. However, it is conceivable that past purchases also matter. Indeed, a customer's activity level or interaction with the company is more accurately reflected by their complete history of purchases. Our second empirical strategy employs the double machine learning estimator (Chernozhukov et al. 2018) to flexibly account for the history of monthly purchases. This technique, in contrast to simply incorporating monthly purchase data in a linear fashion, allows us to account for the (high dimensional) monthly purchase data in a flexible functional form.

We specify the following partial linear model. Let y_i denote the total referrals made by consumer i. The parameter γ captures the difference in referrals between referred and non-referred customers. Z_i collects the intercept and control variables, including tenure and the monthly purchase history of consumer i. The relationship between Z_i and the outcome y_i is modeled using a machine learning approach, denoted as $g(Z_i)$, to flexibly capture the influence of Z_i on y_i.

$$y_i = \gamma \cdot referred_i + g(Z_i) + \epsilon_i. \tag{2}$$

A naive plug-in estimator predicts y_i with control variables Z_i and then "plugs-in" the predicted value in the regression model. This approach, however, can lead to a biased estimate for the main coefficient of interest, $\widehat{\gamma}$, due to regularization and the potential for overfitting. The double machine learning (DML) estimation approach addresses both sources of bias through orthogonalization and sample-splitting. Orthogonalization accounts for the bias introduced by regularization by separately estimating two machine learning models: one predicts the outcome y_i based on Z_i and the other predicts the treatment variable $referred_i$ using the same controls (Equation 3). This process generates residuals that represent the outcome and treatment after "partialling-out" the effect of control variables. The estimate for $\widehat{\gamma}$ is derived by regressing the outcome residuals against the treatment residuals.

$$referred_i = m(Z_i) + e_i. \tag{3}$$

Sample-splitting accounts for the bias introduced by overfitting. This is done by randomly partitioning the data into K subsets. The machine learning models $\widehat{g(Z)}$ and $\widehat{m(Z)}$ are trained on one subset, while the estimation of $\widehat{\gamma}$ is carried out using the remaining subsets. The key is that $\widehat{\gamma}$ is never estimated with the data used to train the machine learning models. Doing so avoids bias that can arise due to overfitting. We refer interested readers to Chernozhukov et al. (2018) and references therein for more detailed technical treatments.

We use the same randomly selected 500,000 consumers in the logistic regression. Table 3 reports results from the double machine learning estimator as well as three benchmark models for comparison. Column (1) is a simple linear regression model with only tenure as a control variable. It shows that referred customers make 0.1270 more referrals on average, which represents a 75% increase over the 0.1702 referrals by non-referred customers. It is worth noting that the estimated effect essentially represents a weighted average of heterogeneous effects across customers of different tenures, with the weights corresponding to the proportion of customers with that tenure. Column (2) further adds the total number of purchase occasions as an additional control. Referred customers make 0.0966, or 57% more referrals compared to non-referred customers. These magnitudes are close to the results from the logistic regression models discussed previously.

Table 3: Number of Referrals

	Dependent Variable: Total Number of Referrals		
	No control for purchases (1)	Linear control total purchases (2)	Flexible control via DML (3)
γ: Referred customers	0.1270***	0.0966***	0.0518***
	(0.0062)	(0.0061)	(0.0074)
β^p: Total number of purchase occasions		0.0032***	
		(0.0000)	
Monthly purchase occasions			flexible function g(·)
β^t: Tenure (in months)	0.0029***	0.0015***	
	(0.0001)	(0.0001)	
Constant	0.0208***	0.0234***	
	(0.0063)	(0.0061)	
Observations	500,000	500,000	500,000
R^2	0.0023	0.0429	0.0569

*** indicates significance at p = 0.01.

In Column (3) of Table 3, we employ the double machine learning estimator, which accounts for monthly purchase occasions and tenure using a flexible machine learning model. Specifically, we use the random forest algorithm to model $\widehat{g(Z)}$ and $\widehat{m(Z)}$. The double machine learning estimate of γ is 0.0522, which represents 31% more referrals for referred customers than non-referred customers. The magnitude of differences measured with the double machine learning estimator is smaller than those in other model specifications. This confirms the importance of controlling for customers' entire purchase history. Given that referred customers are also more active on average, not accounting for purchase history will overestimate the difference in referrals that arises from joining through a referral. Importantly, the effect of higher referrals by referred customers remains statistically significant and economically meaningful across all specifications.

Value of Referred Customers through More Referrals

Referrals are valuable because they grow the customer base and these referred customers contribute through their purchases. Without observing direct revenue or margin data, we approximate customer value using the number of purchase occasions. This is a reasonable measure because the company earns commissions from partner retailers for purchases made through their platform. We use the number of purchases made by referred customers to quantify the value of referrals. For example, if a customer refers three others, the purchase activity of these three referred customers represents the referral value for the focal customer. The referral value of a customer is zero if they made no referrals or their referred customers made no purchases.

Referred customers have a higher number of purchase occasions compared to non-referred customers (31.07 vs. 22.53, $p < 0.001$), or 38% in relative terms. This result is consistent with prior literature documenting that referred customers have a higher lifetime value through their engagements with the firm. Schmitt, Skiera, and Van den Bulte (2011) find a referred customer is approximately 25-35% more valuable than a comparable non-referred customer using data from a German bank. Although the empirical context is very different, the magnitude is reasonably close to the 38% difference found in our paper. Using the number of purchase occasions made by referred consumers as a proxy, we find that referred customers also have a higher referral value compared to non-referred customers (4.44 vs. 2.71, $p < 0.001$) or 64% in relative terms. Therefore, referred customers are more valuable not only from their direct purchases but also through purchases made by those they refer to the platform.

In Web Appendix A, we conduct formal analyses similar to those for the number of referrals to account for tenure and purchase history. The referral value, proxied by the number of purchases by referral recipients, is 2.36−5.33 higher for referred customers across various model specifications. This increment is significant compared to the 9.58 purchase occasions difference in their own purchases, highlighting the economic significance of referrals. The value from referrals accounts for approximately 20−36% of the overall value difference between referred and non-referred customers ($\frac{2.36}{2.36+9.58} = 20\%$, and $\frac{5.33}{5.33+9.58} = 36\%$). Not accounting for contributions from referrals would significantly underestimate the difference in total value between the two groups.

Generalizability

While we have shown that referred customers make more referrals in a large field dataset with over 40 million consumers, one may wonder whether this phenomenon occurs in other contexts. We seek to test the generalizability of this "referral contagion" across a broader spectrum of companies.

We collect additional data through a collaboration with SaaSquatch by impact.com, a platform that creates referral reward programs and tracks customer actions for a wide variety of businesses offering diverse reward sizes and structures (including who receives the reward and required actions). Saasquatch provided us with referral data from a randomly selected group of companies.

Table 4: Generalizability: Successful Referrals among Referred vs. Non-referred Customers

ID	Industry	*Non-referred Customers* Number of customers	*Non-referred Customers* Referral rate (%)	*Referred Customers* Number of customers	*Referred Customers* Referral rate (%)	Difference in referral rate (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Finance	7,558,189	2.07	433,731	3.64	1.57***
2	HR & Staffing	1,805,498	0.48	16,767	3.81	3.32***
3	Telephony & Wireless	880,272	2.41	37,091	5.65	3.25***
4	Software	670,844	0.52	7,308	12.14	11.62***
5	Insurance	648,512	1.37	13,885	6.14	4.78***
6	Manufacturing	522,873	0.01	20,399	0.02	0.01*
7	HR & Staffing	427,158	0.37	5,119	2.93	2.56***
8	Household Goods	299,624	1.30	5,954	2.13	0.83***
9	Retail	281,665	0.43	13,673	0.99	0.57***
10	Publishing	206,715	0.06	9,908	0.27	0.21***
11	Finance	130,877	2.52	5,068	3.24	0.72***
12	Accounting Services	129,900	0.07	3,290	0.33	0.26***
13	Real Estate	122,170	0.07	462	6.28	6.21***
14	Finance	90,405	0.51	1,029	2.53	2.01***
15	Education	44,130	0.48	594	1.85	1.37***
16	Finance	42,583	0.55	5,096	1.14	0.59***
17	Software	37,029	1.71	8,014	8.15	6.43***
18	Management Consulting	28,818	0.62	2,675	0.22	−0.40**
19	HR & Staffing	28,638	0.30	86	2.33	2.02***
20	Software	25,954	0.31	490	6.12	5.81***

*** indicates significance at p = 0.01; ** p = 0.05; * p = 0.1.

Using data from these companies, we compare the differences in successful referral rates between referred and non-referred customers. Table 4 reports data from 20 companies, each with a minimum of 20,000 customers.[5] These companies span a diverse range of industries. The referral

[5]We excluded one program that incentivizes employee referrals rather than customer referrals.

rates for non-referred and referred customers are presented in columns (4) and (6), respectively. Column (7) reports the main variable of interest: the difference in referral rates between referred and non-referred customers. Among the 20 companies, 19 show a higher rate of successful referrals for referred customers, with the difference being statistically significant in 18 cases. In contrast to the individual-level field data described above, the Saasquatch dataset contains only aggregate level referral information. Despite this limitation, the pattern of higher referral rates among referred customers persists across most companies, supporting referral contagion as a common phenomenon across different industries.

What Drives Referral Contagion?

In the previous section, we establish through observational data that referred customers have more successful referrals than non-referred customers. In this section, we seek to identify the causal relationship as well as the underlying mechanism behind the referral behavior of referred customers. This is done through a series of analyses using both observational and experimental data that complement the previous results.

First, we use an additional field dataset to show that referred customers are more likely to send referral invitations. This complements the previous data that only observes successful referrals, and therefore cannot distinguish whether the higher number of successful referrals arises from more referral invitations or a higher acceptance rate. Second, we use controlled experiments to replicate the main effect, which complements the observational analysis that assumes the difference between referred and non-referred customers can be captured by their purchase history. Using controlled experiments, we identify one mechanism that partially explains the main effect: referred customers find referring to be more *socially appropriate*. Lastly, we discuss multiple alternative explanations, including better matching, social enrichment and validation, social status, social network effect, and homophily. While we believe that a combination of these factors likely contributes to the higher referral rate among referred customers, our analysis indicates that the referral gap persists even after considering these alternative explanations.

Referred Customers Send More Referral Invitations

In our primary field dataset, we can only track successful referrals based on new customers signing up using an existing customer's unique referral code but not unsuccessful referrals that did not lead to account registration. This is because the field partner allows their customers to send referral invitations in many ways (e.g., text, email, or social media) without monitoring these communications, as is typical in many referral reward programs. To address this limitation, we obtain another field dataset that records both the referral invitation and acceptance. Using this dataset, we show the higher number of successful referrals primarily arises from referred customers sending more referral invitations.

This additional dataset comes from My Yoga Teacher, a company that provides 1-on-1 or group fitness classes via live video. The company offers a referral program where existing users can refer their friends. Importantly for our purposes, a customer can input a friend's email and the company will send a referral to the friend. This "email-input" referral method allows us to observe both the referral invitation and acceptance. A customer also has the option to share their referral link via private channels such as text messages, emails, or social media, which are not tracked by the company, similar to the main field dataset.

We observe a total of 54,349 customers, of which 2,753 (or 5.1%) joined through a referral. Unlike the main field dataset, this dataset does not contain detailed information on individual customers, such as their tenure or level of activity. Therefore, we focus the analysis on decomposing successful referrals into two key components: the referral invitation and conversion stages. We do so by focusing on the customers who opt for the "email-input" referral method so that we observe whether they send a referral invitation, the number of invitations, and whether the referral recipient converts by creating an account or purchasing a membership.

Figure 2: Decompose Successful Referrals

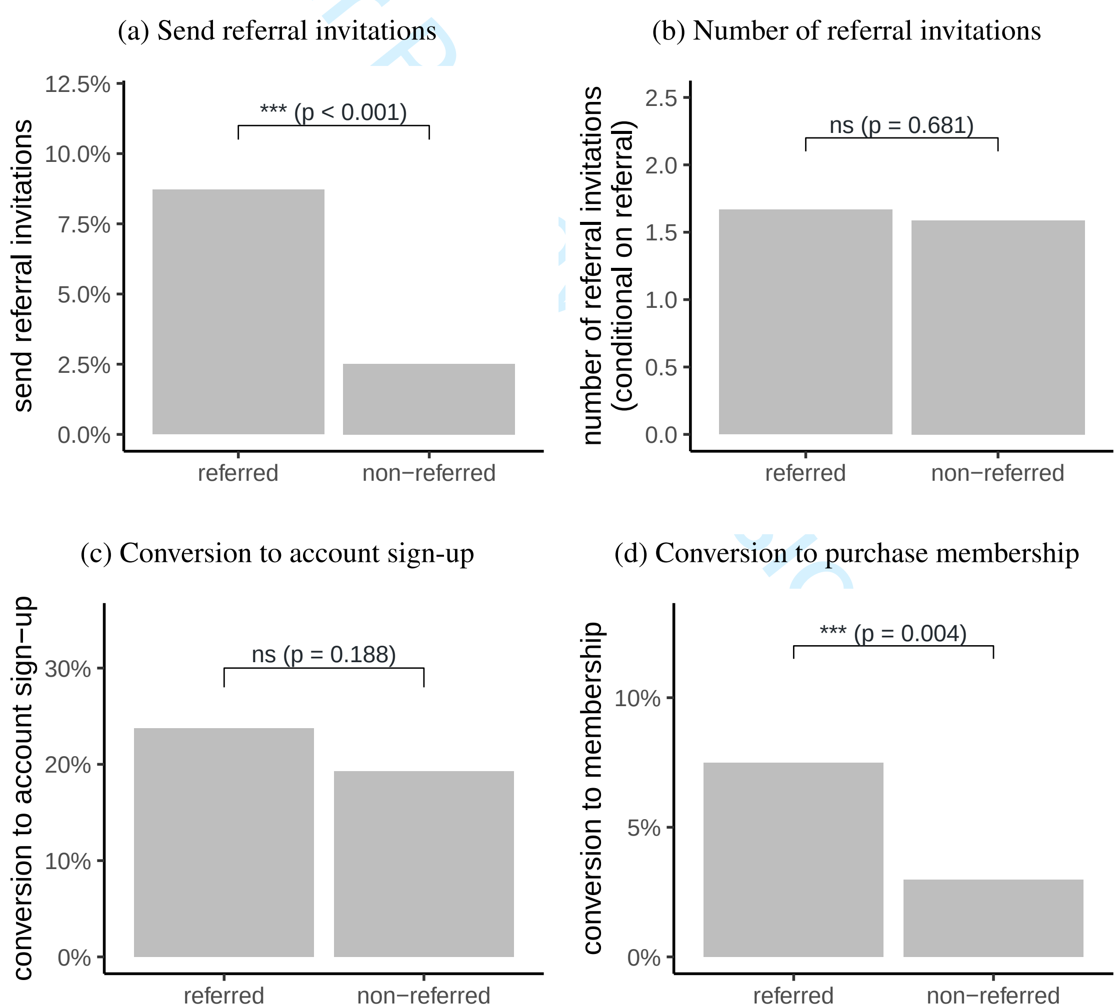


Figure 2(a) plots the percentage of customers sending referral invitations among both referred and non-referred customers. Referred customers are significantly more likely to send referral invitations than non-referred customers (8.72% vs. 2.51%, $p < 0.001$). Conditional on having sent a referral, Figure 2(b) shows that the number of referrals does not significantly differ between the groups (1.67 for referred vs. 1.59 for non-referred, $p = 0.681$). These results suggest that the difference in choice to send referral invitations contributes to the higher number of successful referrals among referred customers. Regarding the conversion rate, Figure 2(c) shows that recipients of referred customers have just a slightly higher rate of account creation compared to those invited by non-referred customers, and the difference is not statistically significant (23.8% vs. 19.3%, $p = 0.188$). The gap in conversion rate is larger when considering membership purchases. As shown in Figure 2(d), recipients of referred customers are more likely to purchase a membership than recipients of non-referred customers (7.5% vs. 3.0%, $p = 0.004$).

This additional dataset provides clear evidence that referred customers are much more likely to send referral invitations than non-referred customers. Although the conversion rate is generally higher among recipients of referred customers, the difference is not as large and robust across different conversion metrics. The definition of a successful referral in the main dataset aligns more closely with the account sign-up metric. Therefore, the propensity to send referral invitations is an important factor contributing to the observed gap in successful referrals between referred and non-referred customers.

While the second dataset distinguishes between referral invitation and acceptance, it does not contain individual-level characteristics or activities. It is possible that referred customers are more engaged with the service than non-referred customers, potentially accounting for their higher propensity to send referral invitations. To complement these observational data analyses, we employ controlled experiments to replicate the observed effect. We also propose and examine one potential underlying mechanism.

Referred Customers Believe Referring is More Socially Appropriate

We use controlled, hypothetical scenario experiments where participants are randomly assigned to having joined through a referral or another method. We replicate the main effect that referred customers are more likely to make referrals. Why are referred customers more likely to refer? Multiple explanations are likely to jointly contribute to the observed difference in referrals between the two groups. Through our experiment, we propose one underlying mechanism that partially drives referral contagion: joining through a referral sets a social norm that referring is more socially appropriate in the current context, thereby increasing the referral intentions of referred customers.

For Studies 1, 3, and 4, which have similar designs, we conducted a power analysis to determine appropriate sample sizes prior to data collection. The power analysis suggested that to achieve 80% power to detect an effect size of Cohen's d = .35 (based on pilot studies), we would need 130 participants per group. Therefore, we preregistered that we would collect 150-200 participants per condition to adequately power these studies following exclusions. Study materials, preregistrations, and data for all studies are publicly available at https://bit.ly/3QToB7x.

Study 1

Methods

As outlined in our preregistered research plan (https://aspredicted.org/3eb2c.pdf), we aimed to recruit 600 participants from Prolific and 607 completed the survey. After excluding participants who failed the attention check, our sample consists of 556 individuals (M_{age} = 38.52

years, 56.66% Female). Participants were randomized into one of two conditions describing how they joined the service. In all hypothetical scenario studies, the incentive for joining is kept consistent across conditions, to control for any potential sense of reciprocity that customers might feel for receiving a sign-up reward.[6]

Participants were first asked to give the first names of two close friends. They were then asked to imagine a service based on the setting of our main field data: "There is a free app that offers you cash back for shopping with their partner brands, either online or in-store. Anyone who downloads the app gets $10." Participants in the ad condition were told "You saw an advertisement for this app", and those in the friend referral condition read, "Your friend, [Friend 1's Name], sent you a referral code to try this app." Participants read "You downloaded the app through [this ad/their referral]."

All participants then read, "You have been using this service and think that it is useful. You receive an email asking if you would like to refer a friend by sending them your referral code. You will receive $10 cash for every person that you refer to this app who then makes a purchase." Participants next responded to the primary dependent variable, "How likely are you to refer your friend, [Friend 2's name] to this app?" (1 = Extremely unlikely to 7 = Extremely likely).

To explore potential psychological mechanisms, we then measured perceptions of making the referral (items counterbalanced). We measured social appropriateness (Aycinena et al. 2022): "How appropriate would it feel to send [Friend 2's name] this referral?" (1 = Extremely inappropriate to 7 = Extremely appropriate). We also measured perceived relationship benefits and psychological costs (Gershon, Cryder, and John 2020). Reputational benefits were measured using

[6] In our field data, customers who join through a referral are also offered the same sign-up bonus as those who join through other means.

a 9-item scale: “How would [Friend 2’s name] view you if you made this referral?” (Generous, Helpful, Friendly, Well-Intentioned, Trustworthy, Warm, Good-Natured, Likeable, Sincere; α = .97). We tested psychological costs using a 6-item scale: “How would you feel if you made this referral?” (Selfish, Deceitful, Guilty, Uncomfortable, Sneaky, Conflicted; α = .94). Psychological costs and Reputational benefits were measured on 7-point Likert scales (1 = Not at all, 4 = Somewhat, 7 = Very much).

Results

Replicating the main effect with the experimental data, we find that participants were more likely to refer if they originally downloaded the app through a referral (M_{Refer} = 5.42, SD = 1.63) than if they joined through an ad (M_{Ad} = 4.79, SD = 1.97, t(554) = 4.15, p<.001, d = .35). This is consistent with statistics from the second field dataset that referred customers are more likely to send referral invitations.

We then compare beliefs about social appropriateness, reputational benefits, and psychological costs between referred and non-referred customers. Participants felt that referring was more socially appropriate if they joined through a referral (M_{Refer} = 5.34, SD = 1.45) than if they joined through an ad (M_{Ad} = 4.92, SD = 1.76, t(554) = 3.07, p = .002, d = .26). Participants predicted that their friend would view them more positively for referring if they originally joined through a referral (M_{Refer} = 5.10, SD = 1.33) than if they joined through an ad (M_{Ad} = 4.83, SD = 1.40, t(554) = -2.35, p = .019, d = .20). Participants also reported that they would feel lower psychological costs for referring if they themselves joined through a referral (M_{Refer} = 1.98, SD = 1.27) than if they joined through an ad (M_{Ad} = 2.21, SD = 1.46, t(554) = 2.05, p = .040, d = .18).

We then conducted a mediation analysis to examine the role of all three mediation constructs (appropriateness, reputational benefits, and psychological costs) on the effect of joining method on referral likelihood. This analysis (10,000 resamples) revealed that perceptions of appropriateness significantly mediated this relationship (indirect effect = .30, SE = .10, 95% CI = [.11, .52], Prop. Mediated = .48). We also found a significant, although smaller, indirect effect of reputational benefits (indirect effect = .066, SE = .03, 95% CI = [.01, .14], Prop. Mediated = .10). There was a non-significant indirect effect of psychological costs (indirect effect = .001, SE = .01, 95% CI = [-.03, .03], Prop. Mediated = .001). The direct effect remained significant (direct effect = .27, SE = .10, 95% CI = [.07, .46], Total Prop. Mediated = .58).

In a direct replication of Study 1, we find that participants were more likely to refer if they originally downloaded the app through a referral (M_{Refer} = 5.57, SD = 1.68) than if they joined through an ad (M_{Ad} = 4.94, SD = 2.03, t(549) = 3.8, p<.001, d = .34). Participants also believed that referring is more socially appropriate if they joined through a referral (M_{Refer} = 5.33, SD = 1.61 vs. M_{Ad} = 5.00, SD = 1.77, t(549) = 2.29, p = .022, d = .20). In this replication, reputational benefits and psychological costs were not significantly different between conditions (p>.20). We then ran a preregistered mediation analysis and found that social appropriateness, but not the other two constructs, mediated the effect of joining method on referral likelihood. See Web Appendix B for full details.

Discussion

In summary, we find that social appropriateness has the strongest effect in explaining the propensity to refer. This is consistent with how individuals use social norms to understand socially acceptable behavior in a given situation. By having joined through a referral, participants feel referring others is more appropriate in this situation than those who joined through an ad. These results suggest that joining through a referral set a norm that referring is socially appropriate and participants used this norm to determine how to behave.

Study 2

We conducted another study to test the role of social appropriateness in the choice to refer in a more realistic referral context by using real companies that the participants have actually joined through a referral or an ad. In addition, the study measures incentive-compatible referral behavior to provide further evidence for referral contagion.

Methods

As outlined in our preregistered research plan (https://aspredicted.org/h8xf8.pdf), we aimed to recruit 600 participants from Prolific and ended up with a sample of 597 participants. After excluding participants who failed the manipulation check, our sample consists of 520 individuals (M_{age} = 37.48 years, 57.12% Female). Participants were asked to think of two brands, apps, or services that they like a similar amount. They read, "One of these should be a company that you learned about through a referral. For example, a friend may have sent you a code, link, or email to try this new brand, app, or service. The other should be a company that you learned about through an advertisement. For example, you may have clicked on a link, banner, or promotional email to try this new brand, app, or service." Participants then wrote in the name of the company that they joined through an ad and the company that they joined through a referral. All participants then wrote their first name and the first name of a friend that they believe does not yet use either of the companies that they mentioned previously. Participants were then told that as part of this study, they could refer that friend to try one of the two companies and if they referred their friend they would get a 20 cent bonus.

Participants were asked: "Would you like to refer your friend, [Friend's name], to try either [Referred Company] or [Advertised Company] by giving us their email address?" ("I would not like to make a referral", "I would like to refer my friend to [Referred Company]", or "I would like to refer my friend to [Advertised Company]", in randomized order). Note, that for privacy purposes, we did not actually ask for their friend's email address following this decision, but we did give a bonus if the participant stated that they would make a referral.

Results

If there was no difference in the preference between referring to the company participants joined through a referral or an ad, we would expect the referrals to be split evenly between the referred and advertised company. However, among the participants who chose to make a referral (200/520, 38.46%), a greater percentage chose to refer to the company that they originally joined through a referral (123/200, 61.5%) compared to the company that they joined through an ad (77/200, 38.5%, $\chi 2 = 10.58$, $p < .01$, $\phi = .23$).

To test the social appropriateness mechanism, participants were asked "Which would you feel is more socially appropriate: referring your friend to [Advertised Company] or [Referred Company]?" on a 7-points bipolar scale (1 = [Advertised Company] definitely feels more socially appropriate, 7 = [Referred Company] definitely feels more socially appropriate). The average was 4.26, which is significantly above the midpoint of 4, ($t(512) = 2.91$, $p = .0037$).

Discussion

The results of Study 2 provide further evidence for referral contagion. Here, rather than using a hypothetical referral scenario, we asked for companies that participants have actually joined through a referral and find a difference in real referral intentions. Furthermore, we find that participants believe it is more appropriate to refer their friend to the company that they joined through a referral than through an advertisement offering additional support for the role of social appropriateness in referral likelihood.

Alternative Explanations

So far, we have identified one potential mechanism explaining referral contagion: referred customers perceive referring others as more socially appropriate. In this section, we discuss several alternative explanations, including better matching, social enrichment and validation, social network effects, and homophily. We find that the gap in referrals persists after accounting for these alternative explanations. In practice, we believe multiple explanations jointly contribute to the observed difference in referrals.

Better Match with the Firm

One possible explanation of referral contagion is that referred customers are often a better match with the firm than customers who joined through other means (Kornish and Li 2010). This superior matching may be due to active factors – customers know their social networks well and screen for the best matches – or to passive factors – consumers tend to form connections with similar others (McPherson, Smith-Lovin, and Cook 2001). One manifestation of the better match is that referred customers use the product or service more. Therefore, referred customers may make more referrals simply because they are a better match with the firm and find it more valuable.

We use both the main field analysis and Study 1 to account for the level of match with the firm. In the main field data analysis, we see that referred customers make more purchases than non-referred customers, suggesting a better match with the firm. Importantly, after controlling for purchases, the difference in referrals persists between referred and non-referred customers. In Study 1, because participants are randomly assigned to the referral or ad conditions, there should be no systematic difference in the level of match with the firm. Here, we continue to find that participants in the referral condition have a higher referral likelihood than those in the ad condition. Therefore, better matching with the firm explains a portion of the difference in referrals between referred and non-referred customers, but it cannot fully account for the gap between the two groups.

Social Enrichment and Validation

Referral contagion may arise from the social enrichment and social validation that come from joining through a referral. Van den Bulte et al. (2018) find that the relationship of a customer with a firm is enriched by the presence of a third party. A third party could also offer social validation. When referring, customers consider the risk that a referred friend will be dissatisfied with their purchase and potentially attribute that dissatisfaction to the recommender (Ryu and Feick 2007). Joining through a referral may therefore increase confidence (and referrals) because it signals that at least one other friend vouches for the brand's strength or the product's quality.

Study 3

In another experiment, we test this potential alternative explanation that social enrichment and validation may drive referral contagion.

Methods

As outlined in our preregistered research plan (`https://aspredicted.org/f23ae.pdf`), we aimed to recruit 300 participants from Prolific and ended up with a sample of 327 participants. After excluding participants who failed the attention check, the sample consists of 287 individuals (M_{age} = 33.98 years, 58.04% Female).

Participants were randomly assigned to one of three conditions based on how they joined the service. They were then asked to give the first names of two friends. All participants were asked to imagine the following, "Amazon has released a new, free loyalty program called Amazon BOLD that showcases new products to program members." Those in the referral condition then read, "Your friend, [Friend 1's name], referred you to Amazon BOLD. You joined the program through their referral." Those in the ad condition read "You saw an advertisement for Amazon BOLD. You clicked on the ad and joined the program." In an additional *ad-social* condition, they read the same scenario used in the ad condition along with "You later learn that your friend, [Friend 1's name] also uses Amazon BOLD."

Participants read, "After joining Amazon BOLD through a [referral/advertisement], you have been using the service and think it is great. You receive an email from Amazon BOLD asking if you would like to refer a friend by sending them your referral code." They also read that Amazon BOLD has a promotion that will give them a $10 Visa gift card if their friend joins the program. We then asked participants, "How likely are you to refer your friend, [Friend 2's name], to use Amazon BOLD? A referral would involve sending them your referral code through either text or email" (1 = *Extremely unlikely* to 7 = *Extremely likely*). Finally, all participants responded to an attention check: "Which of the following is true? I joined Amazon BOLD through [an advertisement/a referral]".

Results

An ANOVA found a main effect of joining method on referral likelihood (F(2, 284) = 4.06, p =.018). Planned contrasts with Tukey method multiple comparison adjustment[7] revealed that participants were more likely to refer a friend if they were originally referred to Amazon BOLD (M_{Refer} = 5.94, SD = 1.32) than if they joined through an ad (M_{Ad} = 5.28, SD = 1.89, t(284) = 2.64, p = .024, d = .31), replicating the main effect. Those in the referral condition were also more likely to refer than those who joined through an ad with a friend who already uses the service

[7]We report the more conservative tests for both this study and Study 4. The preregistered t-tests find similar results.

($M_{Ad-social}$ = 5.37, SD = 1.91, t(284) = 2.26, p = .063, d = .27). There was a non-significant difference between the two ad conditions (t(284) = -.36, p = .931).

Discussion

In Study 3, we find that having another friend that uses the service does not have the same effect on referral likelihood as having a friend refer you. This indicates that the social enrichment and social validation that come from having a friend who is already a customer cannot fully account for the increase in referral likelihood in the referred condition.

Social Status

Social status or popularity can potentially play a role in referral contagion. High-status individuals tend to have significant interpersonal influence (Anderson et al. 2001, Cillessen and Rose 2005, Cheng et al. 2013). It is plausible that consumers referred by individuals with high social status, such as influencers, would be more to likely follow such referral behaviors themselves. To examine the impact of social status on referrals, we compare the behaviors of customers referred by influencers, who presumably have higher social status, with those referred by friends. If social status is the underlying mechanism, we would expect higher referrals from customers referred by influencers than those referred by friends. In this section, we show that the opposite is true using both field data and a randomized experiment. Consistent with the proposed mechanism, we show the role of social appropriateness in explaining the effect of joining through a friend's or influencer's referral on referral likelihood. This result is in line with previous work demonstrating that norms should be particularly influential when they are set by relevant reference groups with whom the actor identifies (Christensen et al. 2004).

In our main field dataset, the company partners with affiliates (i.e., influencers) to promote the cash-back service via their blogs or social media accounts. The influencers receive incentives from the company when their followers create an account with their referral code. In our field data, approximately 3% of customers joined through these influencer referrals. These customers are excluded in our main analysis (see footnote 4), where we focus on the comparison between non-referred customers and those referred by personal connections within their social networks.

Table 5: Number of Successful Referrals

	Dependent Variable: Total Number of Referrals		
	No control for purchases (1)	Linear control total purchases (2)	Flexible control via DML (3)
Referred customers	0.1271***	0.0980***	0.0528***
	(0.0062)	(0.0061)	(0.0075)
Influencer-referred customers	0.0767***	0.0198	−0.0021
	(0.0147)	(0.0144)	(0.0118)
Total number of purchase occasions		0.0030***	
		(0.0000)	
Monthly purchase occasions			flexible function g(·)
Tenure (in months)	0.0030***	0.0015***	
	(0.0001)	(0.0001)	
Constant	0.0179***	0.0237***	
	(0.0062)	(0.0060)	
Observations	520,000	520,000	520,000

*** indicates significance at p = 0.01.

The baseline (omitted) category is the non-referred customers.

Overall, the average number of referrals is 0.32 among customers referred by influencers, just slightly higher than the 0.30 average for those referred by their social network. The average number of purchases, however, is significantly higher for customers referred by influencers (48.2) than those who joined through standard referrals (31.1). To account for different purchase levels as well as tenure, we run a regression using the same random sample of 500,000 customers as before plus a random sample of 20,000 customers who are referred by influencers. Similar to Table 3, we have three model specifications including a double machine learning estimator that controls for monthly purchase history and tenure in a flexible way. The results are shown in Table 5. The baseline category is the non-referred customers. After accounting for purchases and tenure, customers who joined through personal referrals make significantly more referrals than those referred by influencers. That is, influencer-referred customers make more referrals than non-referred customers, but the difference goes away after accounting for purchase activities. Therefore, referral contagion is stronger for customers referred by individuals in their social network than those referred by influencers, despite influencers presumably having higher status.

Study 4

We further test this effect using a randomized experiment.

Methods

As outlined in our preregistered research plan (https://aspredicted.org/e6982.pdf), we aimed to recruit 600 participants from Prolific and ended up with a sample of 601 participants. We excluded participants who failed the attention check, leaving us with a sample of 565 (M_{age} = 38.65 years, 51.68% Female). Participants were randomized into one of three conditions, which manipulated how they joined the service: 1) advertisement, 2) friend's referral, or 3) influencer's referral. After giving the first names of two close friends, participants read about the app using the same description used in Study 1: "There is a free app that offers you cash back for shopping with their partner brands, either online or in-store. Anyone who downloads the app gets $10." Participants in the ad and friend referral conditions were given the same prompts as before, and those in the influencer referral condition read "An influencer that you follow on social media posted a referral code online to try this app." Participants then read "You downloaded the app through [this ad/their referral].” All participants then read, “You have been using the service and think it is great. You receive a push notification in the app to see if you would like to refer a friend by sending them your referral code. If your friend follows through on the referral, you will get a $10 referral reward.”

Participants responded to the primary dependent variable, “How likely are you to refer your friend, [Friend 2’s name] to download the app?” (1 = Extremely unlikely to 7 = Extremely likely). We then test the role of the proposed mechanism of social appropriateness with a 4-item scale (α = .95): “Please answer the following questions about how it would feel to send [Friend 2’s name] this referral”: Appropriate, Inappropriate (Reverse-scored), Acceptable, Unacceptable (Reverse-scored; 1 = Not at all to 7 = Very much so).

Results

An ANOVA revealed a main effect of joining method on referral likelihood (F(2, 562) = 18.81, p <.001). Planned contrasts with Tukey method multiple comparison adjustment revealed that, in line with our previous studies, participants were more likely to refer a friend if they were referred to the app by a friend ($M_{Refer-friend}$ = 5.65, SD = 1.51) than if they joined through an advertisement (M_{Ad} = 4.47, SD = 2.13, t(562) = 6.07, p <.001, d = .51). Those in the friend referral condition were also more likely to refer than those who joined through an influencer’s referral ($M_{Refer-influencer}$ = 4.93, SD = 2.06, t(562) = 3.67, p < .001, d = .31), consistent with the evidence from the field data. Finally, participants were marginally significantly more likely to refer when they joined through an influencer’s referral than an advertisement (t(562) = 2.32, p = .054, d = .20).

An ANOVA also revealed a main effect of joining method on perceptions of social appropriateness (F(2, 562) = 10.14, p <.001). Planned contrasts with Tukey method multiple comparison adjustment found that participants believed referring was more appropriate if they joined through a friend's referral ($M_{Refer-friend}$ = 5.81, SD = 1.34) than through an ad (M_{Ad} = 5.10, SD = 1.71, t(562) = 4.48, p $<$ .001, d = .38). Perceptions of social appropriateness were also higher for those who joined through a friend's referral than through an influencer's referral ($M_{Refer-influencer}$ = 5.40, SD = 1.64, t(562) = 2.58, p = .028, d = .22). There was a directional, but non-significant increase in perceived social appropriateness by those who joined through an influencer's referral compared to those who joined through an ad (t(562) = 1.72, p = .157, d = .16).

As outlined in our preregistration, we ran two mediation analyses to examine the role of social appropriateness. First, we ran this mediation analysis to compare participants who joined through an advertisement versus those who joined through a friend's referral as in Study 1. Again, we found that perceptions of appropriateness mediate this relationship (indirect effect = .64, SE = .15, 95% CI = [.35, .93], direct effect = .55, SE = .13, 95% CI = [.30, .80], Prop. Mediated = .54). We repeated this mediation with participants who joined through a friend's versus an influencer's referral and find that appropriateness mediates this relationship as well (indirect effect = .36, SE = .14, 95% CI = [.09, .64], direct effect = .36, SE = .13, 95% CI = [.11, .61], Prop. Mediated = .50).

Discussion

Results from both the field data and the randomized experiment suggest that customers who were referred by an influencer actually refer less compared to those referred by a friend, despite the higher social status of an influencer. We believe the results are in line with our proposed mechanism. Prior work on norms suggests that norms exert a stronger influence on behavior when individuals identify more closely with the person displaying the behavior. Therefore, in our context, being referred by a friend or someone in your social network (someone you relate to) makes you feel that referring is more socially appropriate compared to being referred by an influencer (someone outside of your social network), in line with research on norm specificity (Cialdini and Goldstein 2004, Goldstein, Cialdini, and Griskevicius 2008, Rabb et al. 2022). Finally, this study offers evidence that priming or demand effects are not solely driving this effect, as both referral conditions mentioned joining through a referral, but did not similarly increase the choice to refer.

Social Network Effect and Homophily

Systematic differences in social networks between referred and non-referred customers may also lead to differences in referral likelihood. For example, the friendship paradox states that, on average, a person's friends tend to have more friends than they do (Feld 1991, Alipourfard et al. 2020), which suggests that referred customers may have access to a larger social network. While referred customers may have different social networks, contributing to the gap in referrals in the field data, the effect persists when we randomize participants into different conditions in our randomized studies. With random assignment, we do not expect any systematic difference between those in the referred and non-referred conditions, including social network differences.

Besides the size of social networks, we explore the concept of homophily and how it may affect referral likelihood. Homophily, often encapsulated by the phrase "birds of a feather flock together," suggests that similarity breeds and bolsters social connections. Homophily can predict higher referrals among referred customers in several ways. First, customers may share similar preferences for products or services with friends who made the referral, making them potentially a better fit for the firm as described in a previous section. To the extent that we can measure fit through how much they use the product, our empirical analysis using the field data controls for purchase activities. Second, it's also possible that referred customers share certain traits (e.g., personality or interest in social interactions) that make them more likely to refer (Mooradian and

Swan 2006) beyond how much they use the product. Our experiments help address this by having participants select a friend to be the referral recipient before being randomized into a condition (referred vs. non-referred). With random assignment, there will be no systematic difference in the traits of that friend between the conditions.

We further show that the degree of similarity between referral recipients and referring customers is not the only driver of referral contagion using an additional preregistered randomized controlled study (See Web Appendix C for full details). In this study, participants were asked to name three friends: one with no additional description, one whose shopping tastes and behaviors are very similar to their own, and one whose shopping tastes and behaviors are very different from their own. Participants were then randomized into one of two conditions based on how they joined a cashback app. They either joined through a referral (by the first friend they listed) or an ad. As in Study 3, participants in the ad condition also learned that the first friend they named is also a customer, therefore the first friend's social validation is held constant across both conditions. Participants in both conditions were then asked how likely they were to refer the other two friends (similar and different, counterbalanced across participants) to download the app. We find a significant difference in referral likelihood based on how participants joined – participants in the referred (vs. ad) condition were more likely to refer to both their similar and different friends ($p<.001$). There was a non-significant interaction between similarity and joining method ($p = .17$).

Increasing Referrals in a Field Experiment

We have established that one mechanism contributing to higher referrals among referred customers is that joining through a referral sets a norm, such that referred customers perceive referring as more appropriate compared to non-referred customers. Leveraging this insight, we propose that one can increase the number of referrals by *reminding* customers that they joined through a referral. This prediction builds on previous research that social norms must first be activated or made salient to influence behavior (Cialdini, Reno, and Kallgren 1990, Aggarwal and Zhang 2006). Thus, we hypothesize that receiving such a reminder will make it more salient that the customer was initially referred, and therefore perceive referring as more acceptable in this context than other referred customers who do not see such a reminder. We implemented this idea using a field experiment with the cashback mobile technology company that provided the first dataset.

Field Experiment Setup

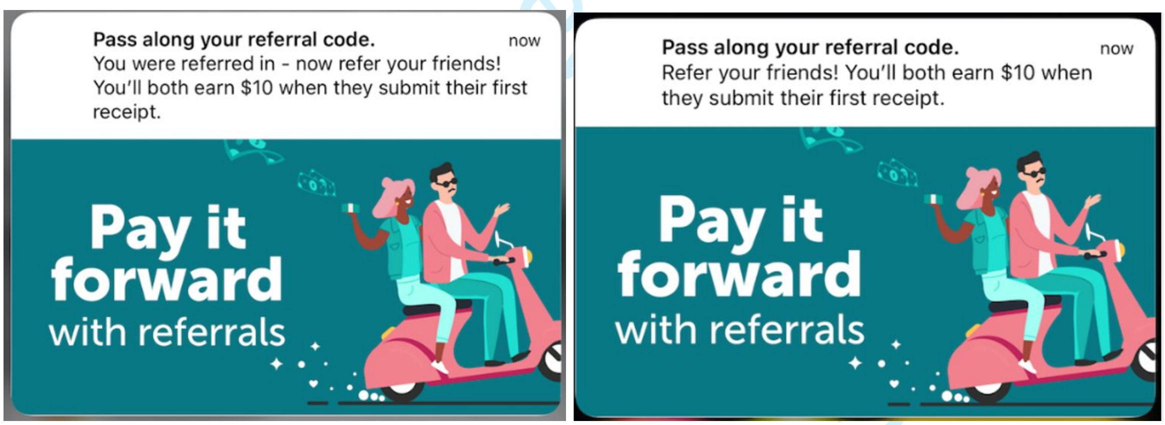
The experiment was implemented with a push notification on the app inviting customers to refer their friends. For referred customers, 45% were randomly assigned to receive the treatment message "You were referred in – now refer your friends!" The remaining 55% of referred customers received the control message "Refer your friends!" Although not a key focus of the experiment, we also sent the control message to the company's non-referred customers. The rest of the content in the push notification as well as the images are identical between the two messages. Figure 3 shows the screenshots of the two creatives used in the experiment, with only the name of the company removed. The push notification was sent out on April 15, 2022. Note that the referral incentives are the same as usual and do not differ between conditions. Also, the "Pay it Forward with referrals" wording is standard in the field partner's marketing messaging and was not related to this specific study. There were no changes in how much the referrer and the referred friend would receive for a successful referral during the short period before and after the field experiment.

Analysis

Since the intervention was done via push notifications, we removed about 16% of customers who unsubscribed from push notifications. We are left with about 10 million referred consumers with 45% in the treatment condition and 55% in the control condition, and 24 million non-referred customers. Our focus is to understand whether the subtle change in the treatment message, which reminds customers that they were referred, will increase referrals compared to the control message. In addition, to replicate the main finding of the paper, we also compare the number of referrals between the referred control group and the non-referred customers, who received the exact same push notification in the same time period.

Figure 3: Push Notifications in Treatment and Control Conditions

(a) Treatment condition (b) Control condition



We tracked the number of referrals among the three groups (referred customers in the treatment group, referred customers in the control group, and non-referred customers) for two days after the push notification was sent. We track this two-day period because we only observe the date that the recipients followed through by registering for an account, which may take some time after they received a referral invitation. We use regression analysis to test whether the number of referrals is different among the three groups. The baseline group is the referred customers in the control group and we compare it with the treatment group as well as the non-referred customers (who also received the control message). To confirm randomization among referred customers, we also compare the referral behavior during the two days prior to the intervention.

Table 6: Change in Referrals after Push Notification

	Dependent Variable:			
	Pre-period Referrals (scale: $1e-3$)		Post-period Referrals (scale: $1e-3$)	
	(1)	(2)	(3)	(4)
Non-referred customers	-0.059***	-0.046***	-0.051***	-0.038***
	(0.006)	(0.006)	(0.006)	(0.006)
Treated referred customers	0.010	0.002	0.031***	0.023***
	(0.008)	(0.008)	(0.009)	(0.009)
Number of purchases		0.001***		0.001***
		(0.00002)		(0.00002)
Constant	0.116***		0.107***	
	(0.005)		(0.005)	
Joining date FE	No	Yes	No	Yes
Observations	35,571,675	35,571,675	35,571,675	35,571,675
R^2	0.000005	0.001967	0.000005	0.000838

*** indicates significance at p = 0.01.

Note: The baseline (omitted) group is the referred customers in the control group.

Results are reported in Table 6. We start by comparing the treatment and control messages among referred customers. The parameter estimate for "Treated referred customers" represents the difference in referrals with the treatment message compared to the baseline control message. In the pre-treatment period (two days prior to the push notifications), there is no significant difference in referrals between these two groups (columns 1 and 2), as expected due to random assignment. In the post-treatment period (two days after the push notifications), the number of referrals is higher with the treatment message (column 3). Column (4) adds control variables for the number of purchases and account registration date, and the results remain largely similar.

Using our preferred specification in column (4), the absolute increase in referrals, $0.023 \cdot e^{-4}$, may seem modest. However, relative to the baseline in the control condition ($0.107 \cdot e^{-4}$), this represents a 21% increase in referrals, an economically meaningful number. Improving the effectiveness of referral messaging by about 20% at no additional costs is a powerful way to grow a customer base through referrals. In Web Appendix D, we run a robustness check with active customers. Since we do not observe the status of each consumer, which is common in a non-contractual setting (Fader, Hardie, and Shang 2010, Gopalakrishnan et al. 2021), we proxy active customers by recent account sign-up or activity (i.e., purchases). We find consistent results with $20-27\%$ increase in referrals when referred customers receive the treatment message.

Although the main objective of the experiment was to compare referred customers in the treatment and control groups, it is worth pointing out that referred customers, even those in the control group, refer significantly more than non-referred customers. Since referred customers in the control group receive the same message as non-referred customers, the number of referrals after receiving the message is directly comparable between the two groups. The estimates for "Non-referred customers" in Table 6 are negative and significant across the different time periods and model specifications. The results suggest that there is a consistently lower number of referrals among non-referred customers compared to the baseline referred control group. This result replicates the main finding that referred customers make more referrals compared to non-referred customers.

Discussion

Our field experiment result suggests that a simple intervention via a subtle change in messaging can improve the effectiveness of a referral program. Reminding customers that they were referred increases their propensity to refer others. This change in messaging can serve as an effective and costless intervention, which can also be used in conjunction with other aspects of the referral reward program, such as choosing an optimal reward amount.

The findings from our field experiment not only offer marketers actionable strategies to increase referrals, but also validate our proposed mechanism: joining through a referral establishes a norm that referring is socially appropriate in this context, thereby increasing customers' referral likelihood. Consistent with other research on norms (Cialdini, Reno, and Kallgren 1990, Kallgren, Reno, and Cialdini 2000), our results suggest that the influence of joining through a referral is stronger when the norm is more salient, such as through a reminder. It is also worth noting that we do not believe this is the only way to increase referrals – rather, any intervention that will increase the perceived social appropriateness of making referrals is likely to increase the propensity to refer.

Finally, these results provide further evidence for our main effect: when referred and non-referred customers receive the same referral invitation and incentives, referred customers bring in more new customers through referrals. This can rule out an alternative explanation that referral contagion may be due to referred customers being more aware of a company's referral reward program. One may be concerned that the length of instruction or sentence logic may be meaningfully superior in the treatment message, which leads to higher referrals instead of the reminder effect. We ran two post-tests on the exact two push notifications used in our field experiment and did not find evidence for this explanation. Details of the post-tests are described in Web Appendix E.

General Discussion and Conclusion

Companies have the opportunity to invest in referral reward programs, encouraging current customers to wield their social influence and bring in new customers. Prior research finds that such programs tend to attract customers who are more valuable in terms of their purchases or engagement with the company. We identify a previously overlooked benefit of referrals – referred customers are also more valuable because they make more referrals. Using large-scale field data, as well as preregistered lab experiments, we show converging evidence that referred customers make more referrals than customers who join through other means. The difference in referrals is economically meaningful: not accounting for the higher number of referrals underestimates about 20–36% of the total difference in value for referred customers.

Why do referred customers make more referrals? While referral contagion is likely driven by multiple mechanisms, we propose one important mechanism – customers who joined through a referral believe that referring is more socially appropriate than those who did not. Joining through a referral, therefore, appears to establish a norm for referred customers that referring is socially acceptable, increasing the likelihood that they will refer as well. Leveraging this insight, we demonstrate that a simple messaging intervention that makes this norm more salient by reminding referred customers that they joined through a referral ("You were referred in – now refer your friends!") can further boost referral likelihood compared to a control message ("Refer your friends!").

Insights and Implications

This work expands our understanding of the motivations behind word-of-mouth and provides novel insights into customers' referral choice. Several factors drive the desire to spread positive word-of-mouth, such as delight with a brand or referral incentives (Biyalogorsky, Gerstner, and Libai 2001, Kornish and Li 2010). Product characteristics, such as usefulness, originality, interest, and public visibility have also been shown to increase WOM behaviors (Moldovan, Goldenberg, and

Chattopadhyay 2011, Berger and Milkman 2012). However, there are also social barriers deterring customers from encouraging their friends to try new products. Referring friends can evoke discomfort due to concerns about impression management and the desire to maintain positive relationships (Xiao, Tang, and Wirtz 2011). To reduce social discomfort, individuals often use social norms to guide how they should act in their interpersonal relationships. We find that joining through a referral makes referring others appear more appropriate, and therefore increases referral likelihood. This is in line with previous research showing that norms are constructed based on observing others' behavior in one's reference group (Kemper 1968). We provide further evidence for the psychological drivers of WOM and the significant influence of others' behavior on consumer judgments and decisions in social contexts.

We also offer clear insights for marketers. First, we document that referred customers have higher social value by bringing in more customers through referrals, beyond their higher customer value from own purchases with the firm (Schmitt, Skiera, and Van den Bulte 2011, Van den Bulte et al. 2018). Our findings suggest that marketers hoping to spread the word about their products should invest in referral reward campaigns to reap these downstream benefits. Further, marketers can increase referrals from their current referred customers using a simple intervention. While extensive literature suggests costly methods for increasing referrals by altering the reward size and structure of referral reward programs (Biyalogorsky, Gerstner, and Libai 2001, Kornish and Li 2010, Garnefeld et al. 2013, Jin and Huang 2014, Wolters, Schulze, and Gedenk 2020), we offer a cost-free method for boosting word-of-mouth specifically among these valuable referred customers. A subtle message reminding customers that they joined through a referral substantially increased successful referrals in our field experiment by $20 - 27\%$. This adds to the evidence that investing in, tracking, and nudging referral behaviors can greatly benefit firms.

Limitations and Opportunities for Future Research

There are several limitations with the current research that would benefit from further follow-up studies. Without observing revenue or margin, we proxy the value of customers by the number of purchases. While it is a reasonable proxy, it is preferable to document the value of customers as well as the value of referrals by their actual contribution margin to the company. In addition, although we demonstrate that referred customers make more referrals using multiple methodologies, including both observational data and hypothetical scenario studies, it is preferable to show this effect with a large-scale field experiment. Such an experiment is not straightforward to design since companies cannot directly manipulate whether a customer is referred or not. However, we call for future research to carry out a cleverly designed experiment to measure a causal effect.

Our field experiment demonstrates one effective intervention to boost referrals by reminding referred customers that they were originally referred by a friend. Since we tend to trust our close social ties and use them as guidance to determine appropriate actions in a given situation, we anticipate experiencing real referral behavior to be particularly effective. We expect other interventions to also boost referrals if they can credibly improve customers' perception of the appropriateness to refer. In an additional study testing this prediction, we find that using a (true) informational norm ("Hundreds of customers download our app through a referral every day.") did not increase referral propensity (see Web Appendix F). It is possible that norm messaging using their customers' actual social network data may be more effective at setting a relevant and credible social norm (e.g., "10 of your friends have referred someone to download our app this month"). Future researchers may identify additional interventions to increase referrals by changing the perceived appropriateness.

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Web Appendix

Referral Contagion: Downstream Benefits of Customer Referrals

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”These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.”

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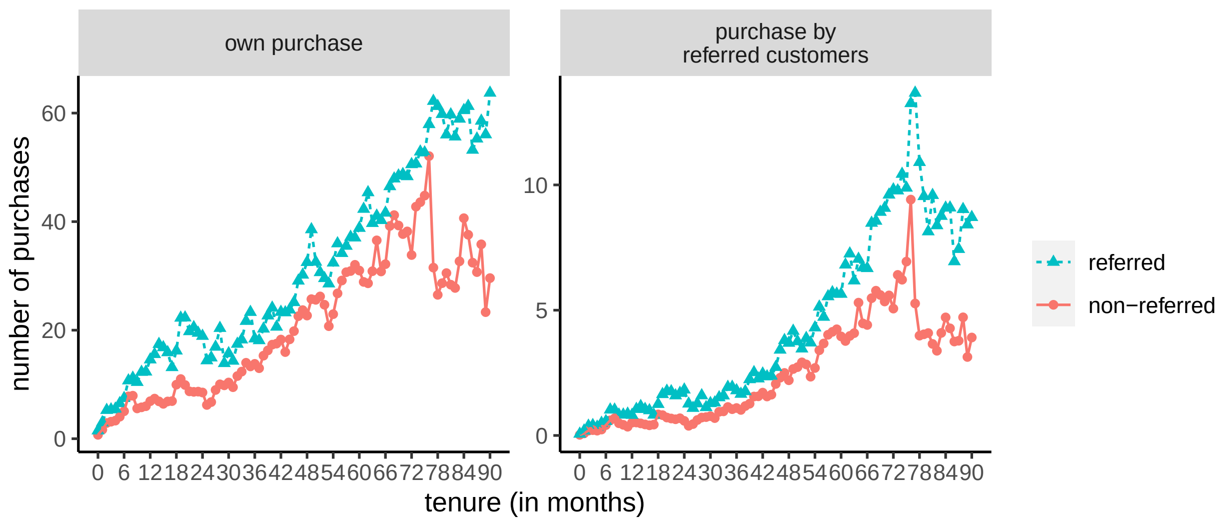
Web Appendix A: Value of Referred Customers through Purchases and Referrals

In the main text, we show that referred customers are more valuable not only because of their own purchases but also from the value of referrals, which is proxied by the number of purchases made by referral recipients. In this appendix, we conduct formal analyses with regression and the double machine learning estimator, similar to those in the analysis for the number of referrals.

Figure W1: Purchases Made by Referred vs. Non-referred Customers



Before discussing the results of the models, we first show both customers' own purchases and those made by referral recipients by tenure. The left panel of Figure W1 plots the number of purchases made by consumers with a certain tenure. This is taken from a cross-sectional analysis where the statistics for each tenure reflect the behavior of customers from a certain cohort. Overall, consumers with longer tenure are more likely to make a higher number of purchases. The right panel of Figure W1 plots the number of purchases made by referral recipients (as a proxy for the value of referrals) with a certain tenure. Compared to non-referred customers with the same tenure, referred customers consistently have a higher value that arises from referrals. For both own purchases and purchases by referral recipients, the gap between referred and non-referred customers persists across different tenures.

We proceed to quantify the higher value of referred customers from both their own purchases and referrals. Using the same random sample of 500,000 customers, we first run a simple linear regression where Z_i includes tenure. y_i is the total number of purchases since joining the company. $referred_i = 1$ if customer i joined through a referral program and 0 otherwise. The main parameter of interest γ represents the difference in the number of purchases between referred and non-referred customers. Regression results are shown in Table W1. Referred customers have 9.58 more purchases on average, which represents a 42% increase relative to the baseline of 22.48 purchases from non-referred customers.

We run the same regression and let y_i be the number of purchases made by their referrals. Table W1 column (2) reports that the total number of purchases from their referrals is higher by 5.33 than non-referred customers. Relative to the baseline of 6.20 from non-referred customers, the difference represents an 86% increase in the number of purchases resulting from referrals (5.33/6.20) by referred customers. Notice that the relative magnitude of the difference is slightly larger when comparing the number of purchases made by these referrals than the number of referrals. This suggests that the higher value from referrals for referred customers comes not only from them referring a higher number of customers but also from them referring more valuable customers.

Column (2) shows that referred customers have higher purchases from their referrals compared to non-referred customers after controlling for tenure. We run multiple model specifications in $g(Z_i)$ to account for the difference in purchases between referred and non-referred customers. Column (3) adds a linear term of the total number of purchases. In our preferred specification, monthly purchases and tenure are added with a flexible functional form in $g(Z_i)$. To obtain a consistent estimate of γ, we "partial out" the impact of Z_i in the propensity to be a referred customer. Similar to the main text, we use random forest to model $g(Z_i)$ and $m(Z_i)$. The result from the double machine learning estimator is reported in column (4). The higher value from referrals persists with flexible controls of purchase history.

Table W1: Difference in Customer Value

	Dependent Variable:			
	through *purchases* (own purchase)	through *referrals* (purchase by referred customers)		
	(1)	(2)	(3)	(4)
γ: Referred customers	9.5773***	5.3323***	3.0046***	2.3445***
	(0.3962)	(0.6107)	(0.6034)	(0.8749)
β^p: Total number of purchases			0.2430***	
			(0.0022)	
Monthly purchases				flexible function g($\cdot$)
β^t: Tenure (in months)	0.4549***	0.2278***	0.1173***	
	(0.0065)	(0.0101)	(0.0100)	
Constant	−0.8424***	−5.4772***	−5.2725***	
	(0.3983)	(0.6138)	(0.6061)	
Observations	500,000	500,000	500,000	500,000

*** indicates significance at p = 0.01.

In summary, we have shown that referred customers are more valuable, not only because of their own purchases but also because they make more referrals. As discussed in the main text, the difference of 2.36−5.33 purchases from referral recipients is economically meaningful. The value from referrals accounts for about 20−36% of the difference in total value between referred and non-referred customers. In other words, when companies evaluate how much they should be willing to spend to attract a new referred customer versus acquiring a customer through other marketing tactics, it is important to consider the contribution from referrals in addition to purchases.

Web Appendix B: Likelihood of Referring Similar vs. Different Recipients

This study is a direct replication of Study 1.

Methods

As outlined in our preregistered research plan (https://aspredicted.org/5xr6r.pdf), we recruited 600 participants from Prolific. After excluding participants who failed the attention check, our sample consists of 551 individuals (M_{age} = 36.64 years, 45.2% Female). We used the exact same methods used in Study 1.

Results

We replicated the primary effects of joining method on referral likelihood and social appropriateness. First, we find that participants were more likely to refer if they originally downloaded the app through a referral (M_{Refer} = 5.57, SD = 1.68) than if they joined through an ad (M_{Ad} = 4.94, SD = 2.03, t(549) = 3.8, p$<$.001, d = .34). Participants also believed that referring is more socially appropriate if they joined through a referral (M_{Refer} = 5.33, SD = 1.61 vs. M_{Ad} = 5.00, SD = 1.77, t(549) = 2.29, p = .022, d = .20). There was a non-significant difference in predicted reputational benefits between the two conditions in this replication (M_{Refer} = 4.99, SD = 1.52 vs. M_{Ad} = 4.83, SD = 1.45, t(549) = 1.27, p = .21). We also found a non-significant difference in psychological costs (M_{Refer} = 2.19, SD = 1.51 vs. M_{Ad} = 2.26, SD = 1.53, t(549) = .52, p = .606).

Finally, we conducted a preregistered mediation analysis to examine the role of all three mediation constructs (appropriateness, reputational benefits, and psychological costs) on the effect of joining method on referral likelihood. This analysis (10,000 resamples) revealed that perceptions of appropriateness significantly mediated this relationship (indirect effect = .26, SE = .12, 95% CI = [.04, .49]). There was a non-significant indirect effect of reputational benefits (indirect effect = .01, SE = .01, 95% CI = [-.02, .03]). There was also a non-significant indirect effect of psychological costs (indirect effect = .01, SE = .02, 95% CI = [-.02, .03]). The direct effect remained significant (direct effect = .36, SE = .10, 95% CI = [.16, .57]).

Web Appendix C: Likelihood of Referring Similar vs. Different Recipients

In this appendix, we demonstrate that the effect of higher referral propensity among referred customers persists for referral recipients who are more similar or more different from the referring customer.

Methods

As outlined in our preregistered research plan (https://aspredicted.org/7ta5x.pdf), we recruited 200 participants from Prolific and excluded participants who failed the attention check (n = 18), leaving us with a sample of 182 (M_{age} = 37.08 years, 58.79% Female). Participants were randomized into one of two conditions based on how they joined the service: an advertisement or a friend's referral.

Participants were first told to think of a friend and write their first name. On the next page, they were asked to think of two additional friends. Think of one whose shopping tastes and behaviors are very similar to their own and another whose shopping tastes and behaviors are very different from their own. Participants then read about the cashback app using the same description used in Studies 1 and 4. They read that anyone who downloads the app gets $10. Participants in the referral condition then read, "Your friend, [First Friend's Name], sent you a referral code to try this app. You downloaded the app through their referral." Those in the advertised condition read, "You saw an advertisement for this app. You downloaded the app through this ad and learn that your friend, [First Friend's Name] uses the app as well." We mention the first friend in both conditions, as in Study 3, such that there is social validation from this friend in both conditions. All participants then read that they received a push notification in the app to see if they would like to refer their friends and that they would receive $10 if their friend follows through on the referral. They were then asked how likely they would be to refer both the similar and different friends (counterbalanced) that they named previously in the study.

Results

The mixed-design analysis of variance revealed a significant main effect of joining through a referral (vs. an advertisement) on referral likelihood, F = 32.05, p<.001. We also see a main effect of similarity, such that participants were more likely to refer the similar (vs. different) friend. However, there is a non-significant interaction between the method of joining and the similarity of referral recipient F = 1.93, p = .17. In the "similar friend" condition, participants were more likely to refer if they joined through a referral, M_{Refer} = 5.67, SD = 1.52, M_{Ad} = 5.08, SD = 1.95, t(180) = -2.30, p = .023. In the "different friend" condition, participants were also more likely to refer if they joined through a referral, M_{Refer} = 5.00, SD = 1.80, M_{Ad} = 3.98, SD = 2.15, t(180) = -3.51, p $<$.001. Here, we show that referral contagion persists for referral recipients who are both similar and different from the referring customer.

Web Appendix D: Field Experiment Results with Recent Customers

In the main text, we see that referred customers have more referrals when receiving the treatment message compared to the control message. The treatment effect is large in relative terms, 21%, but very small in absolute number, 0.000023. One of the reasons for the small magnitude of the absolute number is that many customers may be inactive by the time of the experiment and no longer interact with the app. These customers may have removed the app from their phones and thus are not receiving push notifications. We consider a customer active if she recently registered the account or made a purchase.

Table W2: Change in Referrals among Active Customers

	Dependent Variable:			
	Post-period Referrals			
	Active within 1 month		Active within 3 months	
	(1)	(2)	(3)	(4)
Non-referred customers	-0.000841***	-0.000842***	-0.000574***	-0.000591***
	(0.000185)	(0.000187)	(0.000118)	(0.000120)
Treated referred customers	0.000768***	0.000630**	0.000398**	0.000359**
	(0.000245)	(0.000246)	(0.000157)	(0.000157)
Number of purchases		0.0000005***		0.000001***
		(0.0000002)		(0.0000001)
Constant	0.002810***		0.001787***	
	(0.000156)		(0.000101)	
Joining date FE	No	Yes	No	Yes
Observations	938,418	938,418	1,674,447	1,674,447
R^2	0.000069	0.005228	0.000037	0.003432

*** indicates significance at p = 0.01; ** p = 0.05.

Note: The baseline (omitted) group is the referred customers in the control group.

We repeat the analysis among only likely active customers. Table W2 columns (1) and (2) show the post-treatment results for customers who have been active within 1 month. Among this active customer base, the treatment effect is 0.000630–0.000768 across the two specifications. Relative to the baseline control group, the increase is then 22–27%. Similarly, in columns (3) and (4), we report the results for customers who are active within the past 3 months (registered an account or have made a purchase in the past 3 months). The lift in referrals is 0.000359–0.000398, which is 20–22% compared to the baseline. The non-referred customers have consistently lower referral numbers compared to the referred customers in the control group, in support of the main finding of the paper.

Web Appendix E: Post-tests of the Field Experiment

In a post-test, we measured whether the two push notifications used in the field experiment differed noticeably between conditions. Participants (N = 201, M_{age} = 39.35 years, 47.26% Female, MTurk) viewed one of the two push notifications and then responded to the following: 1) "Please rate the quality of this push notification" (1 = Very low quality, 7 = Very high quality), 2) "To what extent do you think this push notification is eye-catching?" (1 = Not at all, 7 = Very much so), and 3) "How many words are in this push notification?" (1 = Very few, 7 = Very many). We found non-significant differences in all three measures. Specifically, participants viewed the two advertisements similarly in terms of quality ($M_{Control}$ = 4.43, SD = 1.41, M_{Treat} = 4.50, SD = 1.54, t(199) = -.36, p =.719), how eye-catching they appeared ($M_{Control}$ = 4.61, SD = 1.45, M_{Treat} = 4.31, SD = 1.51, t(199) = 1.45, p =.148), and how many words they included ($M_{Control}$ = 4.78, SD = 1.18, M_{Treat} = 5.00, SD = 1.31, t(199) = -1.31, p =.191). This suggests that differences in consumer responses are likely due to message content, rather than the number of words or perceived quality of the messages.

A separate post-test found further evidence that the greater effectiveness of the treatment notification compared to the control notification is not obvious a priori. In fact, we find in this study that participants (N = 201, M_{age} = 40.8 years, 45.27% Female, MTurk) believed the control notification would be more effective. Participants were asked to imagine that they are a marketer for a cashback app and that the company is planning on sending a notification to all customers who joined through a referral. All participants viewed both notifications and were asked, "As a marketer, which push notification do you think would be more effective at getting these customers to refer their friends to download the app?" (1 = Definitely Option A, 7 = Definitely Option B; Order counterbalanced). Participants erroneously believed that the control notification would be significantly more effective than the treatment notification (M = 3.25, SD = 1.94, t(200) = 5.480, p $<$.001, comparison to the midpoint of 4). This further suggests that the benefit of reminding customers that they were originally referred to a product or service may be unanticipated by marketers. We suspect that this type of messaging will only work well if the customers have truly experienced being referred by their friends, which sets the social norm of appropriate behaviors in this context.

Web Appendix F: Informational Norm Manipulation

In this appendix, we describe a study that was designed to test whether an informative norm message about referral behavior can increase referral likelihood.

Methods

As outlined in our preregistered research plan (https://aspredicted.org/kp8mz.pdf), we aimed to recruit 600 participants from Prolific and ended up with a final sample of 602. While we planned to remove participants who failed the attention check, a large portion (43%) of participants failed the attention check (i.e., did not attend to the norm manipulation) and therefore we will present both samples.

Results

Participants were asked to give the first name of two close friends. They were then randomized into two conditions based on whether or not they joined through a referral. All participants read "There is a free app that offers you cash back for shopping with their partner brands, either online or in-store. Anyone who downloads the app gets $10." Those in the referral condition then read, "Your friend, [Friend 1's name], sent you a referral code to try this app. You downloaded the app through their referral." Those in the control condition read, "You downloaded the app." Participants then read that after downloading the app, they have been using the service and think it is great. They receive a notification asking if they would like to refer a friend to try it. Participants were randomized into two conditions and saw either a control message "Hundreds of customers download our app every day!" or a referral-norm message "Hundreds of customers download our app through a referral every day!" They were then asked, "How likely are you to refer your friend, [Friend 2's name], to download the app?" (1 = Extremely unlikely, 7 = Extremely likely). Finally, they responded to the following attention check: Which of the following is true: The push notification said, "Hundreds of customers download our app every day" or The push notification said, "Hundreds of customers download our app through a referral every day".

Of those who passed the attention check (N = 341, M_{age} = 39.75 years, 55.7% Female), we find a directional main effect of the joining method, (F(1, 337) = 2.33, p = .127), a non-significant main effect of the norm messaging condition, (F(1, 337) = .398, p = .528), and a non-significant interaction, (F(1, 337) = .210, p = .647). Of the full sample, (N = 615, M_{age} = 38.39 years, 52% Female), we find a significant main effect of the joining method, (F(1, 598) = 7.38, p = .007), a non-significant main effect of the norm messaging condition, (F(1, 598) = .808, p = .369), and a non-significant interaction, (F(1, 598) = 1.06, p = .305).

Discussion

Overall, we find that the norm message does not successfully increase referral likelihood, though that may be due in part to participants not attending to the message (participants did not do much better than chance on the attention check). Future work may find more effective interventions to increase the perceived appropriateness of sending referrals for referred and non-referred customers.