

# Accepted Manuscript

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PII: S0167-8116(15)00111-1  
DOI: doi: [10.1016/j.ijresmar.2015.09.004](https://doi.org/10.1016/j.ijresmar.2015.09.004)  
Reference: IJRM 1115

To appear in: *International Journal of Research in Marketing*

Received date: 3 June 2015



Please cite this article as: Armelini, G., Barrot, C. & Becker, J.U., Referral programs, customer value, and the relevance of dyadic characteristics, *International Journal of Research in Marketing* (2015), doi: [10.1016/j.ijresmar.2015.09.004](https://doi.org/10.1016/j.ijresmar.2015.09.004)

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# Referral Programs, Customer Value, and the Relevance of Dyadic Characteristics

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September 2015

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## ARTICLE INFO

### *Article history:*

First received on June 3, 2015 and was under review for 3 months.

Replication Editor: Donald R. Lehmann

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## **Referral programs, customer value, and the relevance of dyadic characteristics**

### **Abstract**

Referral programs have become a popular tool to use the customer base for new customer acquisition. We replicate the work of Schmitt et al. (2011) who find that referred customers are more loyal and valuable than customers acquired through other channels. While our results confirm that rewarded referrals indeed reduce the risk of customer churn, we do not find that referred customers are necessarily more valuable. Analysis of the relationship between senders and receivers of referrals demonstrates that demographic similarity drives the referred customer value.

*Keywords:* Customer lifetime value; referral rewards; customer acquisition; financial services

## 1. Introduction

In recent years, referral programs have gained popularity in many industries as a viable means for new customer acquisition. Likewise, referral programs have attracted considerable scholarly interest. Previous studies provide insights on, for instance, optimal reward designs (Biyalogorsky, Gerstner, & Libai, 2001), drivers of participation (Verlegh, Ryu, Tuk, & Feick, 2013), and instruments to stimulate rewarded referrals (Hinz, Skiera, Barrot, & Becker, 2011). One of the most significant contributions in that context was Schmitt, Skiera, and Van den Bulte's (2011; hereafter referred to as SSV) finding that customers from referral reward programs are more loyal and more valuable than those acquired through other marketing channels.<sup>1</sup> The purpose of this paper is to replicate SSV by analyzing the effect of referrals on churn and customer value using similar data from a company with a different product and referral incentive structure.

## 2. Data

To allow for a precise comparison with SSV, the replication also focuses on the financial services sector. While SSV is based on panel data from a German bank, we use panel data from 4,718 customers of a Chilean direct bank. Specifically, we have information on a cohort of 1,677 referred and 1,971 non-referred customers as well as 1,070 referral senders.<sup>2</sup> Similar to SSV, the data encompasses information on customer demographics, contribution margins, and churn behavior over 27 months (2011-2013). *Table 1* provides the key descriptives in comparison with SSV.

>>> Insert Table 1 about here <<<

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<sup>1</sup> The study was the 2011 winner of the MSI/H. Paul Root award and subsequently featured in HBR.

<sup>2</sup> Analog to SSV, the data only includes information on successful referrals.

The bank operates a referral program that rewards every successful referral with vouchers that can be redeemed for a selection of popular consumer goods such as iPads, TV sets, or household appliances. In case of multiple referrals, customers can accumulate coupons to secure higher priced rewards. The fact that the average reward size is almost four times higher than in SSV's study reflects the substantially higher profitability. While, compared with other countries, the German banking industry is highly fragmented and known for its high costs and low profits (Atkins, 2015), Chilean banks realize significantly higher margins. The bank promoted the referral program primarily on its website and through advertising in local newspapers. In addition, branch staff was encouraged to communicate the program to existing customers (similar to the bank providing the data for SSV).

### 3. Replication analyses and results

As in the original study, we first purified the data using the DFBETA criteria and eliminated extreme data points that might excessively influence the results.<sup>3</sup> Consequently, we deleted 140 referred and 220 non-referred customers. To replicate the analysis of the churn behavior of referred versus non-referred customers, we estimate a Cox proportional hazard model. The results in *Table 2* indicate that customers acquired through rewarded referrals indeed show a lower risk of customer churn ( $-0.195$ ;  $p < 0.01$ ). In line with SSV, this finding demonstrates that referred customers are more loyal.

>>> Insert Table 2 about here <<<

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<sup>3</sup> DFBETA statistics are the scaled measures of the change in each parameter estimate. Large values of DFBETA indicate observations that are influential in estimating a given parameter. Belsley et al. (1980) recommend  $2/\sqrt{n}$  as a cutoff value.

Furthermore, we followed SSV's approach and calculated two measures of customer value in addition to the daily contribution. While the observed customer value shows the present value of all contribution margins during the observation period, the customer lifetime value (CLV) captures the present value of the observed and predicted contribution margins (see SSV, p. 49-50, for details). The regression models show interesting results: whereas SSV found an overall positive impact, our results point in the opposite direction and show a negative effect for customers acquired through rewarded referrals regarding the daily contribution margin ( $-107.3$ ;  $p < 0.01$ ), the observed customer value ( $-37,415.0$ ;  $p < 0.01$ ), and the CLV ( $-58,440.5$ ;  $p < 0.01$ ). Similar to SSV, however, the size of the value differential varies across high- and low-margin customers. The segment-specific results in *Table 3* indicate that for low-margin customers, rewarded referrals attract customers with higher CLV ( $12,033.7$ ;  $p < 0.01$ ) while the effect for high-margin customers is negative ( $-196,264.4$ ;  $p < 0.01$ ).<sup>4</sup>

>>> Insert Table 3 about here <<<

Considering the higher loyalty of referred customers, these findings confirm SSV's results and indicate that referred customers indeed have the potential to become more valuable customers. However, there is a need for a deeper look into potential causes for the differing results regarding the CLV.

The product portfolio of the focal bank consists of a variety of products that differ substantially with respect to their profit margin. While simple products such as checking accounts contribute little to the customer value, mortgages in particular are highly profitable

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<sup>4</sup> Analog to SSV, we define high- and low-margin customers as those in the top and bottom decile, respectively.

although less frequent. While, for instance, only 4.8% of all customers in our sample had mortgages, the share among the high-margin customers is 14.0%. We find a significant difference between referred and non-referred customers. Whereas among the non-referred customers 6.9% are mortgage customers, only 3.0% are found among the referred customers ( $t = 3.91$ ;  $p < 0.01$ ), leading to the significantly higher CLV of non-referred customers in this segment. At the same time, we find substantially higher CLVs for referred compared with non-referred customers in the bottom decile where there are no mortgage customers at all.

This observation is in line with previous findings. According to Ryu and Feick (2007), customers are less likely to refer risky products (as in the case of complex and high-volume mortgages). At the same time, because only a small share of customers has experience with mortgage products with the bank, both the willingness to refer such a product and the willingness to accept a referral are lower. In our sample, the likelihood of a non-mortgage customer to refer a mortgage customer is 2.2%, which is four times lower than a referral from a mortgage customer (9.0%). Even if customers have such experience and are willing to make a referral, they would need to have similar friends in their network that are interested in a mortgage contract.

We tested whether customers refer the product to customers that are similar to themselves. We operationalize demographic similarity as the percentage of similar characteristics between the sender and the receiver of referrals. Following Nitzan and Libai (2011), we use the socio-demographic variables such as age<sup>5</sup>, gender, income and neighborhood as well as web and call center use to calculate a score. The score indicates the similarity of sender and receiver in the range from 0 (not similar) to 1 (very similar). A positive influence of demographic similarity implies that the higher the sender's CLV, the higher the CLV of the receiver.

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<sup>5</sup> Age is considered similar if the difference is not larger than 5 years. All variables contributed to the score with the same weight.

>>> Insert Table 4 about here <<<

We test the effect of demographic similarity with a regression model (*Table 4*). The results reveal a strong influence of the CLV of existing customers on the CLV of customers referred by them (0.176;  $p < 0.01$ ). Consequently, targeting high-value customers and providing them information on the referral program yields referred customers of higher value. The positive interaction effect of senders' CLV and demographic similarity (0.098;  $p < 0.01$ ) in *Fig. 1* indicates that customers that have been referred by customers that are high in both CLV and demographic similarity can be expected to be particularly valuable.

>> Insert Fig. 1 about here <<<

#### 4. Conclusion

This study contributes to literature on referral reward programs in two ways. First, we replicate Schmitt et al.'s (2011) results on the positive effect of rewarded referrals on customer loyalty and find that referred customers are indeed more loyal compared with non-referred. Second, we confirm their finding that segment-specific differences exist with respect to the customer value. The fact that our results show that referral programs do not necessarily yield more valuable customers implies that the influence of rewarded referrals on the customer value of referred customers depends on company- and product-specific factors (such as profit margins and perceived risk). Analyzing the dyadic relationship between senders and receivers of referrals, we find that the CLV of referred customers depends substantially on the sender of the referral. The results show that demographic similarity between referral sender and receiver increases the referred customer value, especially if the referring customer has a high CLV.



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**Table 1**  
Sample descriptives

<i>Sample characteristics</i>	<i>SSV</i>	<i>Our Sample</i>
Industry	Banking	Banking
Country	Germany	Chile
Year	2006– 2008	2011– 2013
Observation period	33 months	27 months
Customer sample:		
• Referred customers	5.181	1.677
• Non-referred customers	4.633	1.971
• Referring customers	—	1.070
• Outliers	3.3%	9.9%
Reward	25 Euros	96 Euros <sup>a</sup>
Observed influence of referral reward program on:		
• Churn	–	–
• Customer lifetime value	+	–

Note: <sup>a</sup> Converted from Chilean Pesos (1 Euro = 753 CLP).

**Table 2**  
Impact of referral program

	<i>Differences in daily contribution margins</i>		<i>Differences in customer churn</i>		<i>Differences in observed customer value</i>		<i>Differences in customer lifetime value</i>	
	<i>SSV</i>	<i>This study<sup>†</sup></i>	<i>SSV</i>	<i>This study</i>	<i>SSV</i>	<i>This study<sup>†</sup></i>	<i>SSV</i>	<i>This study<sup>†</sup></i>
Referral program	0.076 <sup>***</sup> (0.010)	-107.312 <sup>***</sup> (37.016)	-0.198 <sup>***</sup> (0.059)	-0.195 <sup>**</sup> (0.093)	49.157 (7.096)	-37,415.04 <sup>***</sup> (8,203.48)	39.906 <sup>***</sup> (7.512)	-58,440.54 <sup>***</sup> (22,273.380)
Age	0.003 <sup>***</sup> (0.000)	6.234 <sup>***</sup> (2.118)	0.011 <sup>**</sup> (0.002)	0.005 (0.005)	1.879 (0.283)	1,552.239 <sup>***</sup> (469.447)	1.626 <sup>***</sup> (0.285)	4,354.45 <sup>***</sup> (1,274.603)
Female	-0.009 (0.010)	-158.015 <sup>***</sup> (36.972)	-0.034 (0.056)	0.003 (0.089)	-4.459 (6.902)	-37,678.21 <sup>***</sup> (8,193.791)	-3.376 (6.958)	-104,249.90 <sup>***</sup> (22,247.080)
January 2011	0.172 <sup>***</sup> (0.039)	-642.605 <sup>***</sup> (103.176)	-1.828 <sup>**</sup> (0.201)	-0.658 <sup>**</sup> (0.262)	228.228 (31.589)	-6,333.752 (22,882.62)	247.960 <sup>***</sup> (31.666)	-206,451.60 <sup>***</sup> (62,128.920)
February 2011	0.063 <sup>*</sup> (0.031)	-536.241 <sup>***</sup> (114.452)	-1.365 <sup>**</sup> (0.160)	-0.525 <sup>*</sup> (0.295)	127.706 (24.172)	19,061.96 (25,383.46)	133.591 <sup>***</sup> (24.411)	-120,072.70 <sup>*</sup> (68,919.000)
March 2011	0.089 <sup>**</sup> (0.026)	-488.967 <sup>***</sup> (86.162)	-1.155 <sup>**</sup> (0.126)	-0.121 (0.228)	136.393 (19.103)	23,993.01 (19,109.35)	135.755 <sup>***</sup> (19.280)	-101,667.20 <sup>*</sup> (51,884.070)
April 2011	0.084 <sup>**</sup> (0.027)	-424.764 <sup>***</sup> (86.747)	-1.215 <sup>**</sup> (0.140)	-0.219 (0.239)	124.793 (18.753)	32,793.69 <sup>*</sup> (19,239.14)	123.153 <sup>***</sup> (18.895)	-68,925.72 (52,236.460)
May 2011	0.082 <sup>**</sup> (0.025)	-325.015 <sup>***</sup> (78.692)	-1.529 <sup>**</sup> (0.150)	0.035 (0.213)	114.302 (16.791)	56,857.02 <sup>***</sup> (17,452.53)	119.426 <sup>***</sup> (16.909)	-35,642.64 (47,385.610)
June 2011	0.066 <sup>**</sup> (0.022)	-420.713 <sup>***</sup> (80.538)	-1.016 <sup>**</sup> (0.122)	0.013 (0.226)	91.090 (14.326)	6,928.355 (17,861.99)	92.643 <sup>***</sup> (14.475)	-110,136.64 <sup>**</sup> (48,497.330)
July 2011	0.062 <sup>**</sup> (0.021)	-276.847 <sup>***</sup> (83.751)	-1.026 <sup>**</sup> (0.122)	0.131 (0.225)	79.574 (12.717)	25,043.17 (18,574.52)	84.200 <sup>***</sup> (12.839)	-49,354.93 (50,431.950)
August 2011	0.059 <sup>**</sup> (0.020)	-240.953 <sup>***</sup> (77.335)	-0.841 <sup>**</sup> (0.119)	0.016 (0.223)	69.213 (12.111)	17,969.54 (17,136.13)	73.167 <sup>***</sup> (12.233)	-29,331.02 (46,526.550)
September 2011	0.077 <sup>**</sup> (0.022)	-305.006 <sup>***</sup> (84.981)	-0.679 <sup>**</sup> (0.126)	0.225 (0.232)	72.213 (13.199)	-7,909.078 (18,819.02)	76.352 <sup>***</sup> (13.335)	-94,106.96 <sup>*</sup> (51,095.780)
October 2011	0.037 (0.020)	-385.503 <sup>***</sup> (82.813)	-0.434 <sup>**</sup> (0.108)	0.455 <sup>**</sup> (0.219)	36.602 (11.133)	-32,379.57 <sup>*</sup> (18,366.55)	39.391 <sup>***</sup> (11.257)	-166,569.50 <sup>***</sup> (49,867.270)
November 2011	0.021 (0.019)	-284.172 <sup>***</sup> (82.616)	-0.217 <sup>*</sup> (0.105)	0.484 <sup>**</sup> (0.222)	19.252 (10.497)	-29,714.85 (18,298.73)	20.551 (10.632)	-124,388.50 <sup>**</sup> (49,683.140)
Intercept	0.154 <sup>***</sup> (0.040)	991.118 <sup>***</sup> (92.224)			66.250 (26.742)	140,972.3 <sup>***</sup> (20,439.3)	120.949 <sup>***</sup> (26.937)	466,331.80 <sup>***</sup> (55,495.020)
Observations	9,495	2,367	9,495	2,369	9,495	2,370	9,495	2,370
R <sup>2</sup>	0.025	0.036	—	—	0.040	0.032	0.040	0.020
Log-likelihood	—	—	-11,715.6	-3,501.1	—	—	—	—

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ . <sup>†</sup> Values in Chilean Pesos (1 Euro = 753 CLP). Standard errors in parentheses. The table only reports the results for the variables that are identical. The original models contained the additional variables “single”, “married”, “divorced”, and “widowed”. For interpretation of the monthly values, note that the focal banks are located in different hemispheres.

**Table 3**  
Results for customer lifetime value in various segments

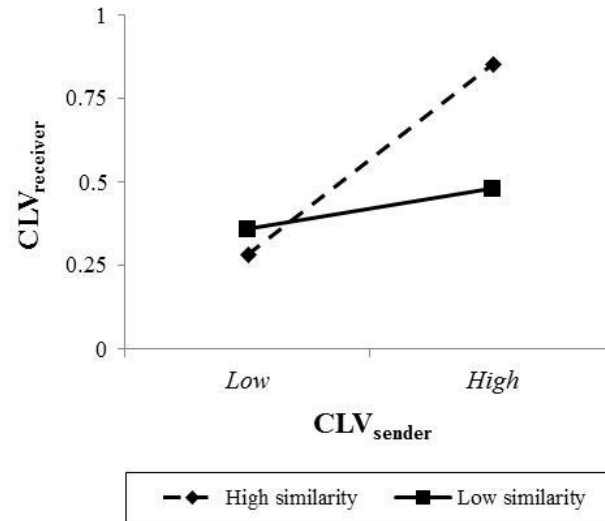
	<i>Observed customer value</i>		<i>Customer lifetime value</i>	
	<i>SSV</i>	<i>This study</i>	<i>SSV</i>	<i>This study</i>
High-margin customers	80.421** (27.768)	-101,363.0*** (21,503.88)	69.803* (28.004)	-196,264.40*** (41,279.80)
Low-margin customers	-1.146 (1.581)	303.409 (1,436.39)	-13.212*** (2.087)	12,033.67*** (2,479.83)
Male customers	51.679*** (10.600)	-34,259.22*** (11,481.01)	42.305*** (10.669)	-56,235.58* (32,178.47)
Female customers	47.437*** (9.604)	-40,649.86*** (11,708.22)	38.274*** (9.690)	-57,735.86* (30,332.04)
≤ 25 years of age	35.662** (12.914)	-68,917.64*** (21,538.41)	17.701 (12.945)	-136,549.20** (65,562.32)
26–35 years of age	101.975*** (14.908)	-33,209.35*** (10,331.43)	85.280*** (14.822)	-52,045.91* (27,461.80)
36–45 years of age	66.148*** (17.534)	-48,525.44** (20,391.39)	57.401** (17.707)	-72,472.83 (55,292.76)
46–55 years of age	62.763** (19.671)	-37,994.43 (34,891.55)	56.834** (19.827)	-87,232.87 (98,602.60)
56–65 years of age	9.433 (21.189)	93,161.72 (76,860.25)	5.122 (21.195)	322,940.90 (209,142.8)

Note: \* $p < 0.1$ ; \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table 4**  
Impact of demographic similarity on CLV

	<i>CLV<sub>receiver</sub></i>		
	<i>Beta</i>	<i>B</i>	<i>Std. Err.</i>
CLV <sub>sender</sub>	0.176***	0.093	0.018
Demographic similarity	0.062*	156,436.9	82,702.01
Demographic similarity x CLV <sub>sender</sub>	0.098***	0.228	0.077
Reward size	- 0.016	- 64.984	136.455
Tenure <sub>sender</sub>	- 0.053	- 599.817	390.746
Intercept		333,958.4	59,658.48
Observations		899	
Adj. R <sup>2</sup>		0.04	

Note: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .



**Fig. 1.** Interaction effects