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Social influence in the adoption of a B2B loyalty program: The role of elite status members

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ABSTRACT

This study investigates the role of elite loyalty program members in influencing other customers to adopt a hierarchical loyalty program (or HLP) in a business market. Drawing from the social psychology literature, the theoretical framework proposes that elite status members exert a disproportionate positive influence on neighboring non-members to adopt the HLP, and that this social influence has an inverse U-shaped effect. A unique dataset from a B2B loyalty program of a firm in the agribusiness industry with detailed information on members and marketing efforts from 1378 zip codes in Germany from 2008 to 2012 is used for the analysis. The study finds that, compared to members in lower status, elite status members have a stronger social influence on non-members. Importantly, as the proportion of elite status members increases, the adoption probability of non-members increases. However, as the fraction of elite status members increases beyond a certain point, the adoption probability of non-members decreases. Overall, the results of this study advances our understanding of loyalty programs in B2B markets, particularly with regard to the drivers of loyalty program adoption and the role played by social influence in driving new member enrollment.

1. Introduction

Unlike past decades, Business to Business (B2B) markets now face increasing competition, reduced demand, market globalization trends, and highly demanding and powerful customers (Lilien, 2016). For firms operating in these markets, gaining customer loyalty has never been as important (Accenture, 2015; Narayandas, 2005). Consequently, in recent years more B2B companies have implemented customer relationship management (CRM) practices (Lilien, 2016). A CRM practice that has gained significant popularity is loyalty programs (Breugelmans et al., 2015; Dorotic, Bijmolt, & Verhoef, 2012) and, increasingly more B2B companies are introducing these programs to build strong relationships with their best customers. For example, Ryder, a provider of transportation services, introduced a loyalty program in November 2014 that rewards customers for their spending with points that are redeemable for a variety of perks. Air BP, a supplier of aviation fuel, introduced a loyalty program in April 2013 which rewards customers for fuel purchased from the firm. Bestway launched a loyalty program which rewards retailers for store discipline, promotional compliance and total expenditures (Colloquy, 2015). However, similar to loyalty programs that operate in a B2C context,

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the mere introduction of the program does not guarantee its success (Dorotic, Verhoef, Fok, & Bijmolt, 2014; Henderson, Beck, & Palmatier, 2011). Rather, the success of a loyalty program begins with a significant number of customers adopting the program. Only then can firms obtain rich insights into their clients' preferences and behaviors. Firms can then improve the effectiveness of future marketing efforts and strengthen their relationships with their customers (Nunes & Drèze, 2006). Therefore, understanding the factors that influence customers' adoption of a loyalty program has become a critical research theme in the marketing discipline (Breugelmans et al., 2015; Dorotic et al., 2012).

While there exists substantial academic research in the field of loyalty programs, past studies have almost exclusively focused on the B2C context. Here, existing research has primarily reviewed the effectiveness and outcomes of such programs, as well as their underlying mechanisms such as 'points-pressure' and 'reward-behavior' effects (Dowling & Uncles, 1997; Kopalle, Sun, Neslin, Sun, & Swaminathan, 2012; Lewis, 2004; Liu, 2007; Nunes & Drèze, 2006; Reinartz, 2010; Sharp & Sharp, 1997). Consequently, the factors that influence customers to adopt a loyalty program in the early years of the program have remained relatively underexplored, and even more so in the B2B context. In this study, we attempt to bridge this significant gap in the literature by investigating customers' adoption of a B2B loyalty program and specifically focusing on the role of 'social influence'. Specifically, the study is conducted in the context of hierarchical loyalty programs (HLPs), also known as customer tier programs (Blattberg, Kim, & Neslin, 2008). HLPs bestow an elevated status to select customers who meet predefined requirements (Henderson et al., 2011). In particular, we investigate whether the time taken by a customer to adopt the HLP is affected by the social influence of current program members, particularly that of members with the highest status in the loyalty program (i.e. elite status members).

Some recent studies have investigated the adoption of loyalty programs in B2C contexts. However, they have focused on factors such as individuals' attitudes and perceptions of program benefits, costs and characteristics (Demoulin & Zidda, 2009; Leenheer, Van Heerde, Bijmolt, & Smidts, 2007) and customers' purchase history (Meyer-Waarden & Benavent, 2009). A few others have focused on customers' intentions to adopt the program (De Wulf & Odekerken-Schröder, 2003). Surprisingly, studies that investigate social influence as a driver of loyalty program adoption seem nonexistent. A notable exception is the work conducted by Allaway, Berkowitz, and D'Souza (2003), who study how the spatial diffusion process of a retailer's loyalty program is influenced by a firm's marketing efforts and number of previous adopters. However, this study is conducted in a B2C context and it does not directly address the social influence of members with different status. Prior studies have emphasized the importance of status for business customers (Park & Westphal, 2013), and their susceptibility to social influence (Iyengar, Van den Bulte, & Lee, 2015; Iyengar, Van den Bulte, & Valente, 2011; Manchanda, Xie, & Youn, 2008). Therefore, understanding social effects can shed new light on the adoption process of a loyalty program by business customers, beyond the impact of other variables such as targeted marketing activities and demographics.

Our study makes at least three important contributions to ongoing work on loyalty programs. First, this study establishes the significant role of top-tier members in the acquisition of new members to a B2B loyalty program. Thus, our study advances prior research in loyalty programs that focuses exclusively on the effects of the tier component of HLPs on current program members (Henderson et al., 2011; Kopalle et al., 2012; Wang, Lewis, Cryder, & Sprigg, 2016). Our study complements these studies by demonstrating that top-tier members also play a vital role in helping the loyalty program get traction and acquire new members. Second, our study demonstrates that the social influence of top-tier members has a non-linear, inverse U-shaped effect on the time taken by potential members to enroll in the program. Specifically, as the proportion or fraction of top-tier members in the vicinity of a non-member increases, the hazard of adopting the program in the first few years of the program increases but only up to a point. As the fraction of top-tier members in the vicinity increase beyond a certain point, the hazard of adopting the program decreases. This finding advances the notion that high status groups that have a limited size are more influential (Drèze & Nunes, 2009). For the HLP that is the focus of this study, we are able to derive the optimal proportion of high status members that maximizes the effectiveness of social influence on adoption. Third, and at a more general level, our study contributes to a better understanding of the factors that influence the adoption of a loyalty program by business customers. After considering a number of relevant variables such as targeted marketing activities, sales efforts, customer demographics, social contagion and spatial differences, social influence emerges as a central driver in the adoption of a loyalty program. A key aspect of this study is that it analyzes the social effects of different groups of loyalty program members, e.g. elite vs. non-elite status members; cumulative vs. recent adopters, and reveals their different influences on the behavior of others (Iyengar et al., 2011; Peres, Muller, & Mahajan, 2010). These results can help firms understand how social effects influence the adoption of their loyalty programs. For instance, the results suggest that if the objective of a loyalty program is to drive new member enrollment, the program could focus on providing top-tier status members exclusive privileges and communicate these benefits to non-members. The study also finds that sales teams can play an important role in driving adoptions by business customers.

2. Theoretical framework

A loyalty program is an integrated system of structured and customized marketing actions designed to build customer loyalty among profitable customers (Dowling & Uncles, 1997). These programs offer their members a wide array of hard benefits and soft benefits (Drèze & Nunes, 2009). Hard benefits refer to rewards, such as gifts, discounts, free goods, or upgrades. Soft benefits refer to recognition, and provide special treatment benefits and privileges to selected customers (Schumann, Wünderlich, & Evanschitzky, 2014). Hitherto, most studies have focused on investigating loyalty programs that offer hard benefits (Leenheer et al., 2007; Lewis, 2004; Liu, 2007; Verhoef, 2003). However, socially relevant stimuli are often believed to be stronger tools for motivating behavior than purely economic stimuli (Henderson et al., 2011).

Hierarchical loyalty programs (HLPs) attempt to leverage this belief by conferring the highest or elite status to select customers. Status, or the position of an individual in a certain group awarded by others, is widely recognized as a strong motivator of human behavior (Frank, 1985; McFerran & Argo, 2014) and perhaps even a "universal human motive" (Anderson, John, Keltner, & Kring, 2001). Elevated status in particular is often an object of desire (McFerran & Argo, 2014), and hence a powerful driver of human behavior across cultures: "*humans are drawn to status-based systems and charmed by opportunities to elevate their status*" (Henderson, Beck, and Palmatier 2011, p. 259). This applies not only to individual customers, but also to businesses (i.e. B2B) who clamor for the most prestigious and privileged positions in a corporate relationship (Park & Westphal, 2013). Building on this evidence, HLPs stratify the customer base into a hierarchical set of status tiers using status-laden precious metals such as platinum, gold, and silver as labels for tiers to reinforce and make visible the notion of a hierarchy among the firm's customers (Drèze & Nunes, 2009). It is important to note that status in the context of HLPs is signaled by providing special benefits to select customers (i.e. rights and privileges such as lower waiting times, access to VIP areas or special events, or personal assistance by courteous personnel), and these benefits carry prestige, power, and entitlement (Drèze & Nunes, 2009). These two components, the benefits received and the prestige that accompany these benefits, are therefore intertwined in the notion of status in HLPs and as such cannot be studied separately. In this study, we investigate the role of status, as defined in the context of HLPs, in driving new members to these programs.

In particular, we focus on the role played by social influence in the adoption of a HLP by business customers. Given the susceptibility of business customers to social influence (Iyengar et al., 2015; Manchanda et al., 2008), social effects are expected to be an important driver in the adoption of a loyalty program. Previous research suggests that social influence drives adoptions through the reduction of perceived risk and through information transfer among individuals (Van den Bulte & Lilien, 2001). Compared with a product innovation, which generally provides relative novel features and characteristics, a loyalty program is a marketing instrument that poses little risk to customers. For instance, customers today participate in many loyalty programs and enrollment in most programs is free of cost. However, HLPs stratify customers by assigning them to different status categories and business customers place importance on status in an inter-firm relationship (Park & Westphal, 2013). Therefore we argue that social influence will impact the adoption of the HLP, but operate in a different way compared to adoption of product innovations: by promoting social comparisons among customers belonging to different status tiers (Festinger, 1954). Social comparisons emerge as a result of both status differences (i.e. customers have a natural drive to elevate their status) as well as differences in the special treatment benefits received (i.e. members who belong to higher status categories receive more exclusive benefits).[1] Thus, as we delineate below, we argue that the adoption of a HLP is affected by the social influence exerted by current members. The magnitude of this influence will differ depending on the status they hold in the program, with elite status members exerting the strongest influence. Specifically, we posit that the time taken by business customers to join the HLP is strongly influenced by the number (or fraction) of top-tier members who reside in their vicinity, and that this effect has an inverse U-shaped form.

To provide the theoretical rationale for our arguments, we first review the relevant literature on social influence. Then, we use arguments from social psychology to understand the way in which potential adopters are influenced by top-tier members.

2.1. Social influence and status

Studies on product diffusion tend to emphasize the role of social effects by noting that adoption behavior is affected by the "*exposure to other actor's knowledge, attitude, or behavior*" (Van den Bulte & Lilien, 2001, p. 1410). Bass (1969) conceptualized social contagion as the 'imitation effect' and ascribed it to the growing number of adopters. Many studies since have demonstrated the importance of social effects (Bell & Song, 2007; Choi, Hui, & Bell, 2010), even after controlling for other important drivers of adoption such as marketing activities (Manchanda et al., 2008; Risselada, Verhoef, & Bijmolt, 2014). At the same time, this stream of research makes an important point that not all customers are equally influential as some wield a disproportionate influence on others' behaviors (Iyengar et al., 2011).

One factor that is particularly relevant in explaining the extent of influence is status (Iyengar et al., 2015; Peres et al., 2010), with high status subjects expected to exert a stronger influence on others. This influence can result from both sharing opinions (i.e. communications) and observational learning (Chen, Wang, & Xie, 2011). As noted by Hu and Van den Bulte (2014), those who possess high status tend to receive more attention than those with lower status. As a result, their behavior becomes more salient and the products or services they adopt and use are more likely to be noticed (i.e. stronger observational influence). With regard to communications, some studies suggest that customers with high status tend to provide more advice and information to others (Lampel & Bhalla, 2007). Their greater experience and knowledge of the firm's products and services make them more capable of providing accurate and detailed information (Iyengar et al., 2011). In addition, an elevated status implies higher social esteem and respect, which in turn increases the credibility of their communications. Thus, status can represent an important factor in explaining the differences in the extent of influence of members in a loyalty program on others.

[1] While we note that social comparisons will be the result of differences in both status and special treatment benefits among non-members and elite status members, given the interrelated nature of these two elements (high status leads to more privileges and special treatment benefits), their effects cannot be separated empirically. Future studies on their relative impact on loyalty program adoption and effectiveness will be welcome. We thank an anonymous reviewer for her/his insightful suggestions in this regard.

2.2. The social influence of top-tier members on loyalty program adoption

In addition to the reasons discussed above, given the stratification of the customer base in different status categories, the adoption of a HLP by business customers is expected to be affected by social influence through promoting comparisons among non-members and current elevated status members. Thus, social comparison theory provides the fundamental theoretical basis to understand how potential adopters are influenced by top-tier members. According to this theory, individuals have an intrinsic motivation to evaluate their abilities by engaging in comparisons with others (Festinger, 1954) and these comparisons have a considerable impact on their behavior (Smeesters, Mussweiler, & Mandel, 2010). While social comparisons can be performed with people who are either in a superior (upward) or inferior (downward) position, Park and Westphal (2013) observe that upward social comparisons are the norm rather than the exception in social contexts which are characterized by competition for the most prestigious and privileged positions.

Festinger (1954) suggests that the pressure to alleviate such discrepancies varies with the importance of the attribute that is being compared, the attractiveness of the group which serves as the comparison standard, and the size (distance) of the discrepancy. With regard to the importance of the attribute being compared, the value placed on achieving an elite status is very strong, especially in Western culture. Consequently, subjects who conduct status comparisons and fall short are motivated to quickly achieve compatibility with the superior group (Festinger, 1954, p. 124). This reasoning is consistent with evidence that some people emulate the consumption behavior of their aspirational groups (Nunes, Drèze, & Han, 2011). An elite status is also extremely attractive as members with such status are often provided exclusive benefits, enjoy several privileges, and receive unprecedented levels of personal attention (Wagner, Hennig-Thurau, & Rudolph, 2009). The group of individuals who occupy the elite status positions are often referred to as the "*inner circle*" (Park & Westphal, 2013, p. 546). As a result, potential adopters perceive the elite status groups as highly desirable. With regard to the size of the discrepancy, social comparison theory posits that those who are distant from the comparison group will show a greater tendency to change their behavior to reduce the discrepancy as soon as possible. Therefore, the gap between the current standing of potential adopters (who are not members yet and hence do not enjoy any benefit) and that of elite status members (which are at the top of the pyramid) will encourage non-members to take appropriate measures (i.e. adoption of the HLP) to reduce the discrepancy in a short period of time. Overall, these arguments suggest that exposure to elite status loyalty program members will influence non-members to speed up adoption of the loyalty program.

At the same time, we argue that the number of people who belong to the exclusive high status group can also sway the extent of influence of elite status members. People have an inherent drive to be different and hence experience negative emotions when they feel similar to many others (Berger & Heath, 2007). Research on customer perceptions of exclusivity suggests that the desirability of an object, situation or position in society increases with its scarcity (Brock, 1968; Gierl & Huettl, 2010; Verhallen & Robben, 1994). Drèze and Nunes (2009) demonstrate that the attractiveness of an elite status group decreases with an increasing number of individuals who are granted elite status. Henderson et al. (2011) also note that consumers prefer being conferred high status when the elite group is small. This is because smaller groups are associated with higher exclusiveness and distinctiveness, and hence more desirable (Pickett, Silver, & Brewer, 2002). Consequently, these arguments suggest that exposure to a very large number of elite status members would have a detrimental effect on non-members' decision to join the loyalty program.

Overall, our theoretical framework indicates that being exposed to members awarded an elite status will have a disproportionate effect on non-members' decision to enroll in the HLP since elite status members are more influential, and upward social comparisons motivate non-members to alleviate this discrepancy. However, we also expect the effect of social influence of high status members on potential adopters to be inverse U-shaped: while exposure to a small number of elite status members influences non-members to adopt the loyalty program, exposure to a large number of elite status members has the opposite effect. We expect these effects to be present even after controlling for other drivers of adoption, such as the social effects of other members (e.g., number of previous program adopters, members in lower status tiers), targeted marketing activities, and individual characteristics (Van den Bulte & Lilien, 2001). We summarize our expectations in the following hypothesis:

H1. *In a HLP the social influence exerted by elite-status members on non-members to adopt the program follows an inverse U shape: an increase in the number of elite-status members to whom a non-member is exposed elevates the likelihood of adopting the program up to a point, from which exposure to additional elite-status members leads to a decrease in the likelihood of adoption.*

3. Research design

3.1. Data

This study was conducted with the assistance of a firm which is a global player in the agriculture industry. The collaborating company specializes in providing solutions to farmers to improve agricultural productivity, and sells a variety of products and services that include, among others, pesticides and seed-growth solutions. In early 2008, the firm introduced a hierarchical loyalty program (HLP) specifically for farmers who were already their customers in Germany. A key motivation for rolling out the program was to gain valuable customer insights since all products were sold through intermediaries such as wholesalers and agricultural traders. An important objective of the firm was also to strengthen customer relationships and increase loyalty (i.e. customers' share of wallet). In this study, we focus on HLP adoption by existing customers of the firm in the southern part of Germany i.e., the state of Bavaria. Comparable to Texas in the US, Bavaria is characterized by a strong feeling of belonging and independence. Different from adjacent states such as Hesse or Saxony, the state of Bavaria can be considered a rather homogenous state within Germany.

While the database provides information for 7494 farmers who joined the HLP over the duration of our data i.e., from 2008 to 2012, the firm began to confer its members a status only at the end of 2008. We therefore discard observations pertaining to 2491 farmers who joined in the first year. The sample for our analyses consists of 5003 farmers from 1378 zip codes who adopted the HLP from 2009 to 2012, representing around 22% of the firm's customers across Germany. As a side note, about 60% of all farms in Germany (measured by farm size) are registered as members in this program. In other words, these registered members can be considered a reliable representation of all farmers in this country.

Enrollment in the program for farmers is free and voluntary. In other words, it requires an activation by the farmer. At the end of each calendar year, the program assigns farmers enrolled in the program to one of four status tiers: standard, silver, gold or platinum. This is done as follows. Based on a variety of factors such as farm size, types of crops, weather patterns, insect and pest patterns in different geographies etc., the company predicts the total fertilizers and pesticides category requirements per farm. The company has been a prominent player in this industry for decades and has a fairly large and widespread sales force which monitors and updates this information periodically. Since purchases by members of the program are electronically recorded, the firm can compute each customer's annual purchase amount from the firm. Consequently, the firm can now compute the share of wallet for each member.

Customers are assigned their status contingent on them meeting certain benchmarks with respect to share of wallet in the calendar year (t), and will hold this status during the following year (t+1) (the benchmarks used by the firm to assign members to different tiers were not altered during the study period). Therefore, while the hard benefits mainly depend on purchase volume, tier membership is not related to farm size or sales volume, but to loyalty to the company only as measured by share of wallet. This also implies that a small farm can belong to the platinum tier if it buys almost all the products needed from the focal firm, while a big farm can be a standard member because only a small fraction of its requirements is purchased from the focal firm (although it may represent a substantial sales volume in absolute terms). For instance, in our data we find that while the average farm size of a platinum-tier farmer is 100.28 acres (SD = 197.14, Min = 1, Max = 3513), the average farm size of farmers in other tiers is 135.68 acres (SD = 338.36, Min = 1, Max = 5270). The figures reveal that both small and large farm owners can attain platinum-status in this loyalty program.

The program offers both hard and soft benefits. With regard to hard benefits, farmers obtain points by purchasing products and services from the company that can be later redeemed for a variety of rewards ranging from TV sets, to camping tents, to agricultural tools. Thus, the number of points obtained primarily depends on sales volume. In addition, silver status members get an additional 10% bonus points at the end of the year, while gold status members receive 20%, and elite platinum status members receive 50% bonus points. Standard members do not receive any bonus points. In addition, only platinum status members receive VIP privileges such as free entrance to trade fairs, guidance on professional development and invitations to industry events. Hence the benefits offered correspond to status. More importantly, the benefits offered, especially soft ones, increase exponentially from the bottom tier to the highest elite tier.

Since the main objective of this study is to examine the social influence of elite status members on adoption, we focus on members who have been accorded 'platinum-status' and are hence in the top tier of the HLP. These members receive special privileges in the form of special receptions at the firm, invitations to restricted areas in agricultural trade fairs, and extra bonuses to obtain additional points to be exchanged by rewards, which are intended to signify prestige, power and entitlement (i.e. an elite status). In our data, while 806 farmers attained platinum-status at the end of the first year of the program, the number of platinum-status farmers in 2012 had steadily grown to 2575 farmers. The influence of elite status (platinum) members on non-members can be strong, especially among farmers living in adjacent regions, as they frequently attend agricultural trade fairs (where non-members can see the special privileges that platinum members receive from the company in restricted VIP areas), or meet regularly in conventions or agricultural meetings in their region.

3.2. Study variables

The annual HLP adoption rate in our data is presented in Table 1. About 60% of the farmers in our sample adopted the program in 2009 and 2010 and the remaining 40% in the next two years. In fact, adoptions in the last year of our data constituted just around 17% of the entire loyalty program customer base in this region. The steep drop in the adoption rate over time suggests

Table 1
Annual Hierarchical Loyalty Program (HLP) Adoption Rate.

Year	HLP adoptions (Freq)	HLP adoptions (%)	Fraction of platinum status members in the vicinity
2009	1637	32%	34.87%
2010	1381	28%	42.71%
2011	1144	23%	40.52%
2012	841	17%	42.67%
Grand total	5003	100%	

that the HLP adoption process in our data follows a concave rather than S-shaped functional form. Given that loyalty programs pose low risk to the potential adopters, as noted before, this is a common pattern of diffusion for such a context (e.g. Allaway et al., 2003). The reducing number of adoptions in the latter years of the program alleviates concerns related to right truncation, and robustness tests carried out during the estimation process further validate this assumption. Below, we explain in detail the operationalization of the independent variables in the study.

Social influence of elite (platinum-status) members. Since we are examining the effect of 'elevated status', we specifically consider whether the time taken by a farmer to adopt the HLP is influenced by the proportion or fraction of platinum-status farmers who live in the immediate neighborhood. We operationalize the social influence of elite status members using information provided by the firm as follows. For each farmer who is already a customer of the firm, we have information on whether or not they are enrolled in the HLP and if so, their status each year. For each farmer i who has yet to enroll in the HLP, we noted the 5-digit zip code in which he/she resides. In our data, farmers are spread across 2319 zip codes at the 5-digit level. Our measure of social influence for farmer i was then calculated as the fraction of the total number of platinum-status farmers who reside in the same zip code and also in adjacent zip codes i.e., 5-digit zip codes that share an edge or border. Table 1 suggests that the average fraction of platinum status farmers has increased slightly since the launch of the program. The descriptive statistics (see Table 2) suggest that an average of 39.64% farmers with platinum-status reside in the vicinity of a farmer yet to enroll in the HLP. Here, it is important to note that our measure of social influence varies over time within zip codes. For instance, the fraction of platinum-status farmers in zip code 84069 (84082) and vicinity changes from 28.94% (43.24%) in 2009 to 35.29% (35.71%) in 2010 to 36.84% (38.08%) in 2011 and to 28.57% (50%) in 2012. The measure of social influence varies over time in other zip codes too. We include both the linear and quadratic term of this measure in the analysis to capture the expected nonlinear effect of social influence, as discussed in the theoretical section.

Social contagion. In addition to examining the effect of elite status members, we consider whether the time taken by a farmer to adopt the HLP is influenced by the number of previous adopters (Allaway et al., 2003). Recent studies (e.g., Risselada et al., 2014) have attempted to make a further distinction between the effect of the number of recent adopters (e.g., members who enrolled in the past year) and that of early adopters (e.g., number of individuals who adopted the product or service before recent adopters). Risselada et al. (2014) clarify that the two measures capture two very different theoretical processes of contagion. Early adopters are generally heavy-users and tend to provide critical evaluations and opinions of the product or service (Van Eck, Jager, & Leeflang, 2011). On the other hand, recent adopters are contagious because they are generally more enthusiastic about the product or service offering than customers who have experienced the product or service for a longer time (Iyengar et al., 2011).

To determine if the social effect of recent adopters differs from that of early adopters, we include two variables in the model. The first variable is the total number of farmers from a certain zip code who adopted the HLP in the year prior to that in which a particular farmer from that zip code enrolled. We call this variable 'recent adopters'. The second variable is the total number of farmers from a certain zip code who adopted the HLP until two years prior to which a farmer from that zip code enrolled. We term this measure as 'early adopters'. The two measures of social contagion vary for different geographies and also over time. Since the loyalty program was introduced only in 2008, the value of 'early adopters' in 2009 is 0. The descriptive statistics for both variables are also in Table 2.

Effect of rewards. Loyalty programs frequently reward their members, especially those with high status, with points that can be redeemed for tangible rewards or 'hard benefits'. In order to disentangle the effects of these rewards or hard benefits from the softer aspect of social influence of status, we analyzed a model that included the number of rewards redeemed by farmers in the vicinity of a potential adopter. Since this number of rewards redeemed across our sample was highly skewed, we carried out a logarithmic transformation of the variable. A positive effect would denote that tangible rewards increase the hazard of adoption. Alternatively, a negative effect would suggest that rewards decrease the hazard of adoption due to high perceived effort to attain

Table 2
Descriptive Statistics ($N = 5003$).

Variable	Mean	Min	Max	S.D.
Individual characteristics				
Farm size	91.22	1.00	3129.00	139.65
Gender (male = 1, female = 0)	0.97	0.00	1.00	0.17
Family (joint family = 1, nuclear = 0)	0.01	0.00	1.00	0.09
Targeted firm activities				
Sales calls	0.73	0.00	70.00	3.30
Marketing activities	0.04	0.00	7.00	0.37
Calls to service center	0.02	0.00	3.00	0.17
Social effects				
Early adopters	3.01	0.00	36.00	4.57
Recent adopters	2.11	0.00	22.00	2.56
Platinum-status	0.40	0.00	1.00	0.21
Gold-status	0.08	0.00	1.00	0.10
Silver-status	0.10	0.00	1.00	0.12
Rewards redeemed	1.53	0.00	126.00	6.21

them (Drèze & Nunes, 2011). An insignificant effect would suggest that hard benefits carry little importance for these customers and do not influence the hazard of adoption.

Control variables. Consistent with previous research (Manchanda et al., 2008; Van den Bulte & Lilien, 2001), we control for various other factors that could influence the time taken to adopt the HLP. We classify these factors into two broad categories – targeted firm activities and individual characteristics. With respect to targeted firm efforts, we include three variables at the individual customer level to account for activities undertaken by the sales, marketing and service center teams. First, we include the total number of visits made by the firm's sales team until the year prior to which the customer adopts the loyalty program. We also include the total number of outbound marketing communications sent by the firm to each customer until the year prior to which the customer adopts the program. Marketing communications typically involve the firm sending out emails to customers and meeting customers' service requests. Finally, we also include the total number of complaints a customer has made to the firm's service center until the year prior to which the customer adopts the loyalty program. We include this variable as the firm has dedicated resources to understand the needs of its customers better and gain potentially valuable feedback.

For all these three variables, we include firm efforts until the year prior to adoption because with annual data it is quite possible that say, sales visits were made after the customer adopted the HLP early in the year. However, it is quite possible that these efforts are endogenous i.e., the firm targets customers who are more likely to adopt the program. We therefore use a two-stage instrumental variable (IV) approach as described in Berry (1994) and Berry, Levinsohn, and Pakes (1995) to tackle these concerns in all the estimated models. This approach is appropriate for dealing with endogeneity in a market setting (Louviere et al., 2005). Specifically, we use the effort exerted by the firm in other geographies as an instrument. For example, for farmer i who adopts the program in year t, we use the number of sales calls to farmers in other geographies until year $t-1$ as an instrumental variable. In the first stage, we carry out a linear regression (OLS) of the number of sales calls for farmer i in year $t-1$ on this instrument while controlling for other variables in the model. In the second stage, we use the predicted value of this endogenous variable as an explanatory variable in the hazard model. The underlying notion behind this approach is that the efforts in other geographies are correlated with the endogenous variable but not with the focal dependent variable which is the time taken to adopt the loyalty program. In other words, the instrument is said to meet the exclusion restrictions and the model is 'just identified'. In our study, it is reasonable to assume that the time taken by a farmer to adopt the program is not influenced by the firm's efforts in other geographies. Additionally, the results from the first stage do indicate a strong positive effect of the instrumental variable i.e., the instrument is not weak. We use a similar approach to control for the endogenous nature of marketing efforts and calls to the service center. The results of the first stage regression are reported in Table 3. The F-statistic model for all the models are above heuristic thresholds ($F > 10$) and the t-statistics for the instrumental variables are high, thus dispelling concerns on issues related to the use of weak instruments.

With respect to individual characteristics, we include variables pertaining to the size of the farm, the gender of the person at the helm of the farm and whether the farm has an extended family or a nuclear family. Since the measure for farm size is highly skewed (Table 2), we include the log-transformed value of farm size in the model. Gender is coded as 1 for male and 0 for female. And farmers with an extended family are coded as 1 and those with a nuclear family as 0. Around 97% of farms have men at the helm and around 1% of farms have an extended family. The inclusion of these variables enables us to control for observed heterogeneity, as there could be potential differences in the attractiveness of the program and of earning status among farms that differ in their size (e.g. larger farms may have a stronger drive to show status, in line with their higher business activity) or in the gender of the person at the helm (e.g. men and women tend to have different propensities to attain status – see Anderson et al., 2001). The descriptive statistics for all the variables are reported in Table 2.

3.3. Estimation methodology

Survival or duration models have been frequently used in prior management and marketing studies. For instance, such models have been used to examine the evolution of firms in the telecommunications industry (Williams & Mitchell, 2004), survival of new and radical innovations in the marketplace (Min, Kalwani, & Robinson, 2006), household-purchase timing (Jain & Vilcassim, 1991), survival of music albums (Bhattacharjee, Gopal, Lertwachara, Marsden, & Telang, 2007) and adoption of high-technology products (Risselada et al., 2014). Survival models have therefore been used to analyze various units of analyses ranging from firms to products to customers. At the same time, the availability of scanner data at the zip code level has also made it possible for academics to study the spatial patterns of consumer behavior. While distance and lattice-based approaches have been used to examine the effects of proximity, many studies (e.g., Bollinger & Gillingham, 2012; Choi et al., 2010; Nair, Manchanda, & Bhatia, 2010) include a random effect to represent different clusters which are assumed to be independent. However, in this study, we account for the fact

Table 3
Results from First-Stage Model.

Dependent variable	Model statistics		Parameter statistics for IV	
	F-statistic	*p*-value	t-statistic	*p*-value
Sales calls	17.94	0.00	6.88	0.00
Marketing activities	16.90	0.00	5.83	0.00
Calls to service center	10.98	0.00	5.36	0.00

IV: Instrumental Variable.

that clusters close to each other may be similar in magnitude. Below, we explain the model development and estimation methodology.

In order to examine the effects of the independent variables on the time taken to adopt the HLP, we utilize the well-known proportional hazard model which takes the form (Cameron & Trivedi, 2005)

$$h\left(t_{ij}|x_{ij}\right) = h_0\left(t_{ij}\right)\phi\left(x_{ij},\beta\right) \tag{1}$$

where the baseline hazard rate $h_0(t_{ij})$ is a function of the time t taken by farmer j in zip code i to adopt the loyalty program, and $\phi(x_{ij},\beta)$ is a function of p vector of independent variables with a corresponding vector of coefficients β that includes the intercept termβ_0. A common function chosen for $\phi(x_{ij},\beta)$ is the exponential form $\exp(\beta^T x_{ij})$ since it ensures that $\phi(x_{ij},\beta) > 0$. Therefore, the hazards $h(t_{ij};x_{ij})$ can be expressed as

$$h\left(t_{ij}|x_{ij}\right) = h_0\left(t_{ij}\right)\ \exp\left(\beta^T x_{ij}\right) \tag{2}$$

We assume a Weibull distribution for the baseline hazard since it is more flexible than other parametric distributions such as gamma or lognormal and also not as restrictive as the exponential form. Since the Weibull hazard takes the form $h_0(t_{ij}) = \rho t_{ij}^{\rho-1}$, we obtain

$$h\left(t_{ij}|x_{ij}\right) = \rho t_{ij}^{\rho-1}\ \exp\left(\beta^T x_{ij}\right) \tag{3}$$

Since we are examining adoptions across an extensive geographical region, it is important to control for stratum-specific effects or *frailties*. Such effects could exist for various reasons such as the type of crops grown in different sub-regions, weather and soil conditions exclusive to certain sub-regions or the capabilities and reputation of the firm in different sub-regions. These factors could play an important role in influencing the time taken by a farmer in a certain sub-region to adopt the loyalty program. Since we lack information on these factors, we control for these unobserved factors using a fixed effects approach. However, it would be tedious to estimate and interpret the effects specific to 1378 5-digit zip codes that are present in our data. Therefore, in the interest of parsimony, we estimate the stratum-specific effects for twenty zip codes at the 2-digit level i.e., using the first two digits of the 5-digit zip code, by including the term W_z, z = 1 to 20. The above Eq. 3 can now be written as

$$h\left(t_{ij}|x_{ij}\right) = \rho t_{ij}^{\rho-1}\ \exp\left(\beta^T x_{ij} + W_z\right) \tag{4}$$

It is also possible that the frailties corresponding to strata in close proximity are correlated to each other. Therefore, we consider the conditional autoregressive (CAR) structure which incorporates information on adjacent regions (Banerjee, Wall, & Carlin, 2003). In this approach, we use the relative geographic positioning of various zip codes at the 2-digit level and specifically account for which zip codes are adjacent to each other such that the frailties $W|\lambda \sim CAR(\lambda)$ (Banerjee et al., 2003). The CAR structure of this model has a joint distribution proportional to $\lambda^{I/2}\ \exp[-\frac{\lambda}{2}\sum_{z\ adj\ z'}(W_z - W_{z'})^2] \propto \lambda^{I/2}\ \exp[-\frac{\lambda}{2}\sum_{z=1}^{20} m_z W_z (W_z - \overline{W_z})^2]$ (Bernardinelli & Montomoli, 1992), where z adj z′ denotes that regions z and z' are adjacent, $\overline{W_z}$is the average of the stratum-specific effects adjacent to$W_{z' \neq z}$, and m_z is the number of adjacencies. We constrain $\sum_{z=1}^{20} W_z = 0$ so that the intercept term β_0 can be identified. The stratum-specific effects have a distribution$W_z \mid W_{z' \neq z} \sim N(\overline{W_z}, 1/(\lambda m_z))$ (Banerjee et al., 2003). We estimate the model following a Bayesian approach. The joint posterior distribution can be written as

$$p(\beta, \mathbf{W}, \rho, \lambda | \mathbf{t}, \mathbf{x}, \gamma) \propto L(\beta, \mathbf{W}, \rho; \mathbf{t}, \mathbf{x}, \gamma) p(\mathbf{W}|\lambda) p(\beta) p(\rho) p(\lambda) \tag{5}$$

where $\mathbf{t} = \{t_{ij}\}$ is a collection of adoption times, $\mathbf{x} = \{\mathbf{x}_{ij}\}$ is a matrix consisting of p vectors of independent variables, $\gamma = \{\gamma_{ij}\}$ is the collection of adoption indicators for all farmers in all zip codes, $L()$ is the Weibull likelihood, $p(\mathbf{W}|\lambda)$ is the joint distribution of the stratum-specific effects and the remaining terms are the prior distributions. Given the Weibull distribution for the baseline hazard, the likelihood can be expressed as

$$L(\beta, \mathbf{W}, \rho; \mathbf{t}, \mathbf{x}, \gamma) \propto \prod_{z=1}^{Z} \prod_{j=1}^{n_i} \left\{\rho t_{ij}^{\rho-1}\ \exp\left(\beta^T x_{ij} + W_z\right)\right\}^{\gamma_{ij}}\ \exp\left\{-t_{ij}^{\rho}\ \exp\left(\beta^T x_{ij} + W_z\right)\right\} \tag{6}$$

Regarding the prior distributions for the parametersβ,ρ and λ, we specify a normal distribution for β and a gamma distribution forρ and λ. Our model therefore estimates not only the effects of social influence in the immediate vicinity of a farmer at the 5-digit zip code level but also 'unobserved' spatial effects that may exist at a larger 2-digit zip code geographic-market level. The parameters in the model were updated by using the Gibbs sampler (Gelfand & Smith, 1990). We used the first 10,000 iterations as burn-in and the next 50,000 iterations for the posterior analysis.

4. Results

4.1. Model fit

We used the approach suggested by Spiegelhalter, Best, Carlin, and Van Der Linde (2002) to compare nested models within a Bayesian framework. Specifically, we used the Deviance Information Criterion (DIC) which is similar to other penalized likelihood criteria such as AIC or BIC used in traditional models. The DIC is defined as the sum of the expected deviance $\overline{D}$ and the effective number of parameters p_D in the model. Smaller values of DIC are desirable since a smaller $\overline{D}$ suggests a better fit and a smaller value of p_D is indicative of a parsimonious model. Similar to other information criteria such as the AIC, a DIC value by itself is meaningless and only differences in DIC values across models are meaningful.

The DIC value for a model with only frailties modeled as fixed effects is 14,440. The DIC value for a model with only frailties modeled with a CAR has a marginally lower DIC value of 14,420. A model with covariates and frailties modeled as fixed effects has a DIC value of 11,650. Finally, a model which includes covariates and frailties modeled using a CAR structure has a much lower DIC value of 11,610. The final model therefore seems to represents the best balance of explanatory power and parsimony. We therefore report and discuss the results for this model in the next section. At the same time, it is important to note that the major findings for our covariates remain unchanged irrespective of whether frailties are modeled with a CAR structure or as fixed effects (results reported in the robustness checks).

4.2. Estimation results

The posterior 2.5, 50 and 97.5 percentiles for the parameters estimated from the benchmark model are reported in Table 4. We can observe for all the parameters estimated that there is very little difference between the mean and the 50 percentile (median) values, suggesting convergence and that the posteriors follow a symmetric distribution. We consider coefficients whose 95% confidence interval does not include zero as significant. In a hazard model, positive (negative) coefficients suggest that the hazard rate as a component of x_{ij} increases (decreases). In other words, if $\beta_j>0$ then a farmer takes less time to adopt the HLP as the corresponding x_{ij} increases and if $\beta_j<0$ then a farmer takes more time to adopt the HLP as the corresponding x_{ij} increases. The shape parameter (ρ) of the hazard function has a value of 2.835. Since this value is significantly different from 1, it provides strong evidence that the hazard does not follow an exponential distribution. Furthermore, the value of ρ is greater than one and indicates an increasing failure rate i.e., the HLP continues to attract new adopters over time. At the same time, the value of the shape parameter is less than 3.5 and therefore suggests that the baseline hazard density function is positively skewed. In other words, a large proportion of farmers join the program earlier than later. In fact, this result is consistent with our data where about 60% of our sample enrolled in the loyalty program within the first two years and the remaining 40% enrolled over the next two years (see Table 1).

Social influence of elite status members. We first report the results for the focal variable of the study, namely the effects of social influence of platinum-status farmers in the immediate neighborhood of a farmer who is yet to adopt the HLP. We can observe in Table 4 that while the coefficient for the linear effect of social influence is positive ($\beta = 1.390$), the coefficient for the

Table 4
Final Results from Hazard Model with CAR Effects.

	Estimate	S.D	2.5%	Median 50%	97.5%
Individual characteristics					
Farm size (log-transformed)	**0.057**	0.020	0.018	0.057	0.094
Gender (male = 1, female = 0)	0.163	0.095	−0.017	0.160	0.351
Family (joint family = 1, nuclear = 0)	0.351	0.181	−0.008	0.353	0.702
Targeted firm activities					
Sales calls	**0.842**	0.044	0.756	0.843	0.929
Marketing activities	**−0.584**	0.296	−1.172	−0.579	−0.015
Calls to service center	**−20.630**	1.168	−22.930	−20.630	−18.350
Social effects					
Early adopters	**−0.171**	0.005	−0.180	−0.171	−0.161
Recent adopters	**0.130**	0.006	0.119	0.130	0.141
Platinum-status	**1.390**	0.202	0.983	1.391	1.790
Platinum-status^2	**−2.246**	0.227	−2.691	−2.247	−1.791
Gold-status	−0.160	0.236	−0.617	−0.161	0.308
Gold-status^2	**−1.752**	0.543	−2.863	−1.735	−0.740
Silver-status	0.439	0.246	−0.043	0.440	0.922
Silver-status^2	**−2.216**	0.443	−3.108	−2.207	−1.376
Program rewards	−0.004	0.010	−0.024	−0.004	0.016
Intercept	**−3.392**	0.136	−3.656	−3.394	−3.119
Weibull shape parameter ρ	**3.269**	0.036	3.199	3.269	3.339
DIC	**11,610**				

Note: coefficients whose 95% CI does not include zero are highlighted in bold.
CAR: Conditional Autoregressive Modeling; DIC: Deviance Information Criterion.

quadratic term of social influence is negative ($\beta = -2.246$), and both of them are statistically significant, thus offering support to our hypothesized effect (H1). The positive coefficient for the linear term suggests that the hazard rate of a farmer adopting the HLP increases when the number of farmers who have attained platinum-status in the immediate neighborhood increases. However, the negative coefficient for the quadratic term suggests that when the number of platinum-status farmers in the neighborhood increases beyond a certain point, the HLP loses its aura of exclusivity and consequently lowers the hazard of the farmer adopting the loyalty program.

We can determine the fraction of platinum members in the vicinity of a potentially new member that results in an optimum level of social influence by solving the first-order differential equation of the hazard function. The optimal number fraction of farmers that maximizes influence on others to join the program can be computed as $\frac{-\beta_l}{2\beta_q} = \frac{-1.390}{2*-2.246} \approx 31\%$ where β_l and β_q are the coefficients of the linear and quadratic measures of social influence respectively. We can also observe that the second derivative has a value less than zero confirming that the effect of social influence is maximum when 31% of farmers who reside near a potential member have platinum status.

In order to verify the magnitude and significance of this non-linear effect, we used the estimates and ran a simulation where we computed the net effect of the linear and quadratic terms of social influence 1000 times. We then computed the average net effect along with its 95% confidence intervals. Fig. 1 provides a visual depiction of the results and confirms that the inverse U-shaped effect is indeed significant.

Social influence of lower status members. We also examined the social influence exerted by members belonging to other status categories in the program (i.e. gold and silver) and tested whether they display a non-linear effect similar to that of platinum status. Recalling social comparison theory (Festinger, 1954), individuals aspire for status that is the highest and farthest from their current position. Since the benefits in most HLPs increase exponentially from one status category to the next, with the top category gaining the most exclusive benefits and preferential treatment, and these benefits are best visible for rewards reserved to highest status members, we anticipate that lower status members would have a weaker effect on non-members than elite status members.

From the results, we can observe that the linear terms for both silver and gold fraction are insignificant and the quadratic terms for both status are negative and significant. We consistently find this result irrespective of the model specification. The results for gold and silver status levels suggest that an increasing percentage of gold or silver status members in the immediate neighborhood decreases the hazard of adopting the program. These results are in line with our initial expectations advanced above, and suggest that the influence of gold and silver customers are different from that exerted by elite platinum status members.

Social contagion. As regards the results for the effects of social contagion, we find that the coefficients for the number of recent adopters and the number of early adopters are both significantly different from zero. The coefficient for recent adopters is positive and suggests that recent adopters influence non-members to adopt the loyalty program. However, a Cohen's d test suggests that the social contagion effect of recent adopters is weaker than the social influence effect of elite status members. The coefficient for early adopters is negative, indicating that individuals who have adopted the program much earlier only delay the time taken by non-members to enroll in the loyalty program. This result is consistent with earlier studies that have examined the contagion effect of low-risk products. Lin and Burt (1975) suggest that evaluation and awareness are two important factors that influence the adoption process. While the diffusion of products which are considered high-risk purchases typically relies mainly on positive

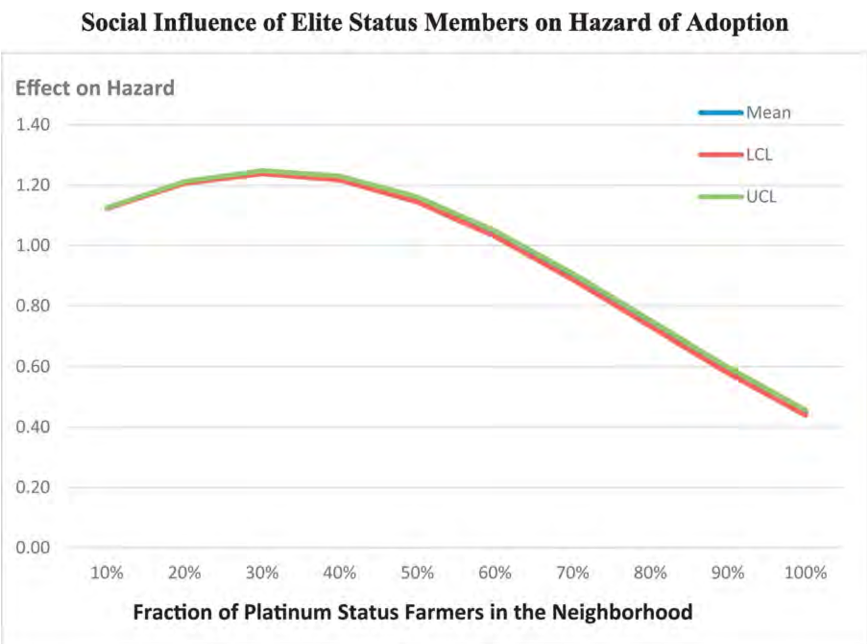

Fig. 1. Social Influence of Elite Status Members on Hazard of Adoption.

evaluations, the diffusion of products which are considered low-risk purchases generally relies more on awareness (Godes & Mayzlin, 2009; Iyengar et al., 2011). In this study, adopting the loyalty program poses little risk to its members. While early adopters are generally more engaged in sharing their opinions and providing judgments on a new product or service (Van Eck et al., 2011), recent adopters are generally considered to be more enthusiastic about their new product or service than early adopters who have used the product or service for a longer time (Iyengar et al., 2011). Therefore, the result that recent adopters influence potential members to adopt the program early while early adopters fail to do so, is consistent with our prior understanding of the different roles that these segments play in the diffusion process of a low-risk product or service. Also, with regard to the negative impact exerted by early adopters, existing evidence suggests that a large number of loyalty program members disengage from the program a short time after the adoption (Wiebenga & Fennis, 2014). Thus, a potentially large number of disengaged customers among the early adopter group may thus discourage the adoption of the program by non-members who are exposed to them. We recognize that other explanations are also plausible, but given our focus on the role of social influence by elite members on non-members in the adoption of a HLP, looking more in depth into these effects goes beyond the scope of the present study.

Effect of redeeming points for rewards. We included the number of rewards redeemed by platinum status farmers in the vicinity of a potential adopter as a covariate. The results show that the number of rewards redeemed by platinum status farmers in the neighborhood does not have a significant influence on the time taken by non-members to adopt the loyalty program. This is an interesting result, as it suggests that soft benefits (i.e. status) are a stronger mechanism to stimulate the adoption of a loyalty program by existing customers than hard benefits (i.e. rewards). In a B2B context, it seems that hard benefits (e.g., household tools and appliances) have lower visibility and presumably carry less importance than soft benefits such as VIP privileges. As noted previously, the number of points accumulated and consequently redeemed for rewards depends primarily on sales volume. However, achieving status and accompanying soft benefits depends on loyalty (i.e. share of wallet), which is attainable for every customer and thus influences motivation to enroll in the HLP differently consistent with our framework. We believe this result has important implications for how loyalty programs are designed, and that soft benefits such as status can be more influential than expensive rewards in influencing customers to adopt the program.

Control variables. Regarding the results for targeted marketing activities, we find that the coefficients for targeted marketing activities by the firm's sales and customer service center teams are significant. Sales calls have a positive effect on non-members' decision to enroll in the program. The role of the customer service center is to address any grievances that a farmer may have about the firm's products and/or services. The results suggest that more such calls lower the hazard of the farmer adopting the

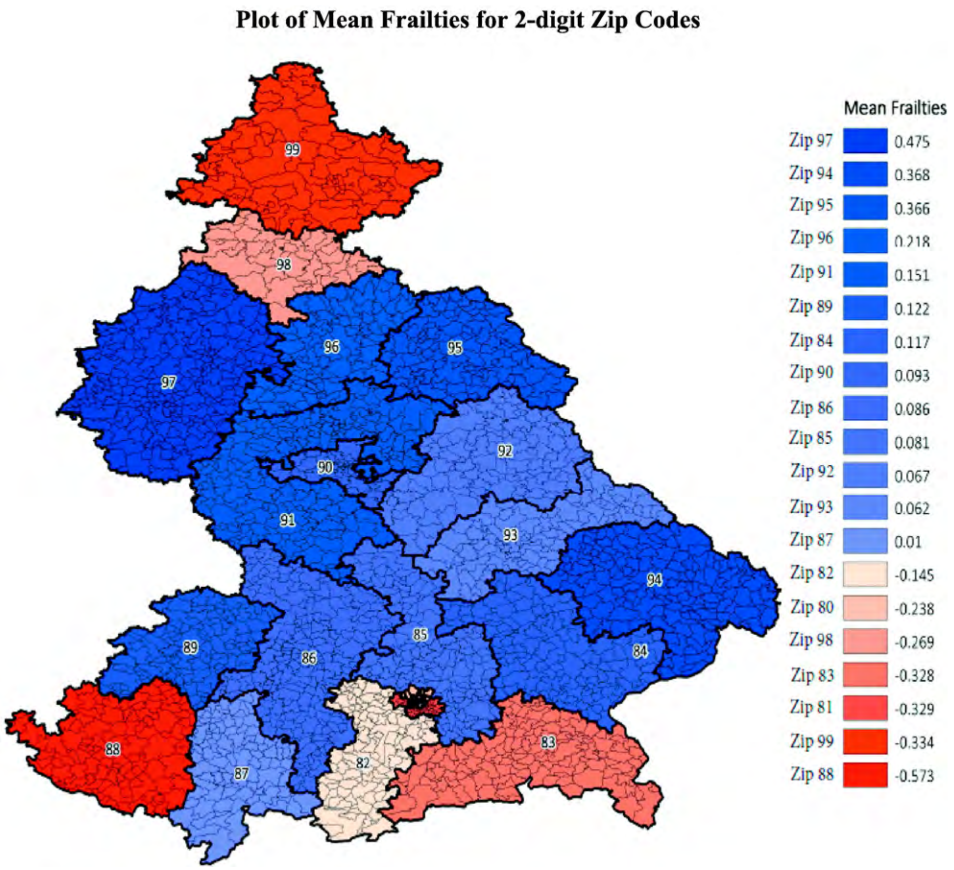

Fig. 2. Plot of Mean Frailties for 2-digit Zip Codes.

program. We find that marketing activities have a negative effect on the hazard rate. A possible explanation may be that marketing activities that convey the benefits of the loyalty program need more time to be processed and are hence less effective in influencing individuals to make quick adoption decisions. Other marketing activities that are promotional in nature may in fact represent a natural substitute for the loyalty program, thus providing alternative economic benefits in the form of rewards. The result also suggests that for B2B firms, communicating the benefits of the loyalty program through marketing activities is less effective than the social influence and accompanying soft benefits of elite status members in influencing new member enrolments. Finally, we also find that as the size of the farm increases, so does the hazard rate of adopting the program.

Frailties. The mean stratum-specific effects or frailties estimated with a CAR structure for the twenty zip codes are reported and displayed in Fig. 2. The results reveal considerable heterogeneity in the adoption patterns of different zip codes. Farmers around the city of Munich (zip code 80) and in surrounding areas to the south, especially in zip code 81, 83 and 88, are slow to adopt the HLP. These zip codes in Southern Bavaria are on the northern slopes of the Alps mountain range. Farmers in this region typically practice mountain farming where the main activities are cattle farming and producing related products such as milk, cheese and meat. As we move to the north, we find that farmers in zip codes 91, 94, 95, 96 and 97 join the HLP early. These regions are extremely fertile and farmers here grow a variety of cereals, fruits and vegetables. In fact, zip codes 96 and 97 lie in the famous wine producing district of Franconia in Bavaria. However, the strong effects of Northern Bavaria do not seem to spill over into the neighboring region of Thuringia where zip codes 98 and 99 are located. Overall, the frailties suggest that farmers who live in regions where agriculture comprises a significant proportion of the region's economy adopted the program earlier than farmers in other regions particularly in Southern Bavaria. These results are consistent with what one would expect and hence lend face validity to the analyses.

4.3. Robustness checks

Here, we provide a detailed description of several robustness tests conducted in order to ensure the validity of our results. The results of the robustness checks are displayed in Table 5.

Social effects. We checked if the effects for elite status members are robust to alternative measures of social influence and social contagion. First, we present the results (Table 5: R1) for a *spatial fixed effects* model without a CAR structure. In this model, we are accounting for factors that may be specific to a 2-digit zip code (e.g., nature of terrain, weather, crop, farming practices etc.) but do not consider any correlations across adjacent geographies. Nevertheless, we can observe that the social influence of platinum status members still exhibits an inverse U-shaped effect.

In the next model (Table 5: R2), we analyzed a model that included the *cumulative number of members* of the loyalty program as an alternative to the two measures of social contagion included in the analyses (Risselada et al., 2014). While the parameter estimated for social contagion (cumulative number of HLP members) was negative and significant, the results for the focal variable elite status were not altered. The number of platinum status farmers in the neighborhood continued to display a significant inverse

Table 5
Results from Robustness Checks.

	R1: spatial fixed effects		R2: total # adopters		R3: small farms		R4: large farms		R5: right truncated	
	Estimate	S.D.	Estimate	S.D.	Estimate	S.D.	Estimate	S.D.	Estimate	S.D.
Individual characteristics										
Farm size (log-transformed)	**0.050**	0.018	**0.058**	0.019	0.051	0.038	0.047	0.048	**0.043**	0.020
Gender (male = 1, female = 0)	0.167	0.092	**0.198**	0.093	0.056	0.121	**0.345**	0.158	0.105	0.095
Family (joint family = 1, nuclear = 0)	**0.359**	0.180	**0.363**	0.181	−0.173	0.313	**0.734**	0.240	0.249	0.181
Targeted firm activities										
Sales calls	**0.751**	0.042	**0.903**	0.042	**0.857**	0.063	**0.719**	0.064	**0.649**	0.043
Marketing activities	**−0.688**	0.296	−0.428	0.296	0.157	0.574	**−0.741**	0.350	**−0.600**	0.301
Calls to call center	**−18.010**	1.093	**−24.860**	1.060	**−21.370**	1.669	**−16.460**	1.727	**−16.460**	1.097
Social effects										
Total adopters	–	–	**−0.075**	0.003	–	–	–	–	–	–
Early adopters	**−0.168**	0.005	–	–	**−0.157**	0.006	**−0.191**	0.008	**−0.129**	0.005
Recent adopters	**0.137**	0.005	–	–	**0.140**	0.008	**0.130**	0.008	**0.091**	0.006
Platinum-status	**1.503**	0.198	**1.767**	0.200	**1.286**	0.268	**1.317**	0.279	**1.119**	0.209
Platinum-status^2	**−2.330**	0.224	**−2.707**	0.229	**−1.956**	0.298	**−2.349**	0.315	**−1.825**	0.233
Gold-status	−0.145	0.235	−0.029	0.240	−0.312	0.298	−0.119	0.322	−0.166	0.243
Gold-status^2	**−1.703**	0.542	**−2.008**	0.574	−0.946	0.604	**−2.276**	0.765	**−1.296**	0.555
Silver-status	0.453	0.253	0.335	0.220	0.420	0.335	0.359	0.274	0.217	0.225
Silver-status^2	**−2.209**	0.437	**−2.119**	0.448	**−2.618**	0.790	**−1.864**	0.461	**−1.540**	0.434
Program rewards	−0.001	0.010	−0.013	0.010	0.002	0.014	−0.008	0.015	−0.001	0.010
Intercept	**−2.663**	0.134	**−2.310**	0.137	**−2.690**	0.204	**−2.694**	0.299	**−1.796**	0.135
Weibull shape parameter ρ	**2.816**	0.030	**2.479**	0.027	**2.880**	0.045	**2.788**	0.042	**2.045**	0.025
DIC	**11,650**		**11,930**		**5888**		**5641**		**12,390**	

Note: coefficients whose 95% CI does not include zero are highlighted in bold; a: Estimate for log transformed value of platinum status.

U-shaped effect. The DIC value for this model is 11,930 suggesting that our model with two separate measures of social contagion for early and recent adopters provides a better fit.

We also split the data into two parts – one with farms that had a size less than the median value of the overall sample and the other with farms that have a size greater than the median value. We again found that the results (Table 5: R3 and R4) for the effects of elite status members was inverted U-shape in both the data sets. However, for large farms we found that gold status members did not have any effect on the hazard rate. Farm size too did not have a significant effect for this subset of the sample. Marketing activities seem to have a significant negative effect for larger farms. The results therefore lend strong support for the main arguments of this study that the influence exerted by elite status members on others is significant as long as there are not too many members. The influence of lower status members on the hazard rate is negative and at best insignificant.

Right truncation. Van den Bulte and Iyengar (2011) show that estimates from a model that fails to consider the fact that the sample is truncated can lead to biased estimates. In this study, we have access to genuinely truncated data unlike prior studies (Manchanda et al., 2008) that select a truncated sample for the analysis. However, we conduct several checks to ensure that our results are unbiased. First, Table 1 suggests that the number of adoptions has continued to decline steadily over time. The initial success of the loyalty program in enrolling a large number of customers suggests that only a few customers remain to be acquired. Hence, the sample for the analysis consists of nearly all the farmers at risk. Second, while nonparametric approaches that take into account right truncation are being developed, some studies (Gross & Huber-Carol, 1992; Kalbfleisch & Lawless, 1991; Woodroofe, 1985) suggest that reversing the time and analyzing the data as a retro hazard model is one way to estimate right truncated data using a parametric approach. We follow this retro hazard model approach and report the results in Table 5: R5. We again find that the result for the focal variable elite status exhibits a significant inverse U-shaped effect.

Additional tests. We also estimated a model with the *number of members* with different status instead of the proportion or fraction of members. We obtained similar directional effects for all the variables in the model. We also checked if a model with a *diminishing positive effect of social influence*, rather than as an inverse U-shaped effect, fits the data better. We therefore carried out a logarithmic transformation of our measure of social influence (after adding a small value of 0.01 to the number of platinum status members in the vicinity) and conducted the analysis again. While the results for this model too reveal a positive and significant effect for the social influence of elite status members, the DIC value for this model is 13,120 and hence much larger than that for the benchmark model. A model that captures the inverse U-shaped effect of social influence therefore seems more appropriate from a statistical point of view and is also consistent with the theoretical framework of the study.

To alleviate concerns on censoring, we 'right censored' the data by leaving out adoptions in 2012 which is the final year of our data and re-estimated the model. We again found that elite status exhibited a significant inverse U-shaped effect. Our benchmark model assumes a constant baseline hazard across the geographic region considered for the analysis. However, it is possible that the hazard varies for different zip codes. We modifed Eq. 4 to allow the baseline hazards for each of the twenty 2-digit zip codes to vary i.i.d such that $\rho_z \sim \text{Gamma}(\alpha, {}^{1}/_{\alpha}), z = 1 \ldots 20$. The parameters estimated from this model too are very similar in both magnitude and direction to those of the benchmark model. Furthermore, the DIC value for this model is substantially higher than the DIC value of the final model reported above. Therefore, accommodating *heterogeneity in the shape parameter* does not substantively change our findings nor does it result in improved model fit. The estimates for these models are available on request from the authors. We would also like to state here that we did not estimate a geostatistical model that incorporated distance as a metric of proximity. Since the analysis comprised of data from 2378 distinct zip codes, estimating a model with a 2378×2378 distance matrix (approximately 5.7 million cells) would be computationally tedious. Moreover, studies (Banerjee et al., 2003) have found remarkably similar results for models that follow a lattice (adjoining) approach that we use in this study and those that follow a geostatistical (distance) approach.

We also checked for various interaction effects e.g., sales and marketing efforts, but did not find any to be significant. To alleviate concerns of autocorrelation in the estimated parameters, we used every fifth simulation for the posterior analysis and found no change in the results. We increased the number of simulations for the posterior analysis from 50,000 to 75,000 and again found no change in the results. Importantly, increasing the variance of the priors i.e., the use of non-informative priors did not change the results. All these tests suggest convergence in the estimated parameters and lend credibility to the analyses.

Discrete time hazard model. We also checked if a discrete time hazard model provided similar results, again using alternative measures to operationalize the effect of social influence. We used the fraction of elite, gold and silver status members in the vicinity of a non-member to measure the effects of social influence for different tiers. The results from these models are reported in Table 6. Statistics used to evaluate nested models such as Likelihood Ratio tests and AIC confirm that the models with covariates significantly outperform the null model.

We first focus on the effects of social influence. We find that platinum or elite status exhibits an inverse U-shaped effect. In fact, the results from the discrete time model are remarkably similar to those discussed earlier. For example, we find that the effect of social influence starts decreasing when the fraction of platinum status members exceeds 30.49% of all members in the vicinity of the non-member. The linear terms for the effect of fraction of gold and silver tier members are insignificant while the quadratic terms for both these tiers are negative and significant. This is again consistent with the results from the earlier model where we find that an increasing fraction of gold and status members lowers the hazard of a non-member adopting the program.

Regarding the effects of social contagion, we find that recent adopters have a positive significant effect while earlier adopters have a significant and negative effect. To evaluate the effectiveness of targeted marketing activities, we used the same IV approach as before. We find that while sales calls increase the hazard of adoption, an increasing number of calls by farmers to the service center, plausibly to convey their grievances, lowers the hazard of adoption. Marketing efforts have a significant negative effect in this model too. Finally, we find that larger farms have a higher hazard of adoption. The effects for gender and nature of family

Table 6
Results from Discrete Time Hazard Model.

	M1: model with fraction of all status			
	Estimate	SE	z-stat	*p*-value
Individual characteristics				
Farm size (log-transformed)	**0.054**	0.014	3.85	0.00
Gender (male = 1, female = 0)	−0.095	0.067	−1.43	0.15
Family (joint family = 1, nuclear = 0)	−0.176	0.138	−1.28	0.20
Targeted firm activities				
Sales calls	**0.282**	0.031	9.20	0.00
Marketing activities	**−1.800**	0.215	−8.37	0.00
Calls to service center	**−8.586**	0.676	−12.70	0.00
Social effects				
Recent adopters	**0.099**	0.005	19.34	0.00
Early adopters	**−0.106**	0.003	−31.91	0.00
Platinum-status	**0.985**	0.150	6.58	0.00
Platinum-status^2	**−1.614**	0.161	−10.01	0.00
Gold-status	−0.115	0.196	−0.59	0.56
Gold-status^2	**−1.221**	0.458	−2.67	0.01
Silver-status	0.246	0.171	1.43	0.15
Silver-status^2	**−1.482**	0.317	−4.67	0.00
Program rewards	0.000	0.001	−0.30	0.77
Likelihood ratio	1266.35			
LR test	$p < 0.0001$			

(joint vs. nuclear) are insignificant. The results for these variables are very similar to those reported earlier. To summarize, the results of the discrete time hazard model corroborate the findings of the benchmark model and suggest that social influence of elite status members is an important driver of loyalty program adoptions.

To conclude, the battery of robustness tests validate the theoretical framework of the study and provide strong support for the premise that social influence driven by elite status has an inverse U-shaped effect on the speed of adopting the loyalty program. We assert that the findings are robust to different model specifications (continuous time vs. discrete time model, truncated vs. non-truncated model), functional form (diminishing vs. decreasing returns), measures (number vs. fraction of elite status members) and inclusion of other variables in the model (status of non-elite members, rewards).

5. Discussion

As more and more B2B companies recognize the importance of building successful long-term relationships with their customers to gain a sustainable competitive advantage (Ganesan, 1994), B2B markets witness the increasing application of CRM activities, including the launch of loyalty programs. Given that growing a critical mass of loyalty program members is essential to the success of any loyalty program, it becomes increasingly necessary to understand the drivers of loyalty program adoption (Breugelmans et al., 2015; Henderson et al., 2011). In this study, we focus on the impact of program members on potential adopters and, specifically, investigate the social influence exerted by elite status members. After controlling for other relevant drivers of HLP adoption and ruling out potential alternative explanations, the results demonstrate that top-tier members have a strong influence on the adoption likelihood of non-members, and that this relationship is non-linear (inverse U-shaped). The findings from this study offer a number of important contributions to loyalty program research in business markets and to business practice.

5.1. Theoretical implications

Current knowledge on loyalty programs comes almost exclusively from the study of B2C markets. Here, the few studies that investigate HLPs and status have predominantly focused on the effect of a program's tier structure on current members' attitudes and behaviors (Drèze & Nunes, 2009; Kopalle et al., 2012; Wang et al., 2016). Our study takes a different perspective. First, we focus on business markets, where status matters much and customers are sensitive to social influences. Second, and most importantly, our study investigates whether members that belong to the highest status category (i.e. top-tier members) of a loyalty program can influence the behavior of customers who are not members of the program yet, by affecting their adoption likelihood. The finding that top-tier members have a significant impact on the probability that a non-member adopts the program contributes to advance current knowledge on the design and effectiveness of loyalty programs. Specifically, it demonstrates the importance of the tier structure, not only for retaining the best customers and building successful relationships with them, but also for attracting new members to the program (Breugelmans et al., 2015; Dorotic et al., 2012). Interestingly, this study also adds to ongoing research into the relative importance of soft (i.e. status) vs. hard (i.e. rewards) benefits provided by loyalty programs at influencing the behavior of – potential and existing – program members (Bijmolt, Krafft, Sese, & Viswanathan, 2017; Dorotic et al., 2014; Drèze &

Nunes, 2009). Specifically, our study demonstrates that, compared with hard benefits, soft benefits (especially those provided to the top tier) are much more important in driving a critical mass of customers to adopt a newly launched B2B loyalty program.

Also, prior research has underscored the importance of social effects in influencing customer behavior in various domains (Ascarza, Ebbes, Netzer, & Danielson, 2017; Haenlein, 2013; Nitzan & Libai, 2011; Stephen & Lehmann, 2016), including B2B (Iyengar et al., 2011; Manchanda et al., 2008). However, despite the amount of accumulated research on loyalty programs, previous studies have frequently ignored the role played by social influence in understanding customer reactions to a loyalty program (Henderson et al., 2011). Our study is one of the first to demonstrate that social effects play a central role in the success of loyalty programs, by influencing customers' adoption likelihood (Allaway et al., 2003). Importantly, we find that the extent of influence of current program members on the adoption timing of non-members differs depending on the status conferred to the members in the program. We show that individuals awarded an elite status membership, i.e. those who enjoy the highest level of preferential treatment through exclusive benefits, rights and privileges, exert a disproportionate influence on potential members to enroll in the program, compared with other member groups (i.e. gold and silver status members, recent/earlier adopters, cumulative adopters).

Importantly, in this study we show that the social influence exerted by elite status members is not linear, but follows an inverse U-shaped form: exposure to elite status members increases the probability to adopt the program up to a point (i.e., 31% platinum members in the vicinity in our empirical application) from which exposure to a higher fraction of elite status members reduces the likelihood of program adoption. This result is consistent with prior research on the interplay between the size of the elite status group and its exclusivity (Drèze & Nunes, 2009; Verhallen & Robben, 1994), and demonstrates that for acquiring members to the program too, the attractiveness of the elite status group decreases with the fraction of individuals who are granted elite status.

Our study also contributes to ongoing research on status. Consistent with prior studies (Anderson et al., 2001; Frank, 1985; McFerran & Argo, 2014), our research shows that status is a powerful mechanism that influences customers' decisions and consequently their behavior. Notably, our focus on B2B demonstrates that status matters for business customers (Park & Westphal, 2013). In these particular markets, status is an appreciated resource, as it signals reputation, quality and trustworthiness that can improve relationships with different stakeholders (e.g. customers, service providers, employees, business partners, etc.) and lead to a competitive advantage. Thus, our results align with the high sensitivity of B2B customers to social influence and demonstrate that whenever these customers have a chance to improve their status (e.g. through enrolling in a program that bestows status to their members), they direct effort toward this particularly valuable strategic goal. At a more general level, our study advances current knowledge about how status influences customer behavior. As we show in our research, the power of status is not limited to individuals who currently possess an elite status level or to individuals who can attain such an elevated status. Our results show that even customers who underperform when making upward social comparisons and may never qualify for elite status (say, farmers who face high switching/contractual costs and hence find it difficult to increase their share of wallet), are nonetheless influenced to act in a manner that moves them toward uniformity (Henderson et al., 2011). As Festinger (1954) notes, an individual's level of aspiration is often greater than their level of performance.

5.2. Managerial implications

As the number of B2B companies introducing loyalty programs grows rapidly, the results of this study can offer managers a number of recommendations to help grow a critical mass of members and ensure a successful launch. One central aspect involves the design of the loyalty program and the role of status, a strong force that drives customer behavior both in B2C and B2B. Our study suggests that firms must consider including a tier component in the loyalty program (i.e. HLP) that stratifies the customer base in different status categories. In addition to its positive impact on building successful customer relationships (Dorotic et al., 2012), our study shows that having a tier structure can help acquire a critical mass of program members in a short period of time. This is because the status component promotes social comparisons that lead current non-members to pursue improvements in status by enrolling in the program (Festinger, 1954). However, our study suggests that the social influence of status is the strongest for elevated members, i.e. those at the top of the hierarchy. This is likely because the benefits that they receive are both more exclusive (e.g. access to VIP areas or special events, large amounts of bonus points, personal assistance by courteous personnel) and, thus, more desirable, and more visible (e.g. farmers attending a trade fair see elite status members enjoying VIP access to restricted areas). Thus, to leverage the role of social influence in the adoption of a loyalty program, B2B firms are advised to implement an exponential design of the program (with benefits escalating more than proportionally from one status category to the next), and provide benefits to high status customers that are highly visible to other customers (either current members or non-members).

Importantly, the criteria employed by firms to bestow status to program members should align with the strategic objectives of the organization. For example, business markets with a finite number of customers but with large economic transactions (Lilien, 2016), make customer loyalty a strategic mandate (Narayandas, 2005). One way to achieve this is with a loyalty program design that assigns status based on share of wallet, an important loyalty measure in B2B (Bowman & Narayandas, 2004), but one that has not been frequently employed to bestow status in conventional B2C programs. Instead, B2C companies, characterized by a much larger customer base, frequently design their programs in a way to promote spending and/or usage, which does not necessarily imply more loyal customers.

Another important aspect to consider, while designing a tier structure for the loyalty program, is that the attractiveness of the top-tier group decreases when its relative size increases beyond a certain point (Drèze & Nunes, 2009): smaller groups are associated with higher exclusiveness and distinctiveness, and hence are more desirable (Pickett et al., 2002). Thus, the results of our study imply that while the most valuable benefits provided by HLPs, especially soft benefits associated with status, should be reserved for the highest tier, firms should also limit the size of the top-tier status group and keep it exclusive. This is possible by setting standards that only the most loyal customers can attain (Drèze & Nunes, 2011). For the agricultural company that is the focus of this research, the threshold to become elite was set at 50% SOW, a reasonable figure as indicated by the cooperating firm given the common tendency among business customers to purchase from multiple vendors. While this is a context-specific decision, our empirical approach emphasizes that firms should aim at determining the optimal number or fraction of top-tier members that maximizes the attractiveness of the highest status group and, as a result, its social influence on others.

In addition to helping attracting new members to the program, leveraging the social influence of top-tier members can also lead to efficiency improvements. The costs involved in launching a new loyalty program (e.g. communications, economic incentives, etc.) are usually substantial (Demoulin & Zidda, 2009), and can become an important barrier to introducing new programs. For example, B2B firms often have to offer expensive incentives to their customers to enroll in their loyalty program. Given the limited resources that B2B companies usually devote to customer relationship management activities, our study underscores the importance of social effects in the diffusion process of a loyalty program and hence identifies alternative ways to grow membership of the program in a very cost-efficient manner.

5.3. Limitations and future research

While the study makes important contributions to ongoing work on loyalty programs, B2B, and social influence, it is not without limitations. The results are based on loyalty program adoption data for one firm that operates in the agriculture industry. Clearly, more work needs to be done using data from other B2B (and B2C) firms. For example, we demonstrated the high sensitivity of business customers to status in the context of loyalty programs, and argued that these customers seek status as this is a valuable resource to improve their competitive position. Is status as powerful in consumer markets? Certainly, looking at the relative impact of status in loyalty programs in B2C and B2B deserves further attention. Also, previous research has found that middle-status customers can be more susceptible to social influence (Hu & Van den Bulte, 2014). While the fact that customers only receive their status in the program once they become members has prevented us from looking at this issue in our study, future investigations can examine how HLP members who have different status categories prior to enrolment (by achievements or their inherited position) respond differently to the influence of other status members. More generally, and given the lack of research in the adoption of loyalty programs, we make an explicit call for more research that looks at the processes and mechanisms that explain the decision to adopt a loyalty program.

Our study benefited from the cooperation of a B2B company that provided access to a very rich and detailed longitudinal dataset on a substantial number of customers (more than 5000, representing more than 20% of the firm's customers). These are good numbers in light of the difficulties of data accessibility in B2B (Lilien, 2016). Still, we should note a number of data limitations that prevented us from digging deeper into some aspects of the adoption of the loyalty program. For example, the data available is of an aggregated nature (we observe adoptions in a year). More granular information would enable future studies to have a more accurate picture of the adoption process, as there are factors that change within the year (e.g. participating at trade fairs) that can affect the decision to adopt the program and the strength of the social influence. Also, in line with previous research, we used geographical information (zip codes) as a measure of social influence. However, given the availability of detailed information in contexts such as telecommunications, recent studies have started to consider more sophisticated measures (Ascarza et al., 2017; Nitzan & Libai, 2011; Risselada et al., 2014). We encourage the development of future studies that consider these (or other) measures of social influence to improve our understanding of the role of social influence in loyalty programs. As we noted in our work, the program implemented by the cooperating company used share of wallet as the criteria to assign status. While we controlled for the impact of marketing activities developed by the firm on the adoption likelihood, we acknowledge that competitive marketing actions can affect share of wallet and, thus, the status of current members. In addition, trade fairs can play an important role in the visibility of HLP status in our empirical application. However, the lack of data on this information prevented us from testing the reinforcing effect of these events on the adoption of the HLP. Finally, due to lack of relevant data, we controlled for unobserved factors using a fixed effects approach. Future studies can perhaps take a deeper look at why certain geographies are more receptive to new products and services than other regions.

To carry out our analyses, we used data on customer behavior. However, it would be interesting to also include data on customers' perceptions and attitudes toward the program. For example, future studies can complement our work by looking at how changes in status affect customers' motivation (or creates negative emotions) to progress through the hierarchies in the program, or how status influences satisfaction and loyalty toward the program and the firm. Examining the underlying motivations and emotions of consumers such as (dis)satisfaction, (dis)engagement and frustration in the context of a loyalty program seems a promising avenue for future research. Using this type of information could also facilitate the understanding of the mechanisms that drive the social influence exerted by top-tier members. We speculated that both status per se as well as the exclusive benefits that accompany status (e.g. access to VIP areas, bonus points, reduced waiting times) are driving the social effect. An interesting avenue for future studies would be to identify the relative importance of these two mechanisms in explaining the strength of social influence.

To summarize, while the study has its limitations, we consider it an important stepping stone for future research on B2B loyalty programs.

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