FACULTY OF ECONOMICS AND
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Advances in referral marketing using social networks

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Summary

Customer referral programs have been receiving increasing attention from marketing scholars and practitioners. Concretely, customer referral programs are marketer-directed word-of-mouth initiatives in which existing customers are rewarded for attracting friends, family members or acquaintances as new customers (Kumar, Petersen, & Leone, 2010). Whereas direct marketing focuses on directly targeting potential customers to convince them to join the company, referral marketing encourages existing customers to recommend the firm to their social network.

Existing literature regarding the value created by customer referral programs has shown that referred customers are more valuable than customers acquired through other channels (Armelini, Barrot, & Becker, 2015; Schmitt, Skiera, & Van den Bulte, 2011; Villanueva, Yoo, & Hassens, 2008). They spend more money and are more loyal, resulting in a higher total customer lifetime value (CLV). Schmitt et al. (2011) quantified the total difference in value due to higher revenue and lower churn between referred and non-referred customers to be between 16% and 25%. A recent study was the first to investigate the mechanisms underlying the value creation by referral programs (Van den Bulte, Bayer, Skiera, & Schmitt, 2018). They showed that the interactions between the parties involved in a referral program affect the value of the referred customer. Despite these first insights, an in-depth understanding on the drivers of the value of referral marketing is still lacking.

This dissertation contributes to the research on referral marketing by investigating the mechanisms driving the value created by customer referral programs based on the social connections underlying customer referrals. The first chapter describes the objective

of the dissertation and provides an introduction to the topic. In Chapter 2, we evaluate simulation-based algorithmic approaches to the influence maximization problem using real referral data. The research then continues by investigating the value of referred customers and the factors driving the value of referred customers (Chapter 3) and the resulting customer base growth (Chapter 4). The last chapter of this dissertation (Chapter 5) presents a general conclusion including interesting avenues for future research. In the following, we will give a short overview of the three research studies on referral marketing.

One of the steps in setting up a customer referral program is identifying the group of customers who will be targeted. Ideally for referral marketing, the target group consists of those customers whose influence will affect as many potential customers as possible. This problem is called the influence maximization problem (Kempe, Kleinbert, & Tardos, 2003). A common approach to this problem is to use diffusion models to simulate influence cascades over the links in the social network. The study in Chapter 2 contributes to the literature by evaluating these principles using real-life referral behaviour data. We use a game-theoretic approach for assigning each individual in the network a value that reflects the likelihood of referring new customers. We also explore whether these methods can be further improved by looking beyond the one-hop neighbourhood of the influencers. Our experiments demonstrate that using traditional simulation-based methods to identify influencers can result in overestimating the actual referral cascade. The results further suggest that looking at the influence of the two-hop neighbours of the customers improves the influence spread and product adoption. Hence, this study shows that it is useful for companies to collect data on customer referrals as this can enhance their ability to identify influencers and brand advocates. When no referral data is available, simulation-based approaches can be improved by including the indirect neighbors in the model.

Customer referral programs have been observed to bring in new customers who have higher contribution margins and longer lifetimes than customers acquired through other channels (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018). A recent study documents two theory-driven phenomena that underlie this difference in value. The main mechanisms responsible for this value gap can be related back to the interactions involved in a customer referral program. The study presented in Chapter 3 first investigates whether this value gap can also be detected in a different setting (namely telecom rather than banking) and then proceeds to investigate the role of the relationship between the referrer and the referred customer for the value of the latter to the company. We use both pseudo-contractual models and a Hidden Markov Model to relate the effect of this social connection to the three aspects of customer lifetime value of a referred customer (revenue, loyalty and cost). The results show that a stronger relationship between the referrer and the referred customer is associated with a more valuable referred customer in all three facets of customer lifetime value. Additionally, we find that, also in a telecom context, referred customers are more valuable than non-referred customers.

Based on the findings of Chapter 3 one would advise marketing managers to stimulate referrals over strong social connections as these result in highly valuable new customers. However, this sole focus on referrals over strong ties does not take into account the theory of the strength of weak ties. This theory is an important theory in sociology that argues that weak social connections are more likely to be bridges to other social communities compared to strong social ties. Extending this reasoning to customer referral programs, we hypothesize that referrals over weak ties also provide value to a firm by accessing new communities of potential customers. So whereas Chapter 3 focusses on the value of the referred customer to the firm, Chapter 4 investigates the long-term customer base growth as a result of subsequent referrals. We find empirical support for the theory of the strength of weak ties in customer referral programs, indicating that referrals over weak social connections are more likely to reach new communities of potential customers. Hence, it is important for marketing managers to not solely incentivize referrals over strong ties as this might limit customer base growth.

In sum, this dissertation sheds light on the role of the social interactions underlying referrals for the value created by customer referral programs. These findings can provide useful insights and guidance for marketing managers when designing and setting up customer referral programs.

Beknopte samenvatting

Bestaande literatuur over de waarde gecreëerd door referralprogramma's heeft aangetoond dat aangebrachte klanten waardevoller zijn dan klanten die via andere kanalen verworven zijn (Armelini e.a., 2015; Schmitt e.a., 2011; Villanueva e.a., 2008). Klanten aangebracht door bestaande klanten geven meer geld uit en zijn loyaler, wat resulteert in een hogere totale klantenwaarde (CLV). Schmitt e.a. (2011) berekende dat het totale waardeverschil als gevolg van hogere opbrengsten en lagere churn tussen verwezen en niet-verwezen klanten tussen 16% en 25% ligt. Een recente studie was de eerste om de mechanismen te onderzoeken die ten grondslag liggen aan de waardecreatie door referralprogramma's (Van den Bulte e.a., 2018). Deze studie toonde aan dat de interacties tussen de partijen die betrokken zijn bij een referralprogramma invloed hebben op de waarde van de aangebrachte klant.

Dit proefschrift draagt bij aan de inzichten in referral marketing door de mechanismen te onderzoeken die invloed hebben op de waardecreatie van referralprogramma's. Meer specifiek maken we gebruik van inzichten in het onderliggend sociale netwerk en de sociale interacties tussen de betrokken partijen. Het eerste hoofdstuk beschrijft de doelstelling van het proefschrift en geeft een inleiding in het onderwerp. In Hoofdstuk 2 evalueren we simulatie-gebaseerde methodes voor invloedsmaximalisatie aan de hand van data over echte referrals. Vervolgens wordt de waarde van aangebrachte klanten onderzocht alsook de factoren die deze waarde (Hoofdstuk 3) en de resulterende groei van het klantenbestand (Hoofdstuk 4) sturen. Het laatste hoofdstuk van dit proefschrift (Hoofdstuk 5) bevat een algemene conclusie en biedt interessante mogelijkheden voor toekomstig onderzoek. In wat volgt geven we een kort overzicht van de drie studies rond referral marketing.

Een van de stappen bij het opzetten van referralprogramma's is het identificeren van de groep klanten die wordt getarget. Idealiter bestaat de doelgroep uit klanten wiens invloed zoveel mogelijk potentiële klanten zal beïnvloeden. Dit probleem wordt het probleem van de invloedmaximalisatie genoemd (Kempe e.a., 2003). Een veelgebruikte aanpak hiervoor is het gebruik van diffusiemodellen om invloedcascades te simuleren via de sociale connecties in het netwerk. Het onderzoek in Hoofdstuk 2 draagt bij aan de literatuur door deze principes te evalueren aan de hand van geobserveerde referrals in het echte leven. We gebruiken een speltheoretische benadering om elk individu in het netwerk een waarde toe te wijzen die de referralkans weergeeft. We onderzoeken ook of deze methoden verbeterd kunnen worden door verder te kijken dan de directe connecties van de influencers. Onze experimenten tonen aan dat het gebruik van traditionele simulatie-gebaseerde methoden om influencers te identificeren een overschatting van de daadwerkelijke referral cascade kan veroorzaken. De resultaten suggereren verder dat het kijken naar de invloed van de indirecte buren van de klanten de verspreiding van de invloed en adoptie verbetert. Deze studie geeft dus aan dat het verzamelen van data over referrals gemaakt door klanten nuttig kan zijn voor bedrijven. Het kan hen namelijk helpen in het identificeren van influencers en brand advocates. Indien dergelijke data niet voorhanden is, is het mogelijk om de resultaten van simulatie-gebaseerde methodes te verbeteren door te kijken naar indirecte sociale connecties.

Het werd reeds aangetoond dat referralprogramma's nieuwe klanten aantrekken die meer spenderen en een langere levensduur hebben dan klanten die via andere kanalen zijn aangetrokken (Armelini e.a., 2015; Schmitt e.a., 2011; Villanueva e.a., 2008). Een recente studie documenteert twee theoretische mechanismen die ten grondslag liggen aan dit waardeverschil. Deze mechanismen hebben te maken met de sociale connecties die betrokken zijn bij een referralprogramma voor klanten. De studie in Hoofdstuk 3 onderzoekt eerst of dit waardeverschil ook kan worden gedetecteerd in een andere setting (namelijk telecom in plaats van banking) en onderzoekt vervolgens de rol van de relatie tussen de referrer en de aangebrachte klant voor de waarde van deze laatste voor het bedrijf. We gebruiken zowel pseudo-contractuele modellen als een Hidden Markov Model om het effect van deze sociale connecties te relateren aan de drie aspecten van klantenwaarde (opbrengst, loyaliteit en kost). De resultaten tonen aan dat een sterkere relatie tussen de referrer en de aangebrachte klant geassocieerd is met een hogere waarde van de nieuwe klant, waarneembaar in alle drie facetten van de klantenwaarde.

Op basis van de bevindingen in Hoofdstuk 3 kunnen we marketingmanagers adviseren om referrals te stimuleren over sterke sociale connecties, aangezien deze resulteren in zeer waardevolle nieuwe klanten. Echter, deze sterke focus op referrals over sterke connecties houdt geen rekening met de theorie van de strength of weak ties. Dit is een belangrijke sociologische theorie die stelt dat zwakke sociale connecties vaker een brug vormen naar andere sociale gemeenschappen dan sterke sociale banden. Als we deze redenering doortrekken naar referralprogramma's kunnen we veronderstellen dat referrals over zwakke banden ook waarde creëren voor een bedrijf door toegang te bieden tot nieuwe gemeenschappen van potentiële klanten. Dus terwijl Hoofdstuk 3 zich richt op de waarde van de aangebrachte klant, onderzoekt Hoofdstuk 4 de groei van het klantenbestand op lange termijn als gevolg van referrals. We vinden dat referrals over zwakke sociale connecties inderdaad vaker nieuwe gemeenschappen van potentiële klanten bereiken. Deze studie verschaft een empirische bevestiging van de theorie van de strength of weak ties in referralprogramma's. Bijgevolg is het belangrijk dat marketingmanagers niet alleen referrals over sterke relaties stimuleren, omdat dit de groei van het klantenbestand kan beperken.

Samengevat verwerft dit proefschrift kennis in de rol van de sociale interacties die ten grondslag liggen aan referrals voor de waarde gecreëerd door referralprogramma's. Deze bevindingen bieden nuttige inzichten en richtlijnen voor marketingmanagers bij het ontwerpen en opzetten van referralprogramma's.

1

Introduction

"Refer a friend and get rewarded."

We have all seen messages like this that aim to convince people to bring in friends, family or acquaintances as new customers. People have the tendency to talk to each other about their experiences. It is this kind of word-of-mouth behavior that marketers aim to leverage in customer referral programs[1].

Concretely, customer referral programs are marketer-directed word-of-mouth initiatives in which existing customers are rewarded for attracting friends, family members or acquaintances as new customers (Kumar et al., 2010). Whereas direct marketing focuses on directly targeting potential customers to convince them to join the company, referral marketing encourages existing customers to recommend the firm to their social network. The aim of customer referral programs is thus to invoke word-of-mouth referral cascades that result in other people joining the company. Examples exist in different industries such as banking (e.g., Hello Bank, American Express), travel (e.g., Booking.com, Airbnb), taxi services (e.g., Uber, Lyft), e-commerce (e.g., Groupon, LensOnline), telecom (e.g., OnePlus) and gambling (e.g., Unibet). Probably the most well-known example of a referral program is that of Dropbox, a file sharing and storage provider. Both the referring and the referred party were offered a free increase of 500MB storage space when the latter signed up as a new user. Thanks to this program, Dropbox' user base grew from about 100,000 users to 4 million in a 15-month period (Veerasamy, 2016). Clearly, such programs can

[1]The terms 'customer referral programs' and 'customer referral marketing' are used interchangeably and refer to the marketing practice of acquiring new customer through incentivized referrals of existing customers.

potentially greatly impact the growth and success of a business.

Customer referral programs have been receiving increasing attention from marketing scholars and practitioners. This can be attributed to a combination of factors such as the marketing literature recognizing the importance of customers' social networks for marketing applications. Extant research has shown that word-of-mouth is transferred over social connections between individuals (Godes & Mayzlin, 2004; Ma, Krishnan, & Montgomery, 2014). Referrals are particularly powerful because people put more trust in the opinions of those in their close social circle than in those of others (Nail, 2004). As a result, word-of-mouth is the most influential source of information to a customer (Keller, 2007) and therefore a highly effective marketing strategy (Trusov, Bucklin, & Pauwels, 2009). Research has shown that people who have a social connection influence others' opinions and behaviors (Centola, 2010; Christakis & Fowler, 2013; Godes & Mayzlin, 2004; Hill, Provost, & Volinsky, 2006). Moreover, even when individuals do not actively influence each other through word-of-mouth, the mere presence of a social connection can still be predictive of certain consumer behavior (McPherson, Smith-Lovin, & Cook, 2001). Recent marketing research has focused on leveraging social influence among individuals to acquire and retain customers (Benoit & Van den Poel, 2012; Hill et al., 2006; Iyengar, Van den Bulte, & Valente, 2011; Verbeke, Martens, & Baesens, 2014). Typically, social influence traverses social connections even without intervention by marketers. In customer referral programs, however, marketers explicitly stimulate customers to talk to others about their product or service. Referral marketing thus explicitly leverages social influence for acquiring customers. It is a way of transforming the social capital of customers into economic capital for companies (Van den Bulte et al., 2018).

These advances in marketing research, together with the growing availability of data on customer interactions, set the scene for this dissertation. It contributes to the state-of-the-art on the value of customer referral programs by providing novel insights in what drives their success. Such insights are useful for marketing managers to design effective referral programs.

Existing literature on referral marketing has investigated the design of referral rewards (Kornish & Li, 2010; Ryu & Feick, 2007), explored the impact of opportunistic behavior (Meyners, Barrot, Becker, & Bodapati, 2017) and provided guidance on how to set up and manage referral programs (Berman, 2016). Regarding the value created by customer referral programs, previous studies have shown that customers acquired through word-of-mouth or referrals are more valuable than customers acquired through other channels (Armelini et al., 2015; Schmitt et al., 2011; Villanueva et al., 2008). They spend more money and are more loyal, resulting in a higher total customer lifetime value

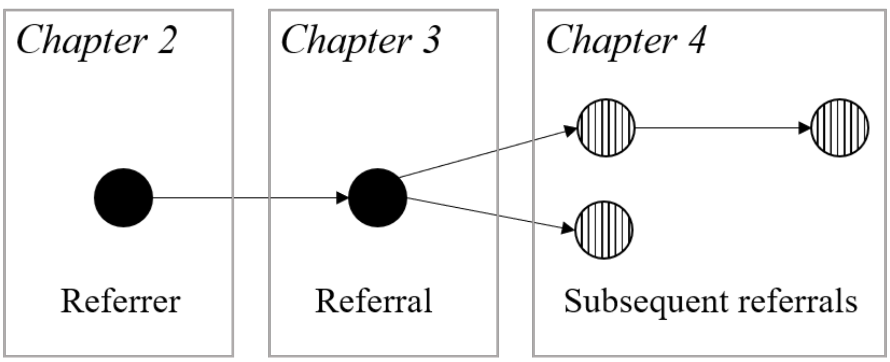
(CLV). Schmitt et al. (2011) quantified the total difference in value due to higher revenue and lower churn between referred and non-referred customers to be between 16% and 25%. A recent study was the first to investigate the mechanisms underlying the value creation by referral programs (Van den Bulte et al., 2018). They showed that the interactions between the parties involved in a referral program affect the value of the referred customer. A referrer with a stronger connection to the firm makes referrals that generate more revenue as a result of better matching. In addition, the presence of the referrer affects the lifetime of the referred customer through social enrichment (we refer the reader to Van den Bulte et al. (2018) for a more elaborate explanation). Hence, this study shows that the underlying relationships affect the effectiveness of referrals.

The objective of this dissertation is to advance the literature on referral marketing by exploring the underlying social connections. This dissertation contributes to the research on referral marketing by investigating the mechanisms driving the value created by customer referral programs based on the social connections underlying customer referrals.

Understanding referral marketing success using the customer network

Customer referral programs aim to stimulate the spread of referrals over the connections in the social network of customers. As such, customer referral programs can be studied by taking a social network perspective. This dissertation aims to do exactly that, namely advancing the state-of-the-art on referral marketing using insights from the underlying social network. Figure 1.1 visualizes the social interactions involved in a customer referral program. It illustrates the referrer who convinces a social connection, the referral, to join the company's services, after which the referral in turn becomes a referrer by referring the firm to two social connections and convincing them to join the company. Each chapter of this dissertation focusses on one specific facet of these social interactions, as represented in Figure 1.1.

Figure 1.1: Dissertation structure based on the social interactions involved in customer referral programs.



One of the steps to take when launching a customer referral program is deciding to which existing customers this program will be targeted (Berman, 2016). Ideally, the influence of the target set, also called seed set, will reach as many potential customers as possible through the diffusion of word-of-mouth. In the first study of this dissertation, presented in Chapter 2, we examine how a referral network can be leveraged to identify the most influential individuals who are best suited to be involved in a referral program. Unfortunately, people's influence through word-of-mouth and referrals are not straightforward to observe. Some research measures referrals by surveying people about their willingness to refer. However, previous studies have discovered that people typically overstate the number of individuals they would refer (Kumar, Petersen, & Leone, 2007, 2010). Another approach that some studies take is to simulate influence flow over social connections based on diffusion models. Such algorithmic approaches aim to approximate potentially present referrals with simulations. Although such methodologies have been widely studied, research has not yet explored how this problem can be addressed using referral data. By addressing this gap, our research integrates referral networks into social influence research. In particular, we do so by combining a game theoretic approach and referral network analysis.

It is important to realize that not all customers are equally valuable to a firm. Customers differ in terms of generated revenue (Schmitt et al., 2011; Van den Bulte et al., 2018), lifetime (Schmitt et al., 2011; Van den Bulte et al., 2018) and cost-to-serve (Reichheld, 2006). Since referral marketing is a customer acquisition method, its effectiveness and success can be measured by the value of the customers acquired through referrals (Schmitt et al., 2011). As argued by (Kumar et al., 2010), there are two facets to customer value. First, the profit that the company accrues thanks to this customer. And second, the growth in the customer base as a result of the customer's referrals. Chapter 3 and 4 of this thesis build on this idea.

Whereas earlier work on customer referral programs focuses on documenting the value gap between referred and non-referred customers (Armelini et al., 2015; Schmitt et al., 2011; Villanueva et al., 2008), knowing that such differences exist, recent research has turned its attention to investigating where this difference in value stems from (Van den Bulte et al., 2018). Chapters 3 and 4 of this work extend this line of research by studying why some referrals lead to more favorable outcomes than others. These outcomes are respectively profit and long-term growth in Chapter 3 and 4.

In Chapter 3 the effect of the tie strength between the referrer and referred customer on the value of the latter to the firm is examined. We further extend the research into customer referral program value drivers by investigating the effect of being referred on all three facets of CLV, namely revenue, lifetime and cost-to-serve. This provides us with an exhaustive view of the differences between referred and non-referred customers.

Chapter 3 examines the role of the referral dyad strength for customer profitability.

However, some customers might not demonstrate high revenue and have a long lifetime, but provide great value to the firm through their referral potential. Chapter 4 builds on this idea and investigates the role of referral dyad characteristics on customer network growth through referrals. We draw on existing theories in sociology and extend this literature stream by examining the effect of referral dyad connectivity on customer network growth driven by customer referrals. In particular, this study empirically examines the theory of the strength of weak ties that posits that there is great value in weak social connections because they are more likely to be bridges to other social communities.

In short, the first empirical chapter (Chapter 2) shows that simulation-based approaches for selecting the most influential customers overestimate the actual influence flow when compared to actual referral behavior. The second empirical chapter (Chapter 3) documents the value gap between referred and non-referred customers and shows that a stronger a relationship between the referrer and the referred customer is associated with a higher value of the latter to the firm. The third empirical chapter (Chapter 4) complements the previous chapter by illustrating the capability of referrals over weak social connections to contribute significantly to long-term customer base growth by reaching untapped social communities of potential customers.

Dissertation composition

This manuscript consists of three essays, presented in separate chapters, such that each chapter can also be read independently. Each chapter is in preparation for submission to a scientific journal (Chapter 3 and 4) or has already been published (Chapter 2). Since referral marketing is the main theme throughout this dissertation and every essay is written according to the structure of a scientific paper, there might be common elements in the theoretical parts of the essays. Nevertheless, each essay provides unique insights in and contributions to referral marketing literature.

2

Identifying influencers in a social network: The value of real referral data

2.1 Introduction

Customers are crucial assets for a firm but they can be costly to acquire. The focus of this study is on customer acquisition, which is of utmost importance to any organisation. Ensuring a decent inflow of customers, larger than the outflow so that the customer base increases is not at all straightforward. As a result, marketers are in a continuous battle for attracting potential customers' attention and getting into their consideration set. Many have shifted part of their marketing efforts portfolio from directly communicating with potential customers to influencing existing customers to do so (Garnefeld, Eggert, Helm, & Tax, 2013). This is driven by the growing acceptance of the fact that people are highly influenced by information received from others (Godes & Mayzlin, 2004) and that word-of-mouth (WOM) is the most influential source of information to a customer (Keller, 2007). Empirical research confirmed that consumers rely heavily on the advice of others in their personal network when making purchase decisions (Hill et al., 2006; Iyengar

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et al., 2011; Sadovykh, Sundaram, & Piramuthu, 2015; Schmitt et al., 2011; Verbraken, Goethals, Verbeke, & Baesens, 2014) and that positive WOM has a positive effect on business outcomes, i.e. sales (Bao & Chang, 2014; Rui, Liu, & Whinston, 2013). Referral marketing has become an important marketing technique to stimulate WOM in a controlled way and as such acquire new customers (Van den Bulte et al., 2018). A good example of referral marketing success is Dropbox. They managed to expand their customer base from 100,000 to 4 million users in a 15-months period by leveraging the power of referrals. Prior to using referral marketing, Dropbox was using Google's AdWords and affiliate marketing, with a cost of acquisition between $288 and $388 per individual (Veerasamy, 2016). Dropbox's CEO, Drew Houston, calculated the cost of acquiring this large customer base at $10 billion if traditional marketing programs had been used (Berman, 2016). As a consequence, leveraging social influence can greatly decrease the costs of acquiring new customers.

Suppose we have data on the social network of our customers, in which the interactions give an indication of how influence flows between the individuals. If we would like to attract as many new customers as possible by relying on the power of social influence, we want to initially target a few individuals in the hope that they will trigger a cascade of influence in which friends recommend the product to other friends and many will ultimately be attracted as customers. The key question is how to select those initial influencers who will seed this process. In order to do that, managers need to have an intelligent system that supports them in solving this problem and coming up with a list of most influential customers. Selecting a group of individuals who are most likely to generate the largest cascade of influence through WOM is known as the influence maximization problem (Kempe et al., 2003). Multiple approaches to solve this problem have been developed. However, these algorithms typically are not based on data that represent influence flow as it is not straightforward to gather such data set. Rather, they simulate influence spread in a social network at random based on the links that exist in the network according to diffusion models (Chen, Wang, & Wang, 2010; Chen, Wang, & Yang, 2009; Chen, Yuan, & Zhang, 2010; Narayanam & Narahari, 2010).

This work focuses on how the most influential customers can be identified and how well such methods perform compared to actual referral behaviour. In this paper, we combine both social connection data and actual referral data. Social connection data is used in the form of a social network, representing telecommunication behaviour. The referral data comprises the same set of people and can be represented as a referral network. In this work we will answer the following questions: (1) What is the value of simulation-based methods to select the top influencers in a customer network? (2) To what extent does a weighted approach, taking into account interpersonal connection strength, improve on a non-weighted approach? (3) What is the value of using actual referral data for selecting top influencers in a customer network? Does it lead to a performance increase compared to when only connections are considered? (4) Can the method be improved by not only considering the direct social connections of customers that can be influenced, but also the second-hop connections of the customers?

We propose a novel method based on the game-theoretic concept of the Shapley value to compute an influencer score for every existing customer. This list of scores then allows managers to select the top *k* influencers to be involved in a customer referral program. We contribute by assessing the quality of the often-used simulation-based methods that propose to find top influencers by simulating influence spread through a network based on the links in the network. The unique data set used in this study enables evaluating the performance of this type of method by comparing the estimated influence spread of the top *k* influencers with their actual referral behaviour. As such, this study bridges the more design-oriented research from the field of information systems research and the more empirical papers from the field of marketing. In that way this paper contributes to what Probst, Grosswiele, and Pfleger (2013) propose in their comprehensive literature study as a necessary addition to influence maximization literature. Additionally, we add to the literature by responding to the need for simulations that can quantitatively be compared with specific social phenomena as pointed out by Conte et al. (2012) .

The remainder of the paper is organised as follows. We introduce the referral marketing model in Section 2. Section 3 gives an overview of related work. In section 4, the proposed methodology is discussed and Section 5 summarizes the results. Section 6 concludes this paper.

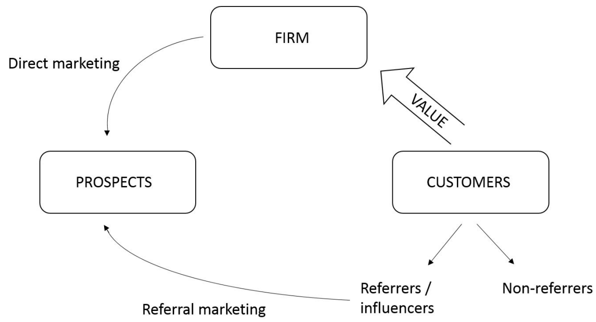
2.2 The referral marketing model

Customer referral programs encourage existing customers to recommend a firm's services or products to their social network. They aim to provoke marketer-directed cascades of word-of-mouth (WOM). In that way, referral programs leverage on the powerful impact of word-of-mouth and the influence of social connections (Godes & Mayzlin, 2004; Keller, 2007). Figure 2.1 illustrates how referral marketing programs create value for firms.

2.2.1 Background

The acquisition efforts used to attract a customer have an important effect on the long-term value of the customer to the firm. Villanueva et al. (2008) show that customers who joined the firm as a result of WOM recommendations of social connections add almost twice as much long-term value to the firm than customers who did not join as a result of

Figure 2.1: Referral marketing leverages the power of word-of-mouth to attract new customers.



WOM. The same was found by Schmitt et al. (Schmitt et al., 2011). They concluded that the difference in customer lifetime value between referred and non-referred customers is at least 16%. Kumar et al. (2010) show that the most valuable customers (with high customer lifetime value) are not always those who buy most, but those whose WOM attracts the most profitable new customers. Next to a difference in value between referred (WOM) and non-referred customers, there is also a difference in costs. Reichheld (2006) argues that referred customers have a lower cost to serve than non-referred customers, as being connected to another customer may provide help with understanding the various offerings and navigating certain procedures without having to rely on the firm's customer support. Therefore, the customer acquisition process has a significant impact on customer value. Many companies have already understood this and referral programs now exist in many industries such as telecommunication, retail, energy providers and restaurants (Garnefeld et al., 2013). Referral programs are often used by service companies since personal referrals work particularly well for experience goods like telecommunication services or gym club membership (Berman, 2016). Moreover, the number of referral marketing programs is expected to increase significantly as a result of the rise in social media usage, the heightened use of customer databases by firms and the growing number of platforms to outsource referral programs (Berman, 2016).

2.2.2 The referral marketing process

As with any marketing program, a process needs to be executed in order to set up and launch a customer referral program. Berman (2016) identifies an eight-step process for planning, implementing and evaluating referral programs, shown in Figure 2.2 on the left side.

Our study focuses on the third step "identifying a group of customers as referrers". The aim of this step is to find a group of customers that is able to influence as many other potential customers as possible through WOM and social influence. This problem is called the influence maximization problem (Kempe et al., 2003) of which the selected group of customers is called the seed set. Marketers need to have an intelligent system that supports them in solving the influence maximization problem and coming up with a list of customers that are most suited to target with a customer referral program. Figure 2.2 provides an overview of the three different decision support methods for seed selection based on different data sources. Selecting the seed set for a customer referral program can be done on a random basis, by using previously proposed algorithms relying on influence simulation through the customer network or by using actual referral behaviour data.

In the first part of this study, we explore the value of using call detail records (CDR) in the form of a communication network to select influencers for the seed set. In a first step, we take an unweighted approach focusing on the existence of a link between any two nodes. In a second step, we use a more complex approach by taking into account the connection strength between individuals. The connection strength has an impact on how likely it is that individuals influence each other: a stronger relationship implies a higher chance of recommending products to each other. Therefore, we examine whether a weighted approach leads to simulations of influence flow that are a better representation of real life.

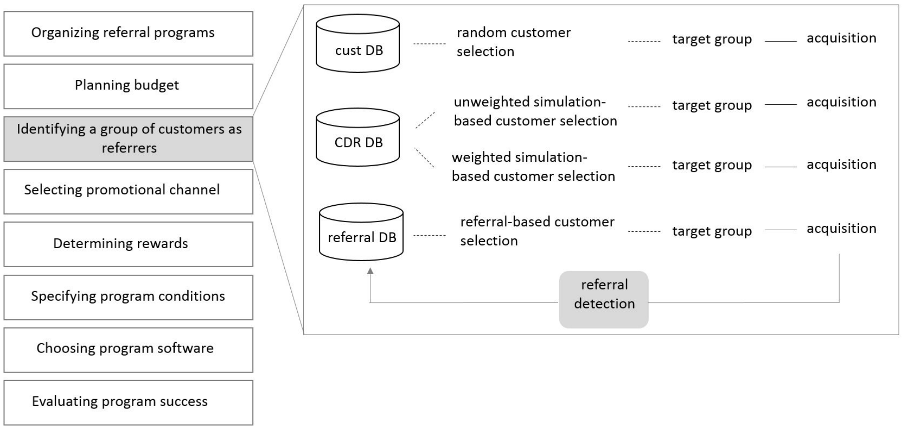
In the second part of this paper, we analyse the added value of using referral behaviour data for selecting the top influencers. In order to be able to use referral data as input to the decision support system, the data needs to be captured every time a new customer is referred. As a result, this requires a referral detection process. This study examines whether implementing such process is beneficial and leads to an optimized selection of influencers thanks to the use of referral behaviour data.

In the third part of this paper, we investigate how much the selection of the seed set improves when taking into account the two-hop neighbourhood of the customers during the selection process. As Li and Shiu (2012) argue, there is no use in targeting a campaign to an influential customer if his connections do not spread the message on their turn. Thus, we incorporate a measure for the influence of a customer's connections and verify whether this results in a better seed set selection.

2.3 Related work

There is a wide literature from sociology, psychology, economics and computer science studying social influence. In this section, we focus on influence diffusion models and the influence maximization problem. Customers and prospects influence each other through WOM and in that sense can be thought to form a network *G(V,E)* in which the individuals (customers and/or prospects) represent the nodes V and the relationships between the individuals form the edges *E*. This representation allows for graph theoretic analysis of

Figure 2.2: Three strategies for selecting a group of customers as referrers.



customer activities. The influence maximization problem identifies a group of customers that leads to the largest influence spread in the social network under a given diffusion model.

2.3.1 Diffusion models

Diffusion models are models that simulate a diffusion process in a complex network. Multiple types of diffusion models exist that take different approaches to the features of the spreading process. In general, the object of the diffusion travels from node to node over the links in the network. Two classical diffusion models based on mathematical sociology are the linear threshold model and the independent diffusion model.

The linear threshold model (LT model) starts with an initial seed set of active customers (in our setting an active customer is a customer who has adopted the product) who have already adopted the product and are selected to start the diffusion process (all other nodes are inactive). Every node *i* in the network has its own uniformly distributed threshold value $\theta_i \in [0,1]$. This threshold value determines how much influence from the direct neighbours is necessary for this node to also become active. Let us consider node *i* and represent its neighbours by N_i. Node *i* is influenced by its neighbour *j* according to a weight w_{ij}, reflecting the strength of the relationship. These weights are normalized for every node such that $\sum w_{ij} \leq 1$. The decision of node *i* to become active depends on the total influence of *i*'s neighbours scaled by weight. If this total weight exceeds the personal threshold θ_i, such that $\sum_{j \in N_i} w_{ij} \geq \theta_i$ then node *i* will decide to also adopt the product.

The independent cascade model (IC model) considers individual and independent interactions and influence among connections in a network. Initially, a set of active nodes $S \in V$ is fixed that constitutes the start of the diffusion process. Every edge in the network is assigned a probability p_{ij} illustrating the chance of node *i* successfully influencing neighbour *j*. This probability p is assigned uniformly over all edges in the network before simulating the diffusion process. Once a node is active, it will try to activate all its neighbours. However, every node only has one chance per connection to attempt to individually influence it. Whether node *i* can influence node *j* directly depends on the probability p_{ij}. In case none of *i*'s neighbours can be activated, this branch of the diffusion process is terminated. Once a node is activated it remains activated during the rest of the process. This process progresses iteratively until no more nodes can be activated.

These two diffusion models provide a way to model spreading in a network. Influence maximization methods build on these models.

2.3.2 The influence maximization problem

Domingos and Richardson (2001) were among the first to study influence maximization in a social network as an algorithmic problem. They proposed the idea of assigning each customer a value that reflects the influence of this person on other individuals in the network. In contrast to Domingos and Richardson's algorithm that relied on probabilistic methods, Kempe et al. (2003) were the first to formulate the same problem as a discrete optimization problem. They proposed a Greedy approximation algorithm to find the *k* most influential nodes in a network. The Greedy approach starts with an empty seed set *S* = *O*. On every iteration of the algorithm, the node *u* with the largest increase in the expected influence spread $\sigma(S)$ is added to the seed set *S*. When using this estimation method, the chosen seed set *S* activates at least $(1 - \frac{1}{e}) \approx 63\%$ of the nodes in the network compared to the activated nodes by any set S^* of *k* chosen seed nodes. Despite the fact that this problem is NP-hard under both the LT and IC model, this approximation can be reached thanks to certain characteristics of the function $\sigma(S)$ (submodularity and monotonicity, see Kempe et al. (2003) for more details).

Since Kempe et al. (2003) published the Greedy algorithm, many studies have proposed other methods to solve the influence maximization problem. Leskovec, Krause, Guestrin, and Faloutsos (2007) propose a 'Lazy-Forward' optimization as an improvement to the Greedy algorithm. Their CELF algorithm eliminates the need to evaluate all nodes at every iteration thanks to the submodularity property. By ranking the nodes in order of decreasing influence, it suffices to evaluate the influence of only the top few nodes in the ranked list. A similar method for the IC model was proposed by Chen, Wang, and Wang (2010) in which they reduce the size of the graph G by only taking into consideration those edges that have a minimum propagation probability p. Wang, Cong, Song, and Xie (2010) developed a heuristic that first identifies communities in a social network and then discovers influential users within these communities. They argue that influence mainly flows within communities rather than across communities and that for this reason focussing within communities is a reasonable approach. Chen, Yuan, and Zhang (2010) create a local directed acyclic graph (DAG) for every node in the network and consider influence to this node only within its local DAG. A Greedy approach is then used to find the nodes with the largest marginal influence increase within their local DAG. Chen et al. (2009) introduce the degree discount heuristic that accounts for the fact that potential seed nodes might have links to each other. The maximum degree heuristic implies that the seed set should be composed of the *k* nodes that have the highest degree. The degree discount heuristic then adjusts the number of links of every node by accounting for the number of links this node has to other seed nodes. This avoids a situation in which the seed set consists of nodes that have overlapping links. Goyal, Bonchi, and Lakshmanan (2011) developed the credit distribution model which directly estimates influence propagation by assigning an influenceability score to all nodes based on historical data (action logs). Dasgupta et al. (2008) provide evidence that social relations have a large impact on customer churn. They discuss a diffusion-based approach to identify potential churners by taking into account the influence spread and its impact on churn behaviour.

A different angle was taken by Narayanam and Narahari (2010) who developed the SPIN algorithm based on the game-theoretic concept Shapley value to identify influencers in a social network. The SPIN algorithm models the information diffusion process as a cooperative game in which the Shapley value of the individuals in the network reflects their influence. Shapley value can be used to distribute the total influence in the network among all customers based on their individual influence. After ranking the nodes based on influential value — Shapley value — the seed set is chosen by iteratively taking the most influential node from the ranked list that is not adjacent to any node already in the seed set. They found that the SPIN algorithm is more efficient, requiring less computational resources than the previously proposed Greedy algorithm and achieves comparable influence spread.

In addition to the advanced approaches described in this section, many studies use other more simple heuristics based on node characteristics such as maximum degree, maximum betweenness centrality or maximum closeness centrality (Chen, Wang, & Wang, 2010; Chen, Yuan, & Zhang, 2010).

Previous research on influence maximization uses networks such as co-authorship in physical publications (Chen, Wang, & Wang, 2010; Chen et al., 2009; Kempe et al., 2003; Narayanam & Narahari, 2010), political books sold on Amazon.com that are often bought by the same buyers (Narayanam & Narahari, 2010), trust relationships in the online social network Epinions.com (Chen, Wang, & Wang, 2010; Kim, Kim, & Yu, 2013), social connections in Flickr (Cha, Mislove, & Gummadi, 2009), Second Life friendships (Bakshy, Karrer, & Adamic, 2006) and synthetic networks (Chen, Wang, & Wang, 2010; Narayanam & Narahari, 2010). These networks do not constitute actual referral networks, rather they are social networks linking items and/or people. These networks are then used to simulate spreading often based on the LT and/or the IC model that assign randomly generated adoption probabilities respectively to the nodes and the edges in a network. Hence, these networks do not incorporate explicit data on influence spread and resulting product adoption, rather this is simulated by chance based on the LT or IC diffusion models. The underlying method of these simulation-based studies is to simulate which customers in the network will become active based on the ones that already are active and their links to others. This is different from our method since we have real-life data about referrals made by existing customers and resulting product adoption. By using this data set, it is not necessary to simulate which customers become active since this is readily available in the data set.

Table 2.1: Main differences between simulation-based decision methods and our real referral-based method.

	Simulation-based methods	Real referral-based method
Data available	Nodes, links	Nodes, links, real influence cascades
Influence cascade identification	Simulate cascades based on existence of links	Cascades readily available in data
General method	Based on active nodes determine which connections become active	Based on real activation history assign credit to active nodes

2.4 Methodology

As discussed in the previous section, the literature on influence maximization is highly diverse with many different methods and variations on the methods proposed by different authors. In this section we propose a general way of simulating influence spread through a network based on game theory. We use this method for selecting six different seed sets of influencers: a first based on an unweighted communication network, a second based on a weighted communication network, a third based on a real referral network for which no simulations are needed as true referral behaviour is known and three others using the same input data as in the first three but accounting for two-hop influence spread during the seed set selection.

2.4.1 Game-theoretic preliminaries

Every time a new customer joins the telecommunication provider, the total value of the network increases. As such, a customer who has influenced many new customers to join the network has created significant value for the telecom provider. In this regard, the influence of every node in the network can be denoted by the number of referrals that were initiated by the influence of this node. Formally modeling such a situation in which participants contribute to a shared total value can be done by using the concept of a *cooperative game*, which has its roots in game theory.

A cooperative game is defined as the pair *(N,v)* where $N = 1, 2, ...n$ is the set of players and *v* represents the value of the game by a real-valued mapping $v\colon 2^N \to \mathbb{R}$ of a set of players $S \subseteq N$ to their value *v(S)*. Note that 2^N is the set of all possible subsets of *N* and that $v(\emptyset) = 0$.

Every node $i \in N$ contributes to the overall utility of the game with a value *v(i)*. Analogous, a set of nodes $S \subseteq N$ reaches a total utility of *v(S)*, excluding any contribution of the players in $N \backslash S$. The value *v(i)* that every node $i \in N$ contributes to the total utility of the network is typically described as the marginal contribution $mc(i, N)$.

In this study, a cooperative game that captures referral behaviour in a social network is defined. The customers of the telecom provider are the players in the game and the marginal contribution of each player is defined as the number of new customers who joined the provider thanks to the influence of this individual player.

A cooperative game can be analysed using a *solution concept*, which provides a method for distributing the total value of the game among the participants. The Shapley value is a solution concept that formulates an efficient approach to the fair allocation of the total utility *v(i)* in the game among the players (Shapley, 1953). Crucial here is the fairness of the allocation. Fair implies that players who contribute more to the total value should be allocated a larger fraction thereof than players who contribute less to the game. Hence, it provides a way of computing the average marginal contribution *mc(i,N)* of each player *i*. The Shapley value of the cooperative game *(N,v)* is denoted by

$$\phi(N, v) = \phi_1(N, v), \phi_2(N, v), ..., \phi_n(N, v) \tag{2.1}$$

The Shapley value $\phi_i(N, v)$ of player $i \in N$ is given by

$$\begin{aligned}\phi_i(N, v) &= \sum_{S \subseteq N \backslash i} \frac{|S|!(n - S - 1)!}{n!}(v(S \cup i) - v(S)) \\ &= \sum_{S \subseteq N \backslash i} \frac{|S|!(n - S - 1)!}{n!} mc(i, S)\end{aligned} \tag{2.2}$$

where $v(S)$ is the total value of the coalition of players S. The communication and referral network can be analysed as a cooperative game, using the Shapley value to indicate the marginal contribution of every individual player to the overall value of the game. Every node's Shapley value then reflects the number of referrals triggered by the influence of this customer. From this it follows that these values can be used to identify the most influential customers in the network.

2.4.2 The Estimated Referral Rank for finding top influencers

An unweighted approach

Previously proposed methods for finding the top influencers in a network use simulations to mimic influence flow in the network. This is necessary because of the lack of data on actual influence flow. The IC or LT model are used to simulate when nodes in the network have received enough influence from others so that they will also adopt the product. As explained in Section 2.3.1, these methods start by randomly initializing the group of first adopters and randomly assigning an influence threshold to every node or link (in respectively the LT and IC model) that determines how much influence is needed for this node to also adopt the product or how much influence flows to this node.

Contrary to previous research, the unique data set used in this study also contains data on the product adoption timing of the customers in the network. These dates of subscription are used to replicate the adoption sequence. The communication network can then be leveraged for identifying the top influencers using simulations that are similar to previous research. To do so the communication links are used as a proxy for influence flows. When a new customer *j* joins the telecom operator, it is unknown which existing customer *i* has influenced this person. Therefore, we are not able to assign the value *v(j)* of this new customer to the marginal contribution $mc(i, N)$ of the customer who influenced this person to join. We can only make use of the existing communication links in the network and assume that a new customer who joins the operator has been influenced by one of his existing customer connections. Consequently, we need to simulate this by distributing the value of this new customer *j* over all his connections that are existing customers. The resulting measure is called Estimated Referral Rank as it facilitates constructing a ranking of all nodes in the network based on their estimated potential of referring new customers.

Customer *i*'s marginal contribution, or Estimated Referral Rank (ERR), to the network is defined as

$$ERR_i = \sum_{j \in N_1(i)} \frac{\phi_j(N, v)}{n_j} \tag{2.3}$$

in which N_1 symbolizes the one-hop neighbourhood of node j, $\phi_j(N, v)$ is the Shapley value of new customer *j*, which is distributed over n_j connections of *j* that are existing customers.

Figure 2.3 presents an example communication network. Let's say that node *a* is a new customer who recently joined the network and communicates with customers *b*, *c*, *d* and *e*. As we only have communication data, we do not explicitly know which existing customer influenced *a* to join. Therefore, we assign to each connection of *a* an equal portion of the value of *a*, which in this case is 0.25. In this small example, customers *b*, *c*, *d* and *e* are equally influential with an ERR of 0.25.

Figure 2.3: Unweighted example communication network.

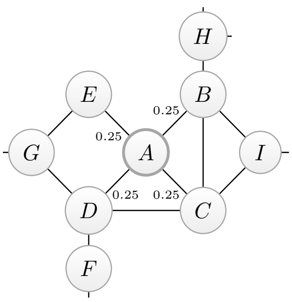
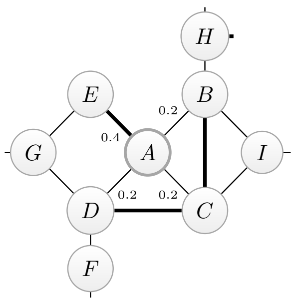


Figure 2.4: Weighted example communication network.



A weighted approach

In the ERR, the weight of an edge between nodes *i* and *j* is one if there is an edge and zero if there is none. However, when data on the edge strengths is available, this can be incorporated in the method for selecting top influencers to render the model more realistic. The distribution of the value of a new customer can be scaled based on the weight of the connections with existing customers. If new customer *j* has a stronger connection with existing customer *i* than with existing customer *k*, it is likely that *i* has a larger influence on *j* because they communicate more often which results in more social influence. As a result, existing customer *i* should be assigned a larger portion of the value of new customer *j* than existing customer *k*. Thus, customer *i*'s Weighted Estimated Referral Rank (WERR) can be computed as

$$WERR_i = \sum_{j \in N_1(i)} \phi_j(N, v) \cdot \frac{a_{ij}}{a_{.j}} \tag{2.4}$$

where a_{ij} is the weight of the edge between node *i* and *j* defined by weight matrix *a* and $a_{.j}$ is the sum of the weights of all connections of node *j*. We define the weight of an edge between two customers in our communication network based on the total duration of phone calls and the number of single SMS's (one long SMS is often processed as multiple SMS's) sent between these two customers. Figure 2.4 provides an example of how the distribution of the value of node *a* over the neighbours is established based on the weights of the connections. Based on the communication frequency and duration between the existing customers with new customer *a*, we can see that existing customer *c* has a stronger connection with new customer *a*. This implies that it is more likely that customer *c* has influenced the new customer to join the network and therefore should be assigned more value than the other existing customers.

2.4.3 The Real Referral Rank for finding top influencers

Although it is not that common yet, management can also gather information on the referrals made by their customers by for example tracking this online. When such information is available, managers could use data on the actual referral behaviour of their customers when selecting the top influencers. In this section we define the Real Referral Rank which uses actual referral behaviour for quantifying individuals' influential value. A customer's Shapley value based on his actual referrals reflects this customer's true contribution to the network, defined as the Real Referral Rank (RRR). A limitation of the data is that every new customer can only be referred by strictly one existing customer. As a result thereof, for every new customer *j* the number of neighbours n_j who are existing customers is equal to 1. This also implies that there is no need to account for edge strength. A customer's RRR is denoted by

$$RRR_i = \sum_{j \in N_1(i)} \phi_j^*(N, v) \tag{2.5}$$

which reflects the total value of the new customers referred by existing customer *i* and where ϕ_j^* is the contribution defined by actual referral data.

2.4.4 Extending the influence area: Two-hop selection

It is important to realize that influence does not suddenly vanish after the one-hop neighbours of a node. According to Christakis and Fowler (2013), noticeable interpersonal influence propagates as far as the two-hop neighbourhood of the influencing node. Moreover, Li and Shiu (2012) also compute influence propagation in a recursive way in their diffusion model. They make the point that there is no use in targeting a campaign to an influential customer if his connections do not spread the message on their turn. Thus, the influence of node *a* in Figure 2.5 propagates as far as the second hop neighbourhood which is the level of nodes *d*, *e* and *f*. Customer *a* has thus referred new customers who are also relatively influential and can further propagate *a*'s influence. For that reason, the marginal contribution of customer *a* should take into account the marginal contributions

Figure 2.5: Example referral network.

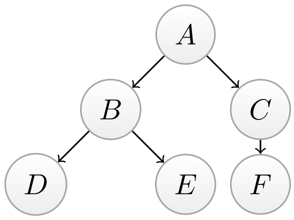
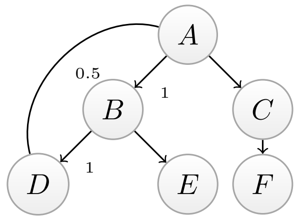


Figure 2.6: Example referral network with a transformed two-hop edge.



of customers *b* and *c*. This seems reasonable as nodes that have a large influence cascade contribute more to the total value than nodes that induce only a short influence cascade.

As the influence of the neighbours of the seed set has a significant impact on the resulting influence spread, we investigate whether the selection of top influencers can be improved by incorporating a measure of second hop influence. In order to do that, we transform two-hop neighbours to one-hop neighbours by using a formula proposed by Verbeke et al. (Verbeke, Martens, Mues, & Baesens, 2011). They propose a novel way to reduce a two-hop link into a one-hop link by computing a weight for the two-hop link that is based on the weights of the one-hop links. They define the weight matrix λ for transforming two-hop edges to one-hop edges as

$$\lambda_{ik} = \max_{j} \frac{a_{ij} \cdot b_{jk}}{a_{ij} + b_{jk}} \tag{2.6}$$

in which λ_{ik} is the new weight between the node *i* and its second hop neighbour node *k* and in which a_{ij} and b_{jk} represent the weights between nodes *i* and *j* and nodes *j* and *k* respectively.

This is illustrated in Figure 2.6, where the two-hop connection between node *a* and *d* is created based on the one-hop connections between nodes *a* and *b* and nodes *b* and *d*.

When extending the influence area considered from one-hop to two-hops, the ERR and RRR of customer *i* become

$$ERR_i^2 = \sum_{j \in N_1(i)} \frac{\phi_j(N,v)}{n_j + \lambda_{.j}} + \sum_{k \in N_2(i)} \frac{\phi_k(N,v) \cdot \lambda_{ik}}{n_k + \lambda_{.k}} \tag{2.7}$$

and

$$RRR_i^2 = \sum_{j \in N_1(i)} \frac{\phi_j^*(N,v)}{\lambda_{.j}} + \sum_{k \in N_2(i)} \frac{\phi_k^*(N,v) \cdot \lambda_{ik}}{1 + \lambda_{.k}} \tag{2.8}$$

where λ is the factor that transforms the two-hop neighbours to one-hop neighbours, as described in Equation 2.6, and the existing customer *i* has new customer *j* as direct connection who in turn has new customer *k* as neighbour. $N_1(i)$ and $N_2(i)$ respectively represent the one-hop and two-hop neighbourhoods of existing customer *i*. The first terms give the total direct contribution of customer *i* received because of *i*'s one-hop neighbours who are new customers. The second terms represent the total indirect contribution of customer *i* because of the influence of *i*'s direct neighbours resulting in *i*'s two-hop neighbours who are new customers. Note that λ will always be 0.5 for the ERR^2 and RRR^2 as edge strengths are either one or zero.

It will be different for the WERR as the edges can have any weight $\in [0.1]$. Extending the WERR to the second hop neighbourhood is done as follows

$$WERR_i^2 = \sum_{j \in N_1(i)} \phi_j(N, v) \cdot \frac{a_{ij}}{a_{.j} + \lambda_{.j}} + \sum_{k \in N_2(i)} \phi_k(N, v) \cdot \frac{\lambda_{ik}}{a_{.k} + \lambda_{.k}} \tag{2.9}$$

Here too, λ is the factor from Equation 2.6 to convert two-hop links to one-hop links. The difference with the ERR formula is that the assigned value is scaled for the weight of the connections by weight matrix *a*.

2.5 Results

2.5.1 Data

We conduct experiments on call detail records (CDR) of a European telecom provider, consisting of 1,6 billion communication records of 211,075 customers. The telecom operator continually runs the same referral program using the same marketing message and incentives. As a result, the impact of the characteristics of the referral program on the referral behaviour of the customers is limited, which benefits the generalisability of the findings. The communication behaviour of the customers defines a network in which the individuals are the nodes and the communication interactions are the links. In addition to communication data, the referrals made by the customers are also available for this study. The total number of recorded referrals is 65,078. The ID of the referring customer is recorded together with the assigned ID of the new customer, as well as the method of referral and the date and time and whether the referral was successful or not. Using referral behaviour, we can construct a referral network in which the individuals are the nodes and the referral-referred customer relations are the links. The communication network used in this study was selected as follows. First, we selected all existing customers who ever communicated with a new customer. A new customer is defined as a customer who joined the telecom operator in the 6 months before the evaluation period. There are 57,551 new customers and 478,109,344 records of communication. Second, we defined a minimum communication threshold of a total of 10 minutes of communication over 6 months to ensure that only intended calls representing a true social connection are considered. As Ma et al. (2014) note in their study, setting such threshold is subjective and can only be based on exploration of the data. It is important that the threshold is not too low because this will lead to including individuals who are not part of the caller's social network, nor too high since it will reduce the power of the analyses (Ma et al., 2014). Our selection of 10 minutes of communication aims to achieve a balance between the two. Exploration of the data showed that results based on different cut-off levels delivered similar results. Applying this threshold results in 130,537,963 CDR records. A total of 65,078 referrals were made by 48,798 customers of this group of 57,551 customers. This means that the communication network has 57,551 nodes and 156,020 edges and the referral network has 48,798 nodes and 65,078 edges.

2.5.2 The evaluation procedure

In order to be able to evaluate the increase in the number of customers, the data set was separated into two distinct sets. One year of mobile communication and referral data was split in six months training set and six months test set. The training set is used for selecting the seed set of influential individuals and the test set is used for generating the resulting product adoption in the network.

Many organisations do not hold data about the referral behaviour of their customers, while communication behaviour on the other hand is more common to have access to. That is why in a first part of the experiments, we only use the communication network for selecting influencers and evaluating the resulting product adoption as those companies would. This is done by simulating influence propagation based on the communication edges in the network (as is traditionally done in influence maximization literature). We use the same ERR and WERR methods on the test data set for evaluating the influence spread of the customers as we did on the training data set for assigning the customers an influencer score. This is referred to as the simulation-based methods in the remainder of the paper. In order to determine the value for companies to gather referral behaviour data, in a second part of the experiments we evaluate the real referral behaviour of the customers based on the referral network. This implies that the influence spread of the customers is determined by the actual number of referrals made by every customer.

To statistically test the results, we analyze the results using Friedman's Chi-square test, which is the non-parametric equivalent of the repeated-measures ANOVA. The results indicate that all differences are statistically significant (p-value < 0.001). As the Friedman test indicates significance, the Nemenyi post-hoc test is employed to analyze the differences between the methods (Coussement, Benoit, & Antioco, 2015). The results show that the differences between all pairs of methods are significant ($p < 0.001$).

2.5.3 The value of real referral data for seed set selection

In the first step of the simulations we compare the simulation-based methods, both the unweighted and the weighted approach (the ERR and WERR respectively), for selecting influencers with the referral data-based method. It is important to realize that in both the training period — when selecting the top influencers — as well as in the test period — when evaluating the resulting product adoption — simulated influence spread and real referral data can be used.

Evaluating on simulation-based influence spread

First, we use the communication network to simulate the influence spread and resulting product adoption in the test period. Figure 2.7 and Table 2.2 illustrate that the RRR method outperforms the ERR method. This implies that even when evaluation is done based on simulated influence spread, using referral behaviour data for selecting the top influencers leads to larger influence spread. Thus, selecting influencers based on referral behaviour data results in more product adoption through a larger influence spread than selecting influencers based on simulations. The lower-bound on performance is a random approach. In order to ensure unbiased results, the process of picking random nodes and simulating network growth is performed 100 times. Per number of k seed nodes, the average of these 100 observation then represents the random spread.

In the second step of the simulations we use the edge strengths in the communication network to compute the WERR. Again, we use the communication network to simulate the influence spread and resulting product adoption in the test period. The results, as visualised in Figure 2.9 and Table 2.4, demonstrate that the difference between the ERR and WERR method is rather small. If the manager would be restricted, because of a lack of real referral data, to evaluate the results on simulated data, only little difference between ERR and WERR would be observed.

Evaluating on real referral behaviour

Second, we use the real referral network to evaluate the resulting product adoption in the test period. In Figure 2.8, the difference in performance between the ERR and RRR method is now significantly larger. The RRR method for selecting influencers performs very well when evaluation is done on real referral behaviour data. It is clear that in case referral data is available it should definitely be utilized when searching for influencers in a customer base. Further, comparing Table 2.2 and 2.3 indicates that evaluating on simulated data underestimates the influence spread when selecting influencers using the RRR method, but overestimates it when selecting influencers using the ERR method.

The fact that the RRR method performs better than the ERR method indicates that better results are attained when the data approximate real life behaviour. However, most organisations only have communication data, so we propose to use the WERR to render the ERR method a better representation of real life. Hence, we use the edge strengths in the communication network to compute the WERR. Figure 2.10 shows that the WERR

Table 2.2: Nr of new customers evaluated using simulation after selecting the seed set based on the two different methods.

Nr of seed nodes	ERR	RRR
50	15	14
100	28	43
300	84	118
500	130	181
1000	265	307

Table 2.3: Nr of new customers evaluated using real referral data after selecting the seed set based on the two different methods.

Nr of seed nodes	ERR	RRR
50	14	165
100	24	235
300	69	363
500	115	445
1000	224	631

outperforms the ERR, which implies that the weighted approach in fact outperforms the unweighted approach. This was not visible when evaluating on simulations, visualised in Figure 2.9. As a result, this method performs better when evaluation is based on the referral data. This implies that incorporating information on edge strength optimizes the identification of influential customers, especially when a large seed set is selected.

Figure 2.7: The RRR method outperforms the ERR method when evaluating on simulated data.

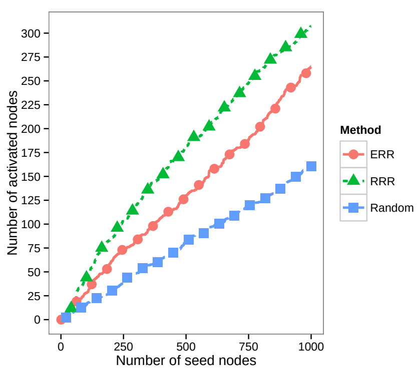
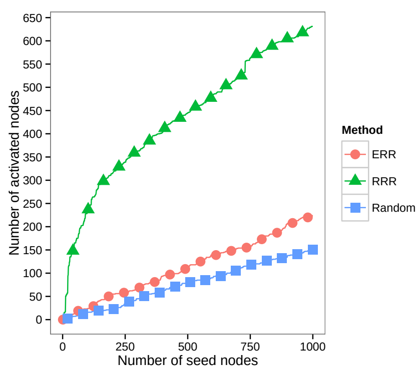


Figure 2.8: The RRR method far outperforms the ERR method when evaluated on real referral data.



An important aspect of the results is the over- and underestimation of these methods. By comparing Table 2.4 and Table 2.5, it can be stated that the influence spread of the influential customers selected with the ERR evaluated on real referral data leads to a lower number of activated new customers than evaluating on simulated data. This implies that

Figure 2.9: The WERR and ERR method perform similarly when evaluated on simulated data.

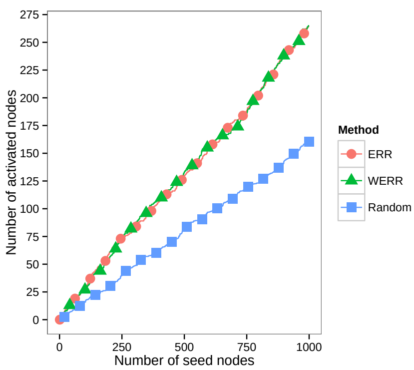


Figure 2.10: The WERR method outperforms the ERR method when evaluated on real referral data.

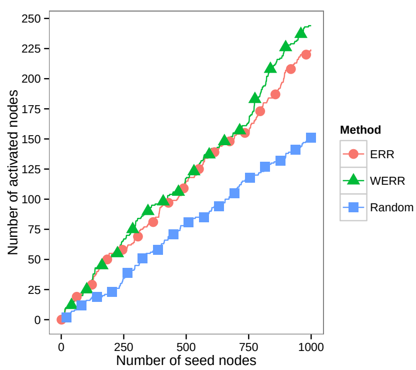


Table 2.4: Nr of new customers evaluated using simulation after selecting the seed set based on the two different methods.

Nr of seed nodes	ERR	WERR
50	15	17
100	28	27
300	84	84
500	130	133
1000	265	265

the product adoption realized by influencers selected based on the links in the network might give an overestimated view of the product adoption in reality.

In conclusion, we find that the RRR method leads to the best selection of influencers when both evaluating on simulated influence spread and on referral behaviour. It is thus beneficial to invest in the referral detection process. If no referral behaviour is available as input to the decision support system for finding influencers, the WERR method should be preferred over the ERR method as it performs slightly better in identifying the top influencers.

Table 2.5: Nr of new customers evaluated using real referral data after selecting the seed set based on the two different methods.

Nr of seed nodes	ERR	WERR
50	14	15
100	24	25
300	69	82
500	115	117
1000	224	244

Table 2.6: Nr of new customers evaluated using simulated data after selecting the seed set based on the three different 2-hop methods.

Nr of seed nodes	ERR	WERR	RRR
50	19	22	16
100	37	35	51
300	96	99	165
500	165	158	208
1000	353	344	387

2.5.4 The value of two-hop selection

So far the experiments only incorporated the one-hop neighbourhood influence spread of every node. In the following, we describe the results of the experiments when taking into account the influence of the two-hop neighbours of the node considered.

Evaluating on simulation-based influence spread

First, we examine the results when evaluating the product adoption in the second period by simulating the influence spread over the communication network links. We again include a lower boundary based on random selection. The experiments show that, for all three methods, considering the two-hop neighbourhood of the customers results in a better selection of influential customers and higher influence spread. Comparing Table 2.2 and Table 2.4 with Table 2.6 shows this. It can be seen from Figure 2.11, Figure 2.12 and Figure 2.13 that the difference even increases as the seed set grows. Consequently, for large seed sets it pays off for managers to take the effort of considering the influence of the customers' two-hop neighbourhood connections.

Evaluating on real referral behaviour

Second, we investigate the results when evaluating the product adoption in the evaluation period by looking at real referral behaviour. The results show that, for all three methods, the performance is better when considering the two-hop neighbourhood. This can be seen by comparing Table 2.3 and Table 2.5 with Table 2.7. However, the improvement is smaller than when evaluation is done based on simulations. Thus, the previous evaluation based on simulated influence spread overestimates the actual product adoption in the test period. Figure 2.14, Figure 2.15 and Figure 2.16 demonstrate that taking into account the influence of the two-hop neighbours indeed results in a larger influence spread and more product adoption.

In conclusion, we can state that the difference in performance between the 1-hop and 2-hop methods is smaller when evaluating on real referral data than when evaluating on simulated influence spread. This indicates that evaluating on simulated influence leads to

Figure 2.11: The ERR two-hop method evaluated on simulated influence spread performs better than the one-hop method.

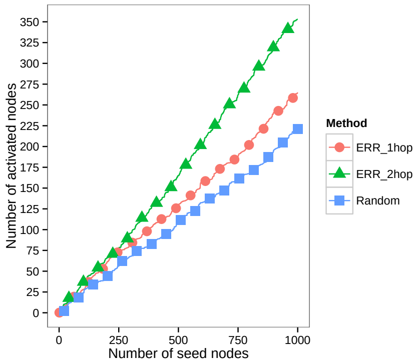


Figure 2.12: The WERR two-hop method evaluated on simulated influence spread performs better than the one-hop method.

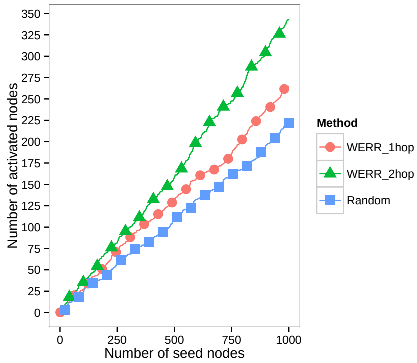
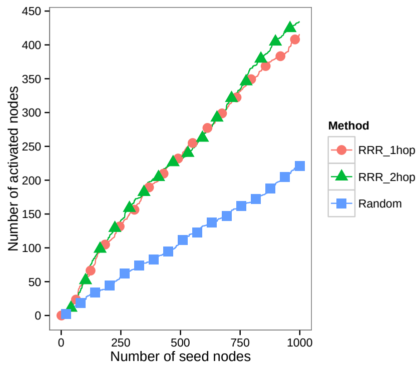


Figure 2.13: The RRR two-hop method evaluated on simulated influence spread performs better than the one-hop method.



an overestimation of the improvement in influence spread when taking into account the 2-hop neighbourhood influence rather than just 1-hop. The results evaluated on real referral data show that there is indeed an improvement when using the 2-hop method instead of the 1-hop method, but this improvement is rather limited.

2.6 Conclusion and discussion

This study investigates an issue critical to the success of referral marketing programs: how can a group of customers be identified who are most influential and can affect the largest number of potential customers through word-of-mouth. Previous research is generally design- and technology-oriented and use simulation-based methods to simulate influence spread over networks. Using a unique data set composed of both communication data and referral behaviour data, this study investigates whether the algorithms based on influence propagation simulations perform well in terms of identifying the most influential indi-

Figure 2.14: The ERR two-hop method evaluated on real referral data performs slightly better than the one-hop method.

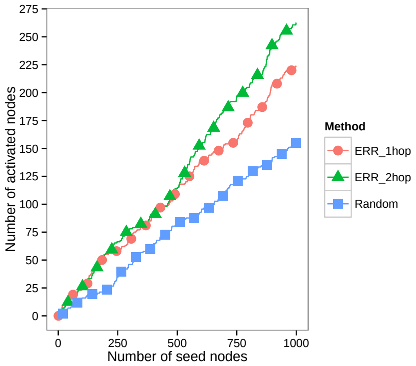


Figure 2.15: The WERR two-hop method evaluated on real referral data performs better than the one-hop method for large seed sets.

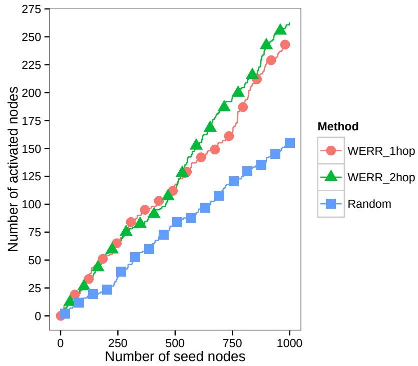
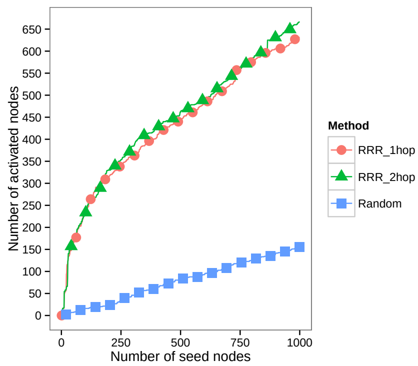


Figure 2.16: The RRR two-hop method evaluated on real referral data performs slightly better than the one-hop method.



viduals in the network and estimating their resulting influence spread. The results show that limiting the decision support method for finding top influencers to simulations leads to overestimating the actual influence spread and resulting product adoption. The best results are attained when referral data is used for selecting top influencers. Unfortunately, it is not that common yet for organisations to capture data about their customers' referral behaviour. In that case, a measure of tie strength between individuals should be incorporated in the selection method as this leads to a larger influence spread than when this is not incorporated. Next to that, the results also prove that it is important to not just look at the influence of the targeted customers, but also at the influence of their connections. If the connections of the most influential customers are not willing to spread word-of-mouth, there is no use in targeting them with a marketing campaign since the influence will not spread very far. Overall, this study shows the value of a referral behaviour detection process. A decision support system for selecting the most influential customers based on referral data allows companies to identify their most influential customers of whom the

Table 2.7: Nr of new customers evaluated using real referral data after selecting the seed set based on the three different 2-hop methods.

Nr of seed nodes	ERR	WERR	RRR
50	14	14	173
100	26	26	230
300	78	78	384
500	114	114	463
1000	263	263	666

influence spread will trigger the largest cascade in product adoption. Fortunately this kind of data is becoming easier to obtain thanks to the widespread use of social media. Hence, an increasing number of organisations that possess any kind of data related to referrals or recommendations can benefit from the approach suggested in this paper. In case no referral behaviour data or proxy data thereof is available, the simulation methods based on network data are already valuable and succeed in identifying influencers in a social network, although less so than those based on referral data.

3

How customer referral programs harness the power of your customers' connections

3.1 Introduction

The presence and role of social networks among customers has received increasing attention in marketing literature. Multiple studies have established the impact of social influence, traversing connections between individuals, on consumer behavior (Benoit & Van den Poel, 2012; Hill et al., 2006; Martens, Provost, Clark, & de Fortuny, 2016; Verbeke et al., 2014). As a result, leveraging social influence for marketing purposes is of key interest to marketing scholars. A practice that builds on leveraging such social influence is referral marketing. Customer referral programs are marketing campaigns that leverage the social connections of existing customers with potential customers to attract and convert potential customers. More specifically, existing customers are rewarded for recommending the firm to others and bringing in new customers. Previous research has shown that referred customers are more valuable to a firm than non-referred customers (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018; Villanueva et al., 2008). These studies have shown that referred customers have a higher contribution margin and

This chapter is co-authored with Philippe Baecke, Dries Benoit and Christophe Van den Bulte longer lifetime than non-referred customers. Schmitt et al. (2011) estimated the difference in value in terms of contribution margin and lifetime between referred and non-referred customers to be at least 16%.

In addition to differences in contribution margin and lifetime, one might also expect a difference to be perceptible in cost-to-serve. Reichheld (2006) argued that referred customers can rely on the help and advise of their referrer, whereas non-referred customers need to turn to firm-provided support for help. Therefore, the present study completes the picture of the differences in customer lifetime value (CLV) of referred and non-referred customers by also assessing the difference in cost-to-serve. This will provide an exhaustive view of the differences in total CLV between referred and non-referred customers. In addition to documenting the value gap, the present study examines a potential driver thereof. A recent study has proposed two theory-driven phenomena underlying the value difference between referred and non-referred customers, namely better matching and social enrichment (Van den Bulte et al., 2018). However, this study mainly investigated the role of the relationship between the referrer and the firm for creating valuable referrals. There are in fact three relationships involved in a customer referral: (1) referrer-firm, (2) referrer-referred customer and (3) referred customer-firm. The research by Van den Bulte et al. (2018) showed that the relationship between the referrer and the firm has an impact on the the value of the referred customer. Hence, their finding suggests that the social relationships involved in customer referral programs play a role in the value creation process of referrals. They also found that referrer churn increases the churn likelihood of the referred customer. This is in line with other previous research that has shown that customers are influenced by each other's consumer behavior through social contagion (Aral & Walker, 2014; Hill et al., 2006). Knowing this, we can extend the findings by Van den Bulte et al. (2018) and hypothesize that the relationship between the referrer and the referred customer impacts customer behavior and therefore customer value. More specifically, we argue that the relationship strength between the referrer and referred customer might also be a factor in the value creation by customer referrals. The present study investigates this effect, exploring how the relationship between the referrer and referred customer impacts the value of the latter to the firm. By doing this, we provide a complete view on the role of the social connections involved in a customer referral program and the underlying mechanisms for generating valuable referrals.

The objective of this study is to extend the insights into how customer referral programs create value for companies. Using a data set from a European telecom operator we answer two main questions: (1) Are referred customers more valuable than non-referred customers in all facets of customer lifetime value? (2) What is the role of the relationship strength between the referrer and referred customer?

In the next section, we review the findings and theories from previous research and build on this to develop new hypotheses. In Section 3.3, we describe our data and modelling method. Section 3.4 outlines the results of our research, which are discussed in Section 3.5. We conclude with implications for theory and practice.

3.2 Theory and hypothesis development

3.2.1 Theory

Previous research suggests that customers who join a firm as a result of word-of-mouth are more valuable than customers acquired through other channels (Armelini et al., 2015; Schmitt et al., 2011; Villanueva et al., 2008). This is not only due to lower acquisition costs, referred customers are also easier to retain (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018; Villanueva et al., 2008), spend more money (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018) and are more likely to make new referrals themselves (Von Wangenheim & Bayón, 2004). Schmitt et al. (2011) quantified the value difference between referred and non-referred customers for a German bank. They found that referred customers are 16% to 25% more valuable than non-referred customers due to higher contribution margins and higher retention rates. Similar effects happen to referrers who also have higher retention rates (Garnefeld et al., 2013) and increased purchases (Kumar et al., 2010) after making referrals themselves. These findings suggest that customer referral programs are a profitable marketing tool.

Motivated by the findings of previous research, Van den Bulte et al. (2018) analyzed where this difference in value between referred and non-referred customers stems from. They found evidence for two phenomena that underlie this difference, namely better matching and social enrichment.

Better matching

Better matching is the phenomenon that referred customers fit better with the firm's services than non-referred customers do. It can occur in two different ways, namely through active matching (i.e., the conscious evaluation of the fit between the firm and social connections) and passive matching (i.e., homophily). Active matching occurs when existing customers actively screen their social network to find the individuals that match up best with the firm. It involves benevolence from the customer towards his social connections and the company. Existing customers who are more satisfied with the firm are generally more willing to make an effort in the search for good referrals. Passive matching on the other hand, is based on the shared characteristics between the referrer and the referred customer. Homophily implies that individuals have similar characteristics, values and perspectives. It is due to these shared observables and unobservables that referred customers value the same type of service as their referrer does. Hence, if the referrer is a satisfied customer with the firm, his needs and wishes correspond well with the firm's offerings, which through homophily implies that the referred customer's needs and wishes have an above-average chance to also correspond well with the firm's offerings.

Social enrichment

Social enrichment is the phenomenon that the relationship with the firm is enriched because of the presence of a common social connection (Figure 3.1). This is explained by triadic closure and balance theory. Thanks to the presence of the referrer, a referred customer is likely to put more trust in the firm, stay longer with the firm (Van den Bulte & Wuyts, 2007) and have an increased ability to overcome (temporary) frustrations. This social mechanism is particularly important for offerings for which trust is an important factor, like services (Berman, 2016). The theory of social enrichment relates to two distinct principles, namely social support and joint consumption. First, social enrichment enables improved social support. Being connected to a fellow customer entails having a person to turn to for help and advice. There will be less need to rely on firm-provided customer support as there is another trusted party that can help with navigating specific procedures and understanding offerings. Referred customers in particular can turn to their referrer for this, whereas non-referred customers do not necessarily have such a go-to-person (Reichheld, 2006). As a result, referred customers are less likely to pass through situations of frustration and more likely to survive them thanks to the help of their referrer. The second aspect of social enrichment is joint consumption. Joint consumption involves the enticement to consume where social connections consume. Ample research has shown that behavior is contagious and people are influenced by each other (Ascarza, Ebbes, Netzer, & Danielson, 2017; Benoit & Van den Poel, 2012; Haenlein & Libai, 2013; Hill et al., 2006; Nitzan & Libai, 2011). Referrers and referred customers are thus also influenced by each other's actions and presence at the firm.

Building on this foundation of theory, we now continue to develop hypotheses that aim to add to the state-of-the-art. Consistent with prior literature, we use the term “referral” in the remainder of the paper to denote both the event in which a customer brings in another customer as well as the referred customer.

3.2.2 Hypothesis development

Value gap between referred and non-referred customers

More research is needed to establish what differences there are between referred and non-referred customers. Whereas Schmitt et al. (2011) found a difference in both the contribution margin and the retention rate of referred and non-referred customers, Armelini et al. (2015) only found a difference in retention rate. We take a broader view and investigate three facets of customer lifetime value (CLV), namely revenue, retention rate and cost-to-serve. We will further be able to draw additional insights from the fact that our study is conducted in a different industry than previous research. The research by Schmitt et al. (2011) and Armelini et al. (2015) was conducted in a banking context, where trust is a very important factor. Our data set, in contrast, stems from a pre-paid telecom operator where the stakes are lower and trust might thus be of less importance. From this, research question 1 follows:

RQ 1: What differences in value are there between referred and non-referred customers?

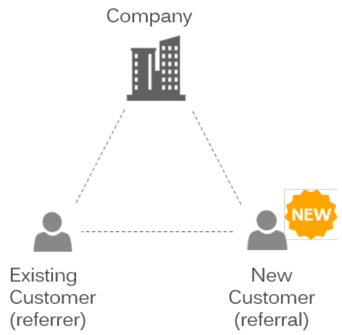
Drivers of the value gap between referred and non-referred customer

According to previous research, two phenomena might be driving the potential difference in value between referred and non-referred customers, namely better matching and social enrichment (Van den Bulte et al., 2018). In the second part of this paper we zoom in on where the difference in value between referred and non-referred customers stems from.

RQ 2: Why are referred customers more valuable to a firm than non-referred customers?

To investigate research question 2, we define multiple hypotheses.

Figure 3.1: Visual representation of the relations involved in a customer referral program.



Both active and passive matching suggest that if a referrer has more experience with the firm, the referral will be more valuable to the firm. Van den Bulte et al. (2018) focused solely on the lifetime of the referrer with the firm to investigate this effect. Next to lifetime of the referrer, we also investigate the referrer's usage intensity of the product/service as a second aspect of the experience of the referrer with the firm. The first hypothesis ascertains that we find evidence for this.

H_1: Referred customers have (i) a higher profitability and (ii) a longer lifetime if their referrer has a stronger connection with the firm when making the referral.

Previous research only investigated the impact of the relationship between the referrer and the firm. Van den Bulte et al. (2018) highlight that similar effects might be at play for the relationship between the referrer and referral, but that they could not investigate this due to data limitations. Indeed, one of the challenges in studying customer referrals is the difficulty of identifying and collecting appropriate data. One needs a realistic social network containing a significant collection of explicitly identified referrals and an indication of connections between individuals. Thanks to our data set meeting these criteria, we are able to extend the reasoning behind Hypothesis 1 and argue that also the relationship between the referrer and the referral is likely to have an impact on the value of the latter to the firm. The second hypothesis reflects this idea:

H_2: Referred customers' (i) profitability is higher and (ii) lifetime is longer if their relationship with the referrer is stronger.

It is well documented that churn behavior is contagious (Benoit & Van den Poel, 2012; Nitzan & Libai, 2011, e.g.,): customers are more likely to churn when social connections churn. Next to social influence impacting churn behavior, the loss of the enriched relationship with the firm could also increase churn. According to social enrichment, the relationship of the referral with the firm is no longer enriched when the referrer churns. As a result, the referral might feel less connected with the firm. Van den Bulte et al. (2018) investigated this effect of referrer churn on the churn behavior of the referral and found that referrals are more likely to churn when their referrer has churned. In addition to the referrer's churn having an effect on the referral's churn, we might expect that it has an effect on the referral's profitability. Multiple studies have demonstrated that people who are social connections typically have similar purchase volumes and purchase frequencies (Ascarza et al., 2017; Haenlein & Libai, 2013; Hill et al., 2006). Thus, referred customers can also exhibit a decrease in profitability when their referrer churns. This reasoning leads to the following hypothesis:

H_3: Referred customers exhibit (i) lower profitability and (ii) a higher churn rate after their referrer has churned.

A customer is not impacted equally by the behavior of all his or her social connections (Aral & Walker, 2014). As a result, the effect of the behavior of the referrer on the referral varies depending on how important the referrer is to the referral. Building on Hypotheses 2 and 4, we believe that the effect of the churn of the referrer is stronger if the relationship between the two is stronger.

H_4: The change in (i) profitability and (ii) churn rate for referred customers whose referrer has churned is even more pronounced for those who have a strong relationship.

Until now, only the impact of being referred on the contribution margin and retention rate has been documented (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018). In addition to these two aspects, being referred can also impact a customer's cost-to-serve. When customers join the firm, they learn how to handle the firm's offering and to navigate firm procedures. However, there is a difference between the learning of referred and non-referred customers. Whereas non-referred customers have to rely on the help desk of the firm and information they can gather on the website, referred customers can turn to their referrer for help and advise (Reichheld, 2006). Therefore, we expect referred customers to rely less on firm-provided customer support and as a result have a lower cost-to-serve. We posit the following hypotheses about the cost-to-serve of referred customers:

H_{5a}: Referred customers have a lower cost-to-serve if their referrer has more experience with the firm when making the referral.

H_{5b}: Referred customers' cost-to-serve is lower if their relationship with their referrer is stronger.

3.3 Model development

3.3.1 Research setting and data

Research setting

We use data from a European telecom provider. It is a single-product company offering a pre-paid mobile phone service in a non-contractual setting. Their customers can choose between multiple packages at different price levels for buying credits. When customers purchase a package, they receive free call minutes, texts and mobile data. These free call minutes, texts and mobile data can be transferred to the next month if they are not all consumed. In addition to getting free minutes, texts and data, customers can call and text other customers for free. So next to the limited free out-of-network calls and texts, customers also receive unlimited free in-network calls and texts. These free in-network calls and texts are only valid for a period of 30 days after the last purchase. After 30 days they are charged at the same rate as out-of-network calls and texts. The free in-network calls and texts are a major benefit of being a customer of this provider and incentivize existing customers to refer friends and family. This operator has been running a referral program since the start of its operations and has always been providing the same rewards for referrals, namely 15 euros added to the referrers account.

Data and characteristics

The customer base consists of over 153,000 customers acquired between October 2010 and July 2013. 57% of the customers were referred by existing customers. All referrals that have been made in that period have been recorded and are available for this study, as well as transactional data, CDR data and demographic data.

The mobile operator initially grew its customer base via social media and as a result attracted a mainly younger audience as its first customers. Even several years after their launch, a significant proportion of the customer base are young people. The age distribution has a clear spike around 23 years old and 60% of the customer base is between 20 and 31 years old, while only 30% is older than 31 (and the other 10% is younger than 20). Further, for the referred customers we see a slight bump in the age histogram (Figure 3.2) between the ages of 45 and 60. This indicates that most of the referred customers are either between 20 and 30 years old or between 45 and 60 years old. This bump is not present in the age histogram of the non-referred customers, as can be seen in Figure 3.3. For all referrals, Figure 3.4 plots the age of the referrer on the x-axis and the age of the referred customer on the y-axis. It illustrates that there exist two main types of referrals, namely peer-to-peer referrals where the referrer and referral have about the same age, and inter-generational referrals where twenty-something customers refer most likely their parents, uncles or aunts. These inter-generational referrals are likely what causes the bump in the number of referred customers between the ages of 45 and 60 in Figure 3.2.

3.3.2 Methodology

In this section, we first discuss why and how we use a matching technique to reduce imbalance between the referred and non-referred customers in our data set. Second, we describe our modelling approach, which consists of both pseudo-contractual models and a latent attrition model to investigate the hypotheses of research question 2.

Figure 3.2: Age histogram of the referred customers.

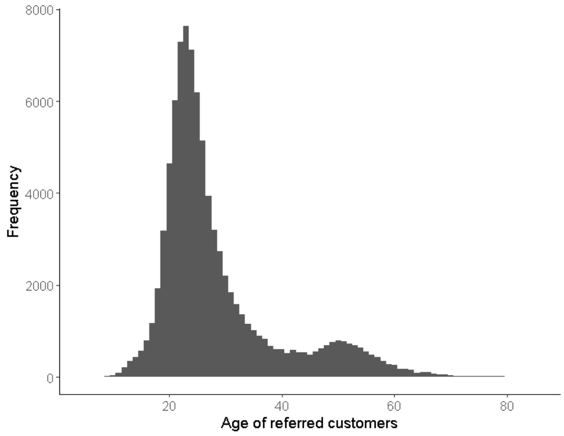


Figure 3.3: Age histogram of the non-referred customers.

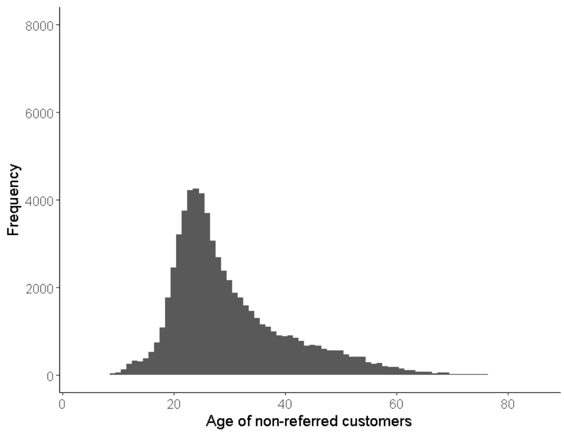
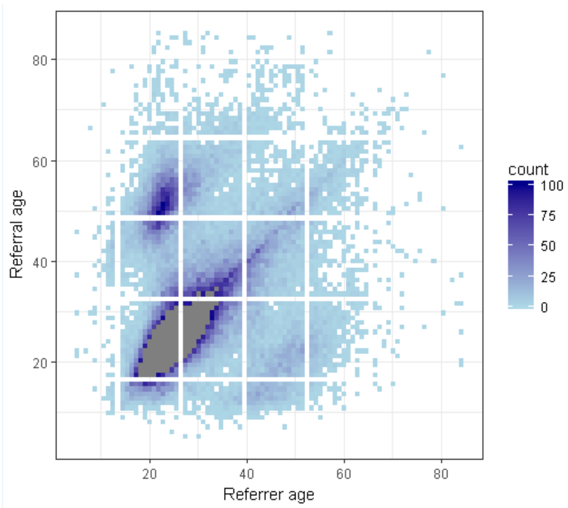


Figure 3.4: Scatter plot of referrer and referral age.



Customer matching technique: Coarsened exact matching

A. Motivation

Previous research on referral marketing has proposed two mechanisms that drive the value created by referral campaigns (Van den Bulte et al., 2018). First, better matching takes place because existing customers who have a long and profitable relationship with the firm are well placed to assess the potential fit of their social connections with the company. The existing customers thus select those social connections who they think match best with the firm. As a result, there is a selection mechanism at play. Due to this selection, referred customers (matched and selected by existing customers) and non-referred customers (not matched by existing customers) might have different characteristics, both observed and unobserved. In order to be able to attribute differences in customer behavior to the acquisition mode rather than to other customer characteristics we use a customer matching technique.

The second mechanism underlying the effects of referral programs is social enrichment. Social enrichment results from the fact that the presence of a referrer generates value for the referred customer. This theory is of a causal nature and to be able to make such causal claims, we need to eliminate likely observable and unobservable effects confouding the causal claims. Again, we want any pattern found in the data to be clean and attributable to being referred or not referred. To ensure this, we use a matching technique that enables us to select pairs of referred and non-referred customers who have similar socio-demographic characteristics. Any difference in customer behavior between those pairs is then not driven by differences in the matching variables.

B. Procedure

Based on the arguments presented in King and Nielsen (2016)[1], we use exact matching to reduce imbalance and bias as much as possible. We specify four variables to asses the match between a referred and a non-referred customer and identify 27,072 pairs of referred customers and their most comparable non-referred customers.

Firstly, age is an important variable to match on because the data show that older customers are more likely to contact the service desk. Evaluating the difference in cost-to-serve for referred and non-referred customers is an important part of this study. By using age decile as a matching variable we prevent that the observed calls to the service desk are confounded by age. Secondly, the customer base consists of more male customers than female customers and as a result of homophily in referrals there are also more male

[1]Whereas propensity score matching results in covariates on average being balanced among the groups, exact matching finds matches with similar values on all covariates and not just on propensity scores. This leads to improved precision of treatment effect estimates and reduces the outcome dependence on modelling choices.

than female referred customers. To ensure that we rule out any differences between referred and non-referred customers due to differences in gender, we also match on gender. Thirdly, since the mobile operator offers free calls and texts to other customers in the network, those who live in areas where many people are a customer of this provider have a stronger reason to use the service more extensively. This is because it is very likely that many of their social connections in their neighborhood are also a customer of the operator and if they would churn they would lose these free calls and texts to other customers. Hence, differences in neighborhood between referred and non-referred customers might impact their churn behavior. To avoid the churn likelihood of referred and non-referred customers being confounded by neighborhood, we match on postal code. Lastly, the customer base first consisted of non-referred customers who then started making referrals so the acquisition time of the first referred customers is generally later than that of the first non-referred customers. By matching on acquisition week, we ensure that any difference in behavioral patterns between referred and non-referred customers is not affected by acquisition time. On top of that, by matching on both neighborhood and acquisition time, any difference in time-varying local quality is controlled for, which is likely very important for request for customer service.

The resulting matched set of 54,144 customers retains the characteristics of the customer base relatively well. The scatter plot of referrer and referral age in Figure 3.6 largely resembles that of the entire customer base in Figure 3.4. The age histogram of the matched set in Figure 3.5 retains all the variation in customer age and a slight bump for older customers. Regarding geographical spread, Table 3.1 shows that the matched set (column 'Matched set 1') has a slightly higher proportion of customers in cities compared to the entire customer base.

When performing matching, an important trade-off needs to be made: on the one hand one wants to control for the unobservables as much as possible by having strict rules for a match and on the other hand enough data should be retained to compute the effects for a relevant population. If, in our case, we would make the match even stricter by matching on exact age, gender, the smallest possible aggregation level of postal code and week of acquisition, the resulting set of 4,413 pairs of matched customers is no longer representative of the customer base. A significant portion of the customers older than 31 are lost in this matched set (Figure 3.7), almost all inter-generational referrals are lost (Figure 3.8) and customers in cities are oversampled (column 'Matched set 2' in Table 3.1). This is because the matching criteria are so specific that it becomes less likely to find a match for customers who are not the most typical in the customer base. Hence, the conclusions drawn from this very narrowly matched set might not hold for the entire customer base.

Figure 3.5: Age histogram of customer set matched on age decile, gender, coarser neighborhood aggregation level and week of acquisition.

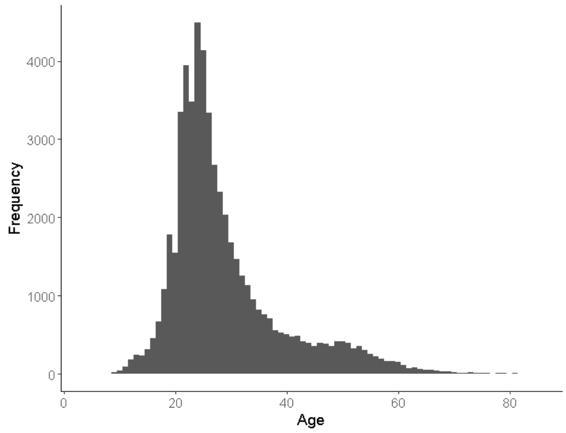


Figure 3.6: Scatter plot of referrer and referral age of customer set matched on age decile, gender, coarser neighborhood aggregation level and week of acquisition.

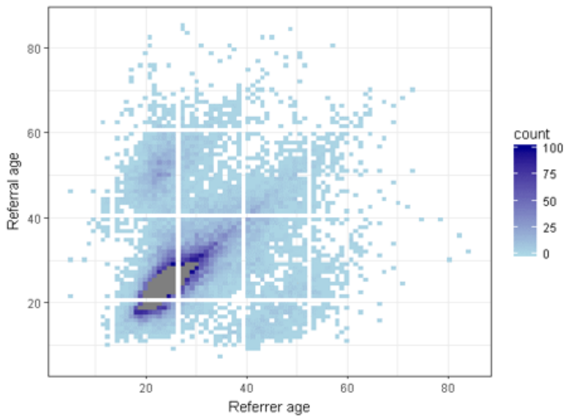


Table 3.1: Percentage of customers living in the top three postal codes with the most customers.

	Customer base	Matched set 1	Matched set 2
Postal code A	3.44%	5.18%	17.99%
Postal code B	1.76%	3.17%	7.8%
Postal code C	1.7%	2.85 %	7.36%
Postal code D	1.57%	2.57%	5.73%
Postal code E	1.3%	1.83%	3.01%

Figure 3.7: Age histogram of customer set matched on exact age, gender, smallest neighborhood aggregation level and week of acquisition.

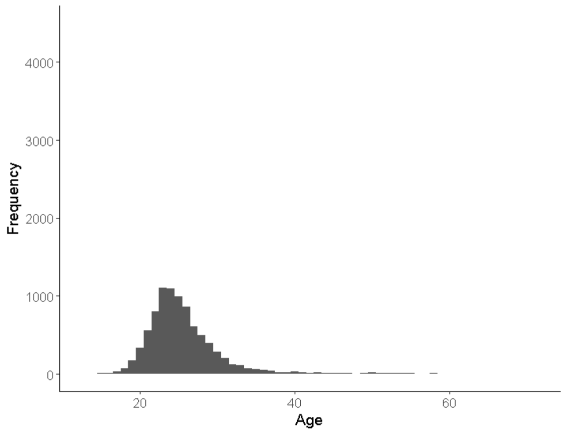
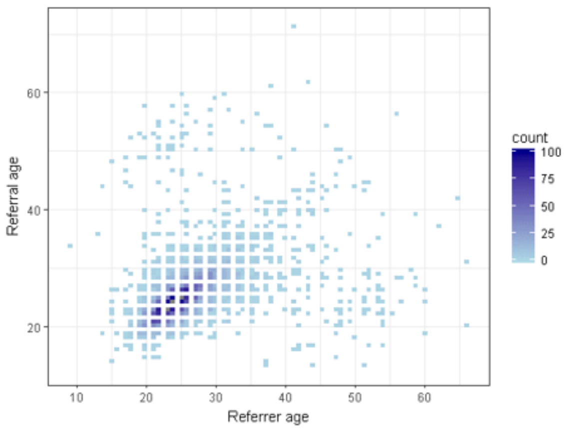


Figure 3.8: Scatter plot of referrer and referral age of customer set matched on exact age, gender, smallest neighborhood aggregation level and week of acquisition.



Pseudo-contractual models

In the following we motivate the design of the model by describing patterns in the data that support the model design decisions.

A. Model motivation

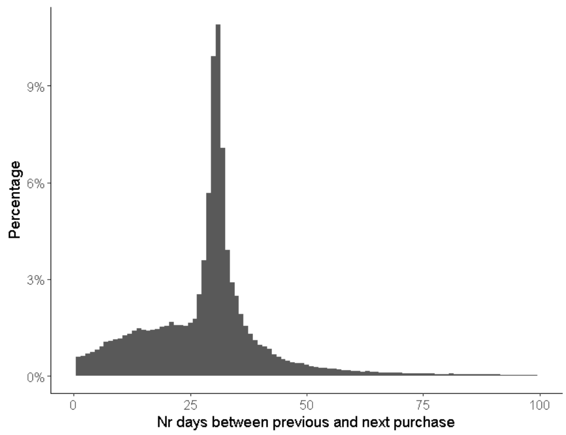
Periodicity The mobile operator incentivizes customers to renew their plan every month. They do that by cancelling the benefit of free calls and texts to other customers 30 days following the last purchase. The 30-day plan renewal interval is visible in the data. Figure 3.9 illustrates the distribution of the number of days between two plan renewals. Two-thirds of the plan renewals happen within 31 days of the previous one and 50% happen between 25 to 35 days after the previous one. Further, Table 3.2 shows the cumulative percentages of the number of plan renewals per customer-month. 89% of the customer-months have either no or 1 plan renewal, another 9% have two plan renewals and the

Table 3.2: Percentage of customer-months with a certain number of plan renewals.

Number of plan renewals per customer-month	Percentage	Cumulative percentage
0	26.7%	26.7%
1	62.1%	88.8%
2	9%	97.8%
3 or more	2.2%	100%

number of customer-months with 3 or more plan renewals drops to 2%. So the majority of the customers renews their plan once a month and only rarely more than once a month. Since only 11% of the customer-months feature more than one transaction and the typical inter-purchase time is strongly centered around 30 days, we analyze the data on a monthly basis.

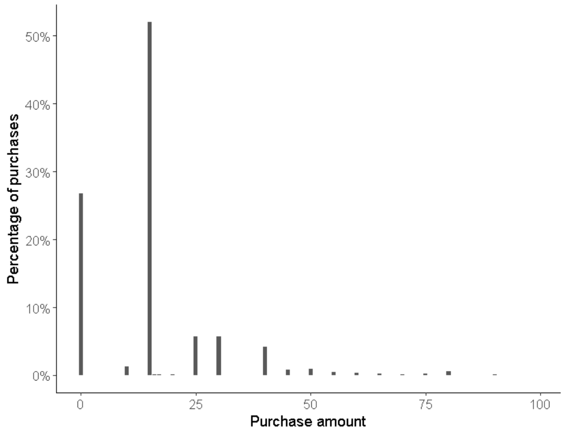
Figure 3.9: Histogram of the number of days between the previous and next plan renewal.



Purchase amounts The mobile operator offers certain benefits to their customers depending on the amount they spend. The number of free calls, texts and mobile data received is different for each package the provider offers. Customers are thus incentivized to spend the exact amounts of the different packages. This is confirmed by Figure 3.10 that shows the amounts spent per customer-month are mainly 0, 15, 25, 30 and 40 euros. In 52% of the customer-months there is a purchase of 15 euros and purchases of 25 and 30 euros account both for about 6% of the observations. Another 27% of the customer-months are inactive (remember that this is a non-contractual setting and thus inactivity might signal churn). We can see that there are only a few values that occur frequently. Therefore, the variable revenue (amount spent per customer-month) should ideally be analyzed as an ordered variable rather than a continuous variable.

Patterns of activity and inactivity The data were captured in a non-contractual business setting. Hence, there is no churn flag or date available that allows us to study the

Figure 3.10: Histogram of the amount spent per customer-month.



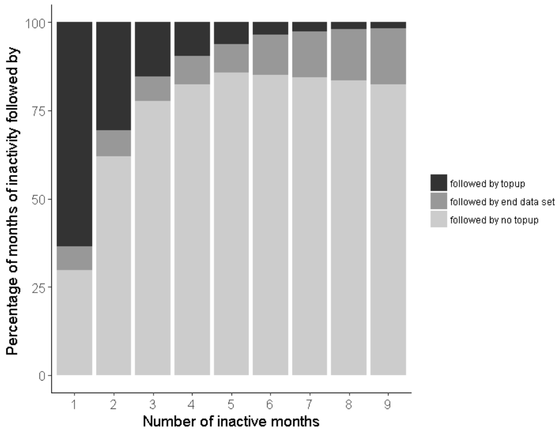
effects put forth in Section 3.2.2. To mitigate this, we define a proxy for churn behavior based on the patterns of activity and inactivity. The data show that there is rarely activity again after a period of inactivity. Almost 30% of the matched customers never has any inactivity, meaning they renew their plan every single month. The other 70% of the customers have at least one month of inactivity some time. If we look at the occasions of 6 consecutive months of inactivity, we see that only 11% of those are followed by any activity at any subsequent time. The other 89% are followed by either the end of the data set or only inactive months. This is visualized in Figure 3.11. In other words, activity after 6 months of inactivity is relatively rare. However, to draw conclusions about churn behavior it is not sufficient to only consider periods of inactivity, rather the clumpiness of the periods of activity after inactivity also matters (Zhang, Bradlow, & Small, 2015). Only 2% of the customer-months following a period of 6 months or more of inactivity are active months. In total, only 0.36% of the matched customers ever have 6 or more months of inactivity followed by three or more consecutive months of activity. Hence, sustained activity after inactivity is extremely rare. This indicates that six months of inactivity is a good proxy for churn. We can thus use this to define churn in the pseudo-contractual analyses.

B. Model design

As described above, we define churn as having six consecutive inactive months and we operationalize the churn date as the month after the last date the customer either made a purchase or made active use of his or her phone.

Using this data-derived definition of churn, we model revenue and customer churn. We use an ordered regression model with an individual-level random effect to model revenue and a discrete-time hazard model with an individual-level random effect for churn.

Figure 3.11: Patterns of activity after inactivity.



Revenue model

Based on the observed frequencies of purchase amounts, displayed in Figure 3.10, we create three ordinal categories of the latent variable revenue $y^\star$ that correspond with revenue categories 1,2 and 3:

$$y_{it} = \begin{cases} 1 & if\ y^*_{it} \leq 14 \\ 2 & if\ 15 \leq y^*_{it} \geq 24 \\ 3 & if\ y^*_{it} \geq 25 \end{cases} \tag{3.1}$$

Revenue is modelled as:

$$y^*_{it} = \delta X_{it} + c_i + e_{it} \tag{3.2}$$

Where:

y^*_{it} is the latent variable reflecting the purchase of customer i at time t,
δ is a vector of coefficients we wish to estimate,
X_{it} is a matrix of customer-month-specific covariates,
c_i is the individual-level random effect, and
e_{it} are the model residuals.

Churn model

The churn model is:

$$f(h_{it}) = \alpha_t + \beta X_{it} + d_i \tag{3.3}$$

Where:

$f(h)$ is the logit link-function,
h_{it} is the discrete-time hazard of customer i churning in month t,
α_t is the baseline hazard,
β is a vector of coefficients,
X_{it} is a matrix of customer-specific covariates, and

d_i is the individual-level random effect.

The X_{it} vectors contain the same variables in the revenue and churn equation. They include a dummy variable indicating whether customer i was referred or not, two variables capturing the relationship between the referrer and the firm, namely the lifetime of the referrer with the firm prior to making the referral and the average monthly revenue of the referrer prior to making the referral, a variable capturing the strength of the tie between the referrer and the referral and control variables. We operationalize the tie strength between the referrer and referral in accordance with previous literature (Meyners et al., 2017; Nitzan & Libai, 2011) as the ratio of the total communication volume between the referrer and the referral and the total communication volume of the referrer[2] in the three months prior to the referral.

The models contain three types of control variables: demographics, neighborhood-related variables and embeddeddness-related variables. First, the demographic control variables are age and gender. Second, the models include 5 time-varying neighborhood-related control variables to exclude any possible confounding effects related to local situations. Since we have already performed matching using neighborhood (see Section 3.3.2), time-invariant neighborhood-related effects between referred and non-referred customers should already be controlled for. The neighborhood-related control variables are wealth index of the customer's neighborhood, percentage of the neighborhood population that is a customer with this firm, cumulative percentage of the neighborhood population that are referrers of this firm, average revenue per customer in the neighborhood and number of service calls per new customer in the neighborhood. These area-related variables are all computed on the four weeks before a customer joined the firm. Third, the models include two control variables that reflect how embedded a referral is in the network of this telecom operator. The first measures how many existing customer this person had contact with in the three months prior to joining the firm. The second variable measures how extensive the communication of this person was with existing customers in the three months prior to joining the firm.

We also include cohort dummy variables reflecting acquisition month in the models. The first 11 cohorts are grouped per two months (and the first three per three months) because there are only few customers acquired in each of these individual months. Since we defined churn as having six consecutive months of inactivity, the last six cohorts by definition cannot churn. Including these customers in the analyses would bias the results. Therefore, all customers acquired later than January 1st 2013 are disregarded in the

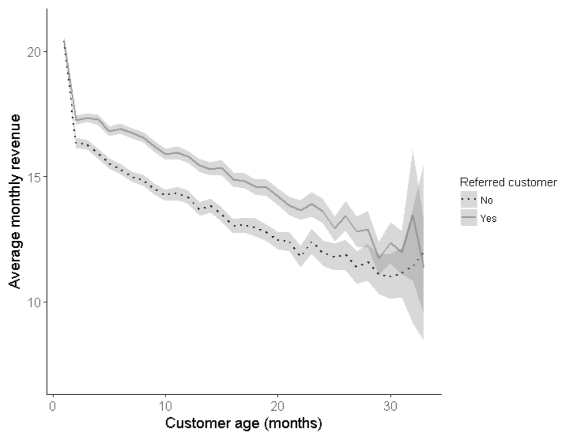
[2]In accordance with previous research, we consider a text message equivalent to a one-minute call (Nitzan & Libai, 2011).

pseudo-contractual analyses and the last cohort is the 27th cohort.

We center all covariates at the referred and non-referred group average to be able to compare the average referred customer to the average non-referred customer. All continuous variables are centered around their group means, displayed in Table 3.3.

Descriptives of the data reveal that the purchase behavior in customers' acquisition month looks significantly different than all subsequent months. This can be due to the fact that customers are obliged to spend a minimum amount in their acquisition month. Figure 3.12[3] shows this inconsistency. To avoid forcing the model to fit this uncommon behavior, we exclude all customers' acquisition month from the observations in the revenue and churn model and allow for a "settling in" month.

Figure 3.12: Average monthly revenue over customer lifetime.



Cost model

The cost to serve a customer is modelled as the costs incurred by the customer through contacting the service desk. The total costs consist mainly of handholding costs reflected in the service desk costs because this telecom operator utilizes the network of a bigger telecom player and thus has limited infrastructure-related costs. Table 3.6 documents that customers mostly call the service desk during the very beginning of their customer lifetime. In particular the first 30 days of customers' lifetime contains the most information. This makes sense as the offering is relatively simple and thus limited learning is needed. Hence, we focus our cost models on these first 30 days. As a result, there are no time-varying covariates in the cost models.

We use two different modelling approaches to model the service costs. First, we use a logistic regression model to model whether a customer called the service desk or not. Second, using a Tobit Type I model we investigate whether a customer called the service desk, and if so, how long the call was. The dependent variable of the Tobit model is the natural logarithm of the duration of the service calls.

[3]The decreasing trend in Figure 3.12 is due to churning customers.

Table 3.3: Mean values of characteristics per group.

	Referred customers	Non-referred customers	All matched
N	27,072	27,072	54,144
Tie strength	0.095	0	0.049
Previous lifetime referrer	0.27	0	0.14
Previous monthly revenue referrer	30.3	0	15.6
Previous monthly referrals referrer	0.4	0	0.2
Previous total referrals referrer	2.5	0	1.3
Referrer churn dummy	0.07	0	0.03
Age	29	29	29
Female	0.3	0.3	0.3
Wealth index	102.4	102.3	102.4
Pct. customers in neighborhood	0.73	0.74	0.74
Pct. referrers in neighborhood	21.77	21.52	21.65
Avg revenue per customer in neighborhood	4.32	4.3	4.31
Nr service calls per new customer in neighborhood	0.046	0.045	0.045
Nr existing customers contacted	12	9	11
Duration contact existing customers	1.6	1.2	1.4

We define a latent outcome y^* such that

$$y_{it} = \begin{cases} y_i^* & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{cases} \tag{3.4}$$

where $y_i^* = \beta X_i + e_i$ and $e_i \sim N(0, \sigma^2)$.

Latent attrition model

As the business setting is non-contractual, there is no explicit churn flag and date. Models that allow for a latent variable reflecting whether the customer is still active or has churned are most appropriate in this setting. In the Hidden Markov Model literature, one of the hidden states can be a churned state. These models allow for customers to transition between latent states representing the level of engagement with the company (Netzer, Lattin, & Srinivasan, 2008). A customer could be in an inactive state for a certain period of time and then transfer back to a more active state when customer behavior, such as purchasing, is observed again. A subset of Hidden Markov Models are buy-till-you-die models, also known as latent attrition models, where a customer can be either active or churned and the churned state is absorbing (Fader, Hardie, & Shang, 2010; Schweidel, Park, & Jamal, 2014). This implies that once a customer has transitioned to the churned state as a result of inactivity, it is not possible for this customer to become active again. Such states and transitions are visualized in Figure 3.13. In Section 3.3.2 we explored patterns of customer activity and documented that the data support an absorbing churn state since activity after inactivity is rare.

A. Model design

In the following we present the design of the latent attrition model by detailing each component of the model.
(1) *The initial state distribution:* All customers start in the active state since the acquisition date of a customer is the date of the first purchase. The probability that customer i is in the active state at time 1 is $P(S_{i1} = Active) = 1$.
(2) *The transition equation:* The transition equation gives the probability q_{it} that customer i will transition from state s_{t-1} to state s_t at time t. Since there are two states in our model, the transition matrix Q is a square matrix[4].

$$Q = \begin{bmatrix} q_{t11} & q_{t12} \\ 0 & 1 \end{bmatrix}$$

The churned state is absorbing, thus the probability of staying in the Churned state q_{t22} is always 1. Further, $q_{t11} = 1 - q_{t12}$. We denote the probability of transitioning from the Active to the Churned state q_{t12} by q in the remainder of the text. Since there are only two states, we model the transition probability using a binary logit model.

$$q = q_{t12} = \frac{exp(d_i + \beta X_i)}{1 + exp(d_i + \beta X_i)} \tag{3.5}$$

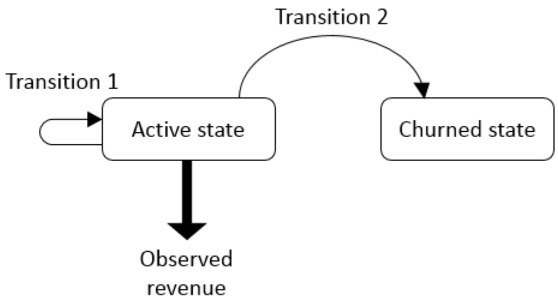
Where:
d_i is a individual-level random effect parameter,
β is a vector of coefficients, and
X_i is a matrix with customer-specific covariates.

(3) *The state dependent outcome equation:* The outcome equation gives the probability $P(Y_{it} = l | S_{it} = s)$ that customer i will make a purchase of category l at time t given customer i's state s. As demonstrated above, the outcome variable revenue can be modelled as an ordered logit variable. We thus define the outcome equation as follows:

$$m_{il} = P(Y_{it} = l | S_{it} = s) = F(\mu_{l-1} - c_i - \delta X_i) - F(\mu_l - c_i - \delta X_i) \tag{3.6}$$

[4]With the first row and column representing the Active state and the second row and column depicting the Churned state.

Figure 3.13: A latent attrition model.



Where:
μ_l is the cut-off point for outcome category l,
c_i is an individual-level random effect parameter,
δ is a vector of coefficients, and
X_i is a matrix of customer-specific covariates.

It is important to note here that the pseudo-contractual models contain more covariates than the latent attrition model does. More precisely, the pseudo-contractual models contain time-varying covariates that are not included in the latent attrition model. The latent attrition model is already quite extensive with a large number of observations and two random effects that are allowed to be correlated. Unfortunately the model ran into convergence issues when time-varying covariates were included.

Heterogeneity: To account for heterogeneity, we define individual-level random effects d_i and c_i in both the transition equation and the outcome equation as specified in equations 3.5 and 3.6. Since they capture unobservables of the same individual, we allow the random effect parameters to be correlated across the two equations.

Putting everything together, as explained in Appendix 3.B, the log-likelihood can be written as:

$$\begin{aligned} LL = \sum_{i=1}^{N}\sum_{t=1}^{T_i}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\Big[& \delta_{it1}\big[log(m_{it1}) + log(\prod_{j=2}^{t}(1-q_{ij}))\big] + \\ & \delta_{it2}\big[log(m_{it2}) + log(\prod_{j=2}^{t}(1-q_{ij}))\big] + \\ & (1-\delta_{it1}-\delta_{it2})\big[log(m_{it0}) + log\big(\prod_{j=2}^{t}(1-q_{ij}) + 1 - \prod_{j=2}^{t}(1-q_{ij})\big)\big]\Big] + \\ & log f(c_i, d_i|M, \Sigma)\, \mathrm{d}c_i\, \mathrm{d}d_i \end{aligned} \tag{3.7}$$

in which $f(c_i, d_i|M, \Sigma)$ is the probability density function of the bivariate normally distributed variables c_i and d_i, with $M = \begin{bmatrix} \mu_c \\ \mu_d \end{bmatrix}$ and $\Sigma = \begin{bmatrix} \sigma_c^2 & \sigma_{cd} \\ \sigma_{dc} & \sigma_d^2 \end{bmatrix}$.

B. Model estimation

We estimate the parameters in the transition equation and state dependent outcome equation, described in Equations 3.5 and 3.6, using the likelihood function defined in 3.7. We allow for heterogeneity by defining diffuse priors on the random-effect parameters c_i, d_i $\sim N_2(M_{c\beta_0}, \Sigma_{d\beta_0})$. We use Hamiltonian Monte Carlo to estimate the model and employ two chains with 2000 iterations each.

3.4 Results

3.4.1 RQ 1: Evidence of the value difference

In the following, we report on research question 1, aiming to identify differences in value between referred and non-referred customers. In a first step, we explore model-free evidence of these differences. In a second step, we add to these insights with results from a buy-till-you-die model.

We measure the value difference between referred and non-referred customers based on the elements of customer lifetime value (CLV), namely revenue, customer lifetime and cost. The first element, predicted future revenues, can be decomposed into three aspects: purchase incidence (does the customer buy or not?), repeat behavior (one-time customer or repeating customer?) and purchase amount (how much is the purchase for?). The second aspect, customer lifetime, reflects for how long the customer stays with the company. The third aspect, the costs to serve a customer, should be subtracted from the revenues generated by that customer.

Based on these three facets of CLV, Table 3.4 gives an overview of the differences between referred and non-referred customers. In accordance with previous research, we find that referred customers are more valuable to a firm than non-referred customers. First, with regard to revenue, referred customers (i) spend more per month and (ii) make more purchases per month. However, referred customers do not spend significantly more per purchase than non-referred customers do. Overall, we find that referred customers have a higher contribution margin than non-referred customers. Concerning the second aspect of CLV, customer lifetime, we find that referred customers are more likely to make at least one repeat purchase and have a higher proportion of active months than non-referred customers. Referred customers thus have a longer customer lifetime than non-referred

Table 3.4: CLV facets.

Variable	Referred customers	Non-referred customers	Difference between referred and non-referred customers (% difference)
Revenue			
Purchase frequency			
Avg total nr of purchases	12.7	11.8	-0.9* (-7.1%)
Avg nr of monthly purchases	0.91	0.85	-0.06* (-6.6%)
Average purchase amount			
Avg total purchase amount	219.8	206.3	-13.5* (-6.1%)
Avg monthly purchase amount	15.5	14.5	-1* (-6.5%)
Avg amount per purchase	16.84	16.81	-0.03 (-0.18%)
Customer lifetime			
Percentage non-repeating customers	3.5	7.2	3.7* (106%)
Avg proportion of active months	0.77	0.71	-0.06* (-7.8%)
Cost-to-serve			
Cost-to-serve during first 30 days			
Avg percentage callers	2.22	2.66	0.44* (19.8%)
Avg nr service calls	0.046	0.054	0.005* (10.9%)
Avg duration service calls (in sec)	4.59	5.82	0.008* (0.17%)

Note: * implies a significant difference

customers.

The question then arises whether the total difference in number of active months is mainly due to a difference in purchase incidence before churning or a difference in churn rate. We can assess this using a buy-till-you-die model (BTYD) (Fader et al., 2010). A buy-till-you-die model estimates the customer lifetime value of an individual by modelling his or her observed purchase and churn rate in a non-contractual setting. Based on this we can predict the expected future number of purchases. We use a BG/BB buy-till-you-die model because the customers have discrete (monthly) purchase opportunities[5]. We again compare the results for referred and non-referred customers.

Figure 3.14 and Figure 3.15 visualize the mean churn and purchase rates for referred and non-referred customers. The BTYD model estimates show that the referred customers

[5]A BG/BB buy-till-you-die model analyzes the data on cohort level. We include only cohorts with at least 1,000 customers and 6 months of remaining data to ensure stable estimates. This leaves us with cohorts 11 to 27.

have a lower churn rate and a higher transaction rate than the non-referred customers per cohort. The results in Table 3.5 show that referred customers are expected to make 27.5% more purchases than non-referred customers in the 60 months after acquisition. Multiplying the expected number of purchases by the average amount spent per purchase we find that referred customers are expected to spend 129 euros, or 28% more than non-referred customers in the first 60 months after acquisition. This is almost 9 times the referral incentive of 15 euros.

Figure 3.14: Estimated mean churn rate per cohort of the buy-till-you-die model.

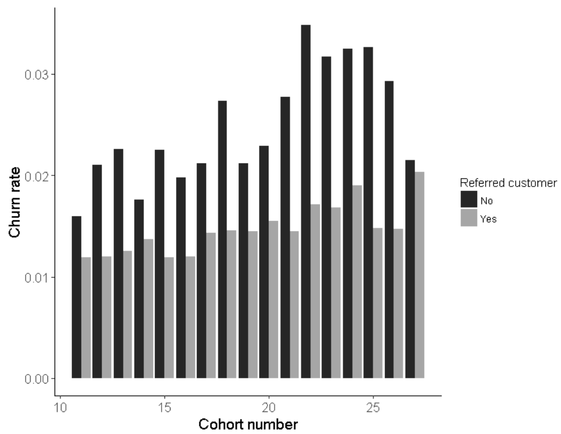


Figure 3.15: Estimated mean incidence rate per cohort of the buy-till-you-die model.

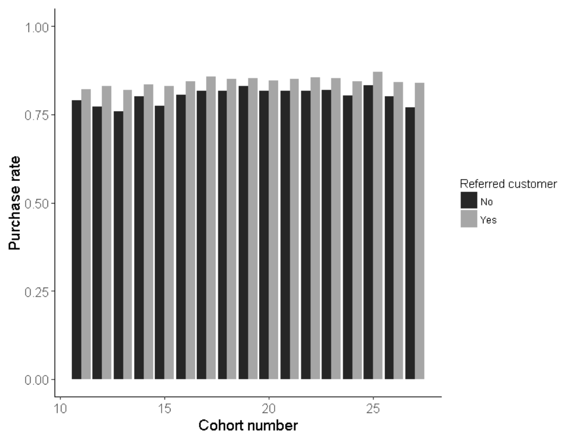


Table 3.5: Results of the buy-till-you-die model.

	Referred customers	Non-referred customers	Difference
Expected nr transactions in first 60 months	35.2	27.6	7.6 (21.6%)
Expected avg amount spent in first 60 months	593	464	129 (21.8%)

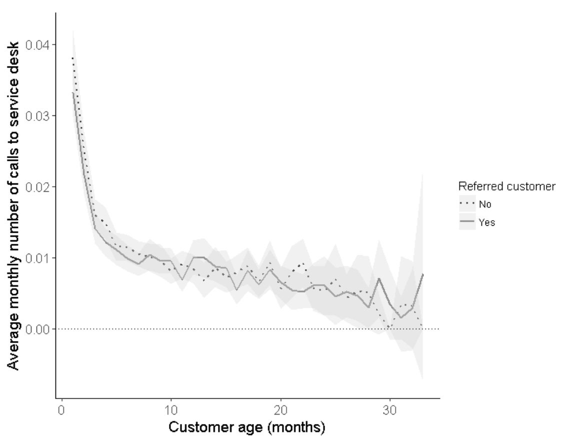
With regard to the third aspect of CLV, cost-to-serve, we find that referred customers

Table 3.6: Cost-to-serve averages per time frame.

Cost-to-serve time frame	Referred customers	Non-referred customers	p-value
First 30 days			
Avg percentage callers	2.22	2.66	0.001
Avg nr service calls	0.046	0.054	0.005
Avg duration service calls (in sec)	4.59	5.82	0.008
31-180 days			
Avg percentage callers	2.70	2.99	0.041
Avg nr service calls	0.059	0.064	0.013
Avg duration service calls (in sec)	5.19	6.18	0.026
$\geq$ 180 days			
Avg percentage callers	3.14	2.94	0.169
Avg nr service calls	0.065	0.062	0.097
Avg duration service calls (in sec)	6.69	6.24	0.171

are less costly to serve. Table 3.4 shows that the number of individuals calling the service desk and the number of service calls made is significantly different for referred and non-referred customers in the first 30 days of the customer lifetime. Figure 3.16 further shows that customers enlist the service desk mostly at the start of their customer lifetime. Table 3.6 shows that the difference in cost-to-serve between referred and non-referred customers decreases rather rapidly with customer lifetime. These observations can be explained by the fact that this business setting concerns a simple offering where the required learning is minimal and happens fast. The first 30 days of the customers' lifetime thus contain most information about service costs compared to later periods.

Figure 3.16: Customer require support mostly at the start of their lifetime.



3.4.2 RQ 2: The drivers of the value difference

In this section, we explore research question 2 and its multiple hypotheses that deal with possible reasons for why referred customers are more valuable to a firm than non-referred customers. We first report the results of the pseudo-contractual models and then present the results of the latent attrition model.

Note that the pseudo-contractual models have fewer observations because we exclude customers acquired in the last six months of the observation period as we cannot observe churn for them based on our proxy.

Pseudo-contractual models

Revenue model
The results of the revenue model are reported in Table 3.7. The results confirm the findings of Section 3.4.1 that referred customers spend more than non-referred customers. We proposed two hypotheses (H_1 and H_2) related to the connections between the three parties involved in a customer referral (firm, referrer, referral). We hypothesized that stronger relationships between respectively the referrer and the firm and between the referrer and the referral are associated with a more profitable referral. The positive estimates for the previous lifetime of the referrer prior to making the referral (0.16; $p < 0.01$) and the previous monthly revenue of the referrer prior to making the referral (0.01; $p < 0.01$) show support for Hypothesis 1. Customers referred by a referrer who has more experience with the firm in terms of both lifetime and product usage (monthly revenue) are more profitable. This is consistent with better matching. We also find evidence for better matching in the positive coefficient of the variable tie strength between the referrer and referral (0.72; $p < 0.01$). Thus, referrals who have a strong relationship with their referrer are more profitable than those who do not have a strong relationship with their referrer (H_2). The results further show that churn of the referrer affects the referral's profitability. When the referrer churns, the profitability of referred customers decreases (-.33; $p < 0.01$) (H_3) and the initial referral gap disappears. This effect is even stronger for those who have a stronger relationship with their referrer (H_4).

The negative coefficients for variables previous monthly referrals and previous total referrals suggest that customers who have made many referrals in the past make less profitable referrals. This makes sense because one would expect a referrer to make referrals in order of decreasing match quality.

Churn model
We next turn to why referred customers have higher retention rates than non-referred customers. We use a discrete-time hazard model with an individual-level random intercept as detailed in Equation 3.3. Table 3.8 reports the estimates of the model. We find that

Table 3.7: Results pseudo-contractual ordered revenue model.

Variable	Coefficient	t-value
Random effect	2.64 (0.02)	
Intercept Level 3	0.76	0.57
Intercept Level 2 or 3	4.17***	3.12
Referral dummy	0.37***	22.26
Customer lifetime	-1.50***	-64.52
Referral dummy x customer lifetime	0.19***	5.77
Tie strength	0.72***	8.95
Prior lifetime referrer	0.16***	3.08
Prior monthly revenue referrer	0.01***	18.3
Prior monthly referrals referrer	-0.09***	-4.97
Prior total referrals referrer	-0.01***	-3.47
Referrer churn dummy	-0.33***	-14.38
Tie strength x prior lifetime referrer	-0.07	-0.21
Tie strength x prior monthly revenue referrer	0.01***	3.42
Tie strength x referrer churn dummy	-1.14***	-7.68
Age	0.01***	16.04
Female	0.11***	5.85
Wealth index	-0.002***	-4.01
Percentage customers in neighborhood	0.02	0.96
Percentage referrers in neighborhood	-0.004**	-2.13
Average revenue per customer in neighborhood	0.01*	1.73
Number service calls per new customer in neighborhood	-0.03	-0.44
Number existing customers contacted prior to joining	0.05***	49.52
Duration contact existing customers prior to joining	0.03***	17.28
Observations	45.700	
Log Likelihood	-563.039	

Note: *p<0.1; **p<0.05; ***p<0.01

Customer lifetime is expressed in thousands of days

referred customers have a lower likelihood to churn than non-referred customers (-0.79; $p < 0.01$). This is in accordance with the model-free evidence provided in Section 3.4.1. The significant and negative coefficient (-0.52; $p < 0.01$) of prior lifetime of the referrer suggests that referred customers have a lower likelihood to churn if their referrer has more experience with the firm (H_1). The effect of the referrer's previous lifetime is even stronger if the referrer and referral have a strong relationship. We find slight evidence for the importance of the usage levels (previous monthly revenue) of the referrer on the likelihood to churn of the referral (H_1). The results are moderately consistent with better matching affecting the retention of the referral. In contrast, better matching between the referrer and referral has a sizeable effect on the retention of the referral. In accordance with Hypothesis 2, we find that a stronger relationship between the referrer and referral is associated with a lower probability to churn of the referral (-1.04; $p < 0.01$). We also find evidence for social enrichment through an increased likelihood to churn after the referrer has churned (H_3). This effect is even stronger if the referrer and referral have a strong relationship (H_4).

Cost model

As explained in Section 3.4.1, we focus on the costs to serve customers during the first 30 days of their lifetime. Since this business context and product offering is very simple, customers do not need to go through much learning to be able to use the service. Therefore, we include the analyses of the first 30 days in the paper and report the later periods that contain less signal in Appendix C.

Table 3.9 shows the estimates and standard errors of the binary logit model and the Tobit model. The results indicate that referred customers are significantly less costly to serve than non-referred customers. This is in accordance with the model-free evidence in Section 3.4.1. We do not find evidence for H_{5a}. The lifetime of the referrer prior to making the referral does not have an impact on the likelihood of the referred customer to call the service desk in the first 30 days of his or her lifetime. This might be because learning happens fast and the referrer does not need much experience to be able to help referrals. The usage intensity (monthly revenue spent) of the referrer before making the referral, however, seems associated with a higher likelihood for the referral to call the service desk. This could be due to homophily, reflecting cases where both individuals have high phone usage levels. Both the logit and Tobit model have a negative coefficient for tie strength, indicating that a stronger tie with the referrer is associated with a lower likelihood of calling the service desk and shorter calls (H_{5b}). This indicates that better matching between the referrer and referral might underlie the referral's cost-to-serve. The results further suggest that referrers who have made many referrals in the past make less costly referrals. This is consistent with both better matching and social enrichment.

Table 3.8: Results pseudo-contractual churn model.

Variable	Coefficient	t-value
Random effect	$3.88E^{-6}$ (0.1)	
Intercept	7.86***	5.00
Referral dummy	-0.79***	-29.81
Customer lifetime	2.04***	18.55
Referral dummy x customer lifetime	0.72***	6.57
Tie strength	-1.04***	-6.19
Prior lifetime referrer	-0.52***	-6.1
Prior monthly revenue referrer	0.001*	1.95
Prior monthly referrals referrer	0.03	1.46
Prior total referrals referrer	0.002	0.76
Referrer churn dummy	1.00***	20.2
Tie strength x prior lifetime referrer	-1.16*	-1.82
Tie strength x prior monthly revenue referrer	0.003	0.46
Tie strength x referrer churn dummy	1.76***	6.51
Age	-0.005***	-4.91
Female	-0.20***	-7.66
Wealth index	-0.004***	-6.03
Percentage customers in neighborhood	0.04	1.44
Percentage referrers in neighborhood	-0.001	-0.65
Average revenue per customer in neighborhood	0.005	0.71
Number service calls per new customer in neighborhood	0.11	1.62
Number existing customers contacted prior to joining	-0.05***	-26.13
Duration contact existing customers prior to joining	-0.15***	-15.7
Observations	45.700	
Log Likelihood	-45,327.05	

Note: *p<0.1; **p<0.05; ***p<0.01

Customer lifetime is expressed in thousands of days

Table 3.9: Cost models for the first 30 days of the customer lifetime.

	Binary model	Tobit model
Intercept	-4.208***	-24.390***
	(0.339)	(1.641)
Referral dummy	-0.231***	-1.093***
	(0.063)	(0.292)
Tie strength	-0.643*	-2.903*
	(0.367)	(1.637)
Prior lifetime referrer	-0.193	-0.880
	(0.230)	(1.049)
Prior monthly revenue referrer	0.006***	0.029***
	(0.001)	(0.008)
Prior monthly referrals referrer	-0.075	-0.380
	(0.089)	(0.413)
Prior total referrals referrer	-0.040**	-0.192**
	(0.017)	(0.075)
Tie strength x prior lifetime referrer	0.377	1.557
	(0.357)	(1.570)
Tie strength x prior monthly revenue referrer	0.435	1.690
	(0.368)	(1.627)
Age	0.027***	0.136***
	(0.003)	(0.014)
Female	-0.288***	-1.307***
	(0.073)	(0.338)
Wealth index	-0.005**	-0.025***
	(0.002)	(0.010)
Percentage customers in neighborhood	0.068	0.297
	(0.064)	(0.302)
Percentage referrers in neighborhood	-0.005	-0.023
	(0.007)	(0.031)
Average revenue per customer in neighborhood	-0.043	-0.212
	(0.037)	(0.169)
Number service calls in neighborhood	0.007	0.098
	(0.238)	(1.120)
Number existing customers contacted	0.015***	0.074***
	(0.003)	(0.016)
Duration contact with existing customers (in sec)	0.009**	0.050**
	(0.004)	(0.022)
Observations	45.700	45,700
Log Likelihood	-5,120.260	-7,895.439

Note: *p<0.1; **p<0.05; ***p<0.01
Customer lifetime is expressed in thousands of days

Latent attrition model

The results of the latent attrition model are in line with those of the pseudo-contractual analyses. We again find that referred customers spend more money and have a lower propensity to churn (RQ1) as the posterior distributions are respectively to the right and left of the value 0. The estimates for the effect of the relationship with the firm suggest that customers who were referred by a customer who has a stronger relationship with the firm spend more money and have a lower likelihood to churn (H_1). In the revenue equation the estimate for the previous lifetime of the referrer is not significant, while it was significant in the pseudo-contractual model. Overall, the same conclusion that referrers with more experience with the firm make more valuable referrals can be drawn from the estimates. Hence, better matching between the referrer and the firm seems to impact the referral's profitability and retention rate. Further, in accordance with previous analyses, the model shows that referred customers who have a strong relationship with their referrer have a higher revenue and a lower propensity to churn (H_2). This further confirms that better matching could underlie the profitability and retention rate of the referral. Additionally, we find that if a referrer has both a strong relationship with the firm and with his referral, that this referral will be even more valuable to the firm. Finally, we see that customers who have made more referrals in the past make less profitable new referrals.

3.5 Discussion

The model-free evidence and model-based findings in this paper confirm that also in a telecom setting referred customers are more valuable to a firm than non-referred customers. We find significant differences in all aspects of CLV, namely revenue, customer lifetime and cost. Using a buy-till-you-die model we estimate this total difference in value between referred and non-referred customers to be 28%. This is slightly higher than Schmitt et al. (2011) who estimated this difference in contribution margin and lifetime to be between 16% and 25% in a banking setting.

We hypothesize that the theory of better matching underlies the match-making process between the firm and referrals. We find support for Hypothesis 1, corroborating findings from past research (Van den Bulte et al., 2018) that referrers who have a stronger connection with the firm refer referrals who have higher revenue and a longer customer lifetime. It should be noted that our analyses are conducted using data from a telecom firm, whereas previous research observed these effects in the banking industry. Banking and telecom differ in terms of trust that a customer has to give as the stakes for banking can possibly be much higher. Confirming the results found in a banking context with results found in a telecom context provides strong evidence of the effect. Further, as a first in the referral marketing literature we illustrate the importance of the relationship between

Table 3.10: Latent attrition model.

	Revenue equation	Churn equation
Intercept	2.31*	-4.34*
	(0.02)	(0.06)
Random effect	2.36*	2.48*
	(0.01)	(0.02)
Referral dummy	0.31*	-0.73*
	(0.02)	(0.03)
Tie strength	0.11*	-0.14*
	(0.02)	(0.03)
Prior lifetime referrer	-0.005	-0.17*
	(0.02)	(0.03)
Prior monthly revenue referrer	*0.44*	0.07*
	(0.02)	(0.02)
Prior monthly referrals referrer	-0.11*	0.03
	(0.02)	(0.02)
Prior total referrals referrer	-0.1*	-0.04
	(0.02)	(0.03)
Tie strength x prior lifetime referrer	-0.02	-0.02
	(0.02)	(0.03)
Tie strength x prior monthly revenue referrer	0.08*	-0.05*
	(0.02)	(0.03)
Age	0.03*	0.11*
	(0.01)	(0.02)
Female	0.06*	-0.18*
	(0.02)	(0.04)
Wealth index	-0.12*	-0.21*
	(0.01)	(0.02)
Percentage customers in neighborhood	0.05*	0.14*
	(0.01)	(0.02)
Percentage referrers in neighborhood	-0.06*	-0.06*
	(0.01)	(0.01)
Average revenue per customer in neighborhood	0.05*	0.03*
	(0.01)	(.01)
Number service calls in neighborhood	0.002	0.01
	(0.01)	(0.01)
Number existing customers contacted	0.46*	-0.53*
	(0.01)	(0.02)
Duration contact with existing customers (in sec)	0.09*	-0.53*
	(0.01)	(0.04)
Observations	54,144	
Log Likelihood	-527,234.74	

Note: Numbers in parentheses are posterior standard deviations;
* implies significancy at the 95% level

the referrer and the referral. We find support for Hypothesis 2, indicating that the stronger the relationship between the referrer and referral is, the higher the revenue and longer the lifetime of the referral will be. The support for Hypotheses 1 and 2 is consistent with better matching.

The third hypothesis we presented involves the effect of referrer churn on the referral's behavior. The results indicate that if a referrer churns, the referral will have lower revenue and a higher likelihood to churn. This is in accordance with the theory of social enrichment. If a referrer churns, the referral no longer experiences an enriched relationship with the firm and as a result feels less connected to the firm and puts less trust in the firm. Particular to our case is the fact that existing customers can call each other for free. Hence, when a referrer churns, the referral loses the benefit of joint consumption with the referrer. It is however impossible to disentangle the effects of joint consumption (consuming where the referrer consumes) and social support (increased trust in the firm thanks to the presence of the referrer). Building on Hypothesis 3, Hypothesis 4 suggests a further evaluation of the effect. It states that the effect of referrer churn on the referral varies with their tie strength. Indeed, we find that the effects on both revenue and churn are even more pronounced if the referrer and the referral have a strong connection. This is in accordance with research by Aral and Walker (2014) who found that individuals are more influenced by those they have a stronger connection with. The support for Hypothesis 3 and 4 reveal that social enrichment likely underlies the value creation process of customer referral programs.

In the first part of the paper, we determined that referred and non-referred customers also differ in the costs incurred to service them. Therefore, we presented Hypothesis 5a and 5b to identify what drives this difference. The results shows no support for Hypothesis 5a, indicating that the connection of the referrer with the firm does not have a significant effect on the costs incurred by the referral. We suspect however that this might be particular to our research setting. Since the offering and service in our study are rather straightforward, customers might not need much experience to be able to successfully help others. We do find support for Hypothesis 5b, revealing that the tie strength between the referrer and referral has an effect on the costs incurred by the referral. The stronger the connection between the two, the less costly the referral is to serve. This suggests that individuals with a strong relationship indeed help each other, rather than turning to the firm's support service. Consequently, social enrichment is likely to influence the help-seeking behavior of referred customers.

To further increase the external validity of the findings about the value creation by customer referral programs, it would be beneficial if the hypotheses were further tested in other contexts than banking and telecom. Testing the hypotheses in settings where the role of trust and social influence differ will increase the robustness of the theory and findings. Another avenue for further research that could add greatly to our understanding of why referred customers are valuable is the study of the costs incurred by referred and non-referred customers. Our results provide the first evidence that, for cost-to-serve too, there is a difference between referred and non-referred customers. It would be beneficial to further study these effects in a different context as well as perhaps investigate different types of costs.

The insights from our study also have practical implications. Managers who want to attract valuable new customers through a customer referral program should ask referrers who have a strong connection with the firm to bring in new customers with whom they have a strong personal relationship. Since people typically have a limited circle of close connections, our findings might suggest that referrers can only make a limited number of valuable referrals. It would be interesting to investigate whether this is true and whether there is any relevant information in the order in which referrers bring in new customers.

3.6 Conclusion

In this paper, we detail in which facets of CLV referred customers differ significantly from non-referred customers. We find that referred customers are more likely to make repeat purchases, spend more per month, make more purchases per month, have a higher proportion of active months and are less costly to serve than non-referred customers. In our context however, when customers spend money there is no significant difference between what is spent by referred and non-referred customers. Overall we quantify the difference in CLV between referred and non-referred customers to be 28%. Knowing that such differences exist, we investigate where these differences stem from. We extend the research into customer referral programs by investigating the effect of being referred on a new dependent variable, namely cost-to-serve. The theory of social enrichment supports our findings that referred customers are less costly to serve and even less so if they have a strong relationship with their referrer. Additionally, we corroborate the findings of Van den Bulte et al. (2018) that the lifetime of the referrer prior to making the referral has a positive effect on the profitability and lifetime of the referral. We further extend these insights by showing that also a higher profitability of the referrer is associated with a higher profitability of the referral. These findings show that better matching is at play in customer referral programs in the relationship between the referrer and the firm. A further important contribution of our paper is that we also find evidence for better matching in the relationship between the referrer and the referral. A stronger relationship between the referrer and the referral is associated with a higher profitability, greater retention and lower costs of the referral. Overall, this paper provides important substantive implications for customer referral research. The model-free evidence coupled with the model-based analyses provide thorough insights into the value-creation process through customer referral programs.

Appendix

3.A Latent attrition model likelihood

Because a customer can only make a purchase if he/she is active, the probability of observing a purchase of level 1 and 2 for customer i at time t is:

$$P(Y_{it} = 1) = P(Y_{it} = 1|S_{it} = a)P(S_{it} = a)$$

$$P(Y_{it} = 2) = P(Y_{it} = 2|S_{it} = a)P(S_{it} = a)$$

An inactive month can be observed in both the active and the churned state. In the churned state, this is the only possible behavior, thus
$P(Y_{it} = 0|S_{it} = c) = 1$. The probability of observing no purchase activity for customer i at time t is:

$$\begin{aligned} P(Y_{it} = 0) &= P(Y_{it} = 0|S_{it} = a)P(S_{it} = a) + P(Y_{it} = 0|S_{it} = c)P(S_{it} = c) \\ &= P(Y_{it} = 0|S_{it} = a)P(S_{it} = a) + (1 - P(S_{it} = a)) \end{aligned}$$

The probability of the sequence of purchases Y for customer i over the entire timeframe is:

$$\begin{aligned} P(Y_i) = \prod_{t=1}^{T} & \big[P(Y_{it} = 1|S_{it} = a)P(S_{it} = a)\big]^{d_{it1}} \times \\ & \big[P(Y_{it} = 2|S_{it} = a)P(S_{it} = a)\big]^{d_{it2}} \times \\ & \big[P(Y_{it} = 0|S_{it} = a)P(S_{it} = a) + 1 - P(S_{it} = a)\big]^{(1-d_{it1}-d_{it2})} \end{aligned} \tag{3.8}$$

where d_{it1} and d_{it2} are dummy variables equal to 1 when y_{it} is respectively 1 and 2.

Let's define the components of this individual-level likelihood.

- $P(y_{it}|S_{it} = a)$
  is the probability of observing a purchase of a specific level by customer i at time t. In this part we model it as an ordered logit variable. We assume that every customer has a latent utility y* for every possible choice that is related to the observed choices by:

$$Y_{it} = l, \quad if \;\; \mu_{l-1} < y^*_{it} \leq \mu_l$$

  where μ_0, ..., μ_l are threshold parameters discretizing the real line, represented by y*, into l categories. We require that $\mu_l > \mu_{l-1}$ and μ_l = ∞ and μ_0 = $-\infty$. Thus,

$$\begin{aligned} P(y_{it} = l|S_{it} = a) &= P(\mu_{l-1} < y^*_{it} \leq \mu_l) \\ &= P(\mu_{l-1} < \beta_0 + \beta_1 X_{it} + \epsilon_i \leq \mu_l) \\ &= P(\mu_{l-1} - \beta_0 - \beta_1 X_{it} < \epsilon_i \leq \mu_l - \beta_0 - \beta_1 X_{it}) \end{aligned}$$

  We define $\epsilon_i \sim$ Normal(0,1) so the above reduces to:

$$m_{itl} = P(y_{it} = l|S_{it} = a) = \Phi(\mu_{l-1} - \beta_0 - \beta_1 X_{it}) - \Phi(\mu_l - \beta_0 - \beta_1 X_{it})$$

  Let's call this probability *m* in the remainder of the text.

- $P(S_{it} = s_{it})$
  is the marginal distribution over states at time t. We get this probability by summing over all possible sequences of states that end in state s_{it}.

$$P(S_{it}) = \sum_{s_{i1}} \sum_{s_{i2}} ... \sum_{s_{it}} P(S_{i1}, S_{i2}, ..., S_{it})$$

  Since in our set-up, the churned state is an absorbing state, a customer who is in the active state will have been in the active state in all previous time periods. So there is only one possible sequence of states that can lead to a customer being in the active state and hence we only need to sum over one possible sequence.

In the equation above, the joint probability of all states in the sequence is:

$$\begin{aligned}P(S_{i1}, S_{i2}, ..., S_{iT}) = &P(S_{iT}|S_{i1}, S_{i2}, ..., S_{iT-1})\times \\ &P(S_{iT-1}|S_{i1}, S_{i2}, ..., S_{iT-2})\times \\ &\dots \\ &P(S_{i2}|S_{i1})\times \\ &P(S_{i1})\end{aligned}$$

According to the Markov property, the state of customer i at time t is only determined by the state of customer i at time t-1. The joint probability of all hidden states in the sequence is thus:

$$\begin{aligned}P(S_{i1}, S_{i2}, ..., S_{iT}) &= P(S_{i1})P(S_{i1}|S_{i2})...P(S_{iT}|S_{iT-1}) \\ &= P(S_{i1})\prod_{j=2}^{t} P(S_{ij}|S_{ij-1})\end{aligned}$$

The first part is the initial distribution representing in which hidden states the customers start their sequence. In our set-up all customers are active at the start of the observation period and thus
$P(S_{i1} = a) = 1$.

The second part represents the transition probability to transition from one state to another. In our set-up, customers can only transition from the active to the churned state and churn is an absorbing state (customers cannot transition back to the active state). Thus, the transition probabilities are:

$$q_{it} = P(S_{it} = c|S_{it-1} = a) = \Phi(\gamma_0 + \gamma_1 Z_{it})$$

$$\begin{aligned}1 - q_{it} = P(S_{it} = a|S_{it-1} = a) &= 1 - P(S_{it} = c|S_{it-1} = a) \\ &= 1 - \Phi(\gamma_0 + \gamma_1 Z_{it})\end{aligned}$$

$$P(S_{it} = c|S_{it-1} = c) = 1$$

$$P(S_{it} = a|S_{it-1} = c) = 0$$

Note that every customer i has an individual acquisition date and thus the time frames vary in length T_i (from acquisition date to the end of data set).

If we put everything together, the likelihood function is:

$$
\begin{aligned}
L = \prod_{i=1}^{N}\prod_{t=1}^{T_i} & \big[m_{it1}\prod_{j=2}^{t}(1-q_{ij})\big]^{\delta_{it1}} \times \\
& \big[m_{it2}\prod_{j=2}^{t}(1-q_{ij})\big]^{\delta_{it2}} \times \\
& \big[m_{it0}\prod_{j=2}^{t}(1-q_{ij}) + 1 - \prod_{j=2}^{t}(1-q_{ij})\big]^{(1-\delta_{it1}-\delta_{it2})}
\end{aligned}
\tag{3.9}
$$

where

$$
\begin{aligned}
m_{it1} &= \Phi(\mu_1 - \beta_0 - \beta_1 X_{it}) - \Phi(\mu_0 - \beta_0 - \beta_1 X_{it}) \\
m_{it2} &= 1 - \Phi(\mu_1 - \beta_0 - \beta_1 X_{it}) \\
m_{it0} &= \Phi(\mu_0 - \beta_0 - \beta_1 X_{it})
\end{aligned}
$$

We can account for cross-customer heterogeneity by defining the intercepts β_0 and γ_0 as individual-specific random effects β_{0i} and γ_{0i}.

$$
\begin{aligned}
L = \prod_{i=1}^{N}\prod_{t=1}^{T_i}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} & \Big[\big[m_{it1}\prod_{j=2}^{t}(1-q_{ij})\big]^{\delta_{it1}} \times \\
& \big[m_{it2}\prod_{j=2}^{t}(1-q_{ij})\big]^{\delta_{it2}} \times \\
& \big[m_{it0}\prod_{j=2}^{t}(1-q_{ij}) + 1 - \prod_{j=2}^{t}(1-q_{ij})\big]^{(1-\delta_{it1}-\delta_{it2})}\Big] \times \\
& f(\beta_{0i}, \gamma_{0i}|M, \Sigma)\,\mathrm{d}\beta_{0i}\,\mathrm{d}\gamma_{0i}
\end{aligned}
\tag{3.10}
$$

in which $f(\beta_{0i}, \gamma_{0i}|M, \Sigma)$ is the probability density function of the bivariate normally distributed variables β_{0i} and γ_{0i}, with $M = \begin{bmatrix}\mu_{\beta_0} \\ \mu_{\gamma_0}\end{bmatrix}$ and $\Sigma = \begin{bmatrix}\sigma^2_{\beta_0} & \sigma_{\beta_0\gamma_0} \\ \sigma_{\gamma_0\beta_0} & \sigma^2_{\gamma_0}\end{bmatrix}$.

3.B Pseudo-contractual model cohort estimates

Table 3.B.1: Revenue model cohort estimates.

Variable	Coefficient	t-value
Cohort 4-5	-0.10	-1.38
Cohort 6-7	-0.12	-1.49
Cohort 8-9	-0.3***	-3.93
Cohort 10-11	-0.26***	-3.45
Cohort 12	-0.06	-0.77
Cohort 13	0.01	0.15
Cohort 14	-0.14*	-1.78
Cohort 15	-0.15*	-1.94
Cohort 16	-0.35***	-4.47
Cohort 17	-0.29***	-3.58
Cohort 18	-0.2**	-2.42
Cohort 19	-0.33***	-3.99
Cohort 20	-0.27***	-3.26
Cohort 21	-0.22***	-2.65
Cohort 22	-0.11	-1.31
Cohort 23	-0.14*	-1.67
Cohort 24	0.03	0.32
Cohort 25	-0.07	-0.82
Cohort 26	-0.01	-0.1
Cohort 27	0.003	0.04

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.B.2: Churn model cohort estimates.

Variable	Coefficient	t-value
Cohort 4-5	-0.11	-1.27
Cohort 6-7	-0.31***	-3.58
Cohort 8-9	-0.25***	-2.98
Cohort 10-11	-0.4***	-4.69
Cohort 12	-0.62***	-6.95
Cohort 13	-0.69***	-8.01
Cohort 14	-0.57***	-6.38
Cohort 15	-0.65***	-6.99
Cohort 16	-0.6***	-6.48
Cohort 17	-0.7***	-7.27
Cohort 18	-0.8***	-8.28
Cohort 19	-0.69***	-6.89
Cohort 20	-0.79***	-7.9
Cohort 21	-0.86***	-8.58
Cohort 22	-0.93***	-9.06
Cohort 23	-0.86***	-8.18
Cohort 24	-0.96***	-9.17
Cohort 25	-0.75***	-7.27
Cohort 26	-0.6***	-5.25
Cohort 27	-0.51***	-3.83

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.B.3: Cost model cohort estimates for first 30 days of the customer lifetime.

	Binary model	Tobit model
Cohort 4-5	0.463	1.974
	(0.355)	(1.561)
Cohort 6-7	0.178	0.723
	(0.362)	(1.581)
Cohort 8-9	0.067	0.243
	(0.387)	(1.685)
Cohort 10-11	0.538	2.417
	(0.355)	(1.563)
Cohort 12	0.408	1.728
	(0.364)	(1.601)
Cohort 13	0.794**	3.536**
	(0.361)	(1.601)
Cohort 14	0.575	2.513
	(0.365)	(1.614)
Cohort 15	0.679*	3.055*
	(0.369)	(1.640)
Cohort 16	0.678*	3.045*
	(0.370)	(1.642)
Cohort 17	0.612	2.662
	(0.375)	(1.662)
Cohort 18	0.806**	3.505**
	(0.368)	(1.639)
Cohort 19	0.820**	3.667**
	(0.367)	(1.633)
Cohort 20	0.373	1.660
	(0.384)	(1.695)
Cohort 21	0.526	2.238
	(0.381)	(1.690)
Cohort 22	0.969***	4.412***
	(0.371)	(1.653)
Cohort 23	0.941**	4.292***
	(0.366)	(1.626)
Cohort 24	0.664*	2.908*
	(0.382)	(1.698)
Cohort 25	0.663*	2.873
	(0.396)	(1.768)
Cohort 26	-0.841	-3.562
	(1.564)	(6.794)
Cohort 27	-0.012	-0.075
	(0.013)	(0.06)

Note: *p<0.1; **p<0.05; ***p<0.01

3.C Latent attrition model cohort estimates

Table 3.C.1: Latent attrition model cohort estimates.

	Revenue equation	Churn equation
Cohort 4-5	0.193*	-0.184
	(0.083)	(0.113)
Cohort 6-7	0.460*	0.147
	(0.092)	(0.103)
Cohort 8-9	0.670*	-0.150
	(0.081)	(0.106)
Cohort 10-11	0.644*	-0.138
	(0.067)	(0.088)
Cohort 12	0.440*	-0.029
	(0.083)	(0.108)
Cohort 13	0.313*	-0.045
	(0.069)	(0.089)
Cohort 14	0.484*	-0.206*
	(0.061)	(0.091)
Cohort 15	0.526*	-0.168*
	(0.070)	(0.092)
Cohort 16	0.848*	-0.245*
	(0.065)	(0.090)
Cohort 17	0.820*	-0.230*
	(0.069)	(0.094)
Cohort 18	0.770*	-0.074
	(0.071)	(0.090)
Cohort 19	0.880*	-0.290*
	(0.070)	(0.097)
Cohort 20	0.840*	-0.184*
	(0.064)	(0.091)
Cohort 21	0.769*	-0.167*
	(0.060)	(0.089)
Cohort 22	0.636*	-0.065
	(0.068)	(0.098)
Cohort 23	0.639*	-0.143
	(0.061)	(0.094)
Cohort 24	0.376*	-0.049
	(0.057)	(0.090)
Cohort 25	0.431*	-0.214*
	(0.047)	(0.080)
Cohort 26	0.279*	-0.356*
	(0.056)	(0.094)
Cohort 27	0.233*	-0.350*
	(0.070)	(0.113)

Note: Numbers in parentheses are posterior standard deviations;
* implies significancy at the 95% level

3.D Cost models after the first 30 days of customer lifetime

Table 3.D.1: Cost models for 30-180 days of the customer lifetime.

	Binary model	Tobit model
Intercept	-4.184***	-23.234***
	(0.290)	(1.403)
Referral dummy	-0.097*	-0.425*
	(0.057)	(0.255)
Tie strength	-0.520	-2.226
	(0.318)	(1.374)
Previous lifetime referrer	0.212	0.927
	(0.191)	(0.857)
Previous monthly revenue referrer	0.007***	0.035***
	(0.001)	(0.006)
Previous monthly referrals referrer	-0.045	-0.241
	(0.067)	(0.313)
Previous total referrals referrer	-0.028**	-0.128**
	(0.012)	(0.054)
Tie strength x previous lifetime referrer	0.099	0.470
	(0.326)	(1.401)
Tie strength x previous monthly revenue referrer	0.104	0.466
	(0.343)	(1.475)
Age	0.038***	0.185***
	(0.002)	(0.012)
Female	-0.243***	-1.067***
	(0.066)	(0.297)
Wealth index	-0.007***	-0.030***
	(0.002)	(0.009)
Percentage customers in neighborhood	0.044	0.151
	(0.060)	(0.273)
Percentage referrers in neighborhood	-0.0004	-0.003
	(0.006)	(0.027)
Average revenue per customer in neighborhood	0.039*	0.190*
	(0.023)	(0.108)
Number service calls in neighborhood	-0.039	-0.016
	(0.228)	(1.019)
Number existing customers contacted	0.023***	0.114***
	(0.003)	(0.014)
Duration contact with existing customers (in sec)	0.008**	0.045**
	(0.004)	(0.020)
Observations	45.700	45,700
Log Likelihood	-5,871.694	-9,186.196

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.D.2: Cost models cohort dummies for 30-180 days of the customer lifetime.

Cohort 4-5	0.711**	3.307**
	(0.301)	(1.321)
Cohort 6-7	0.468	2.312*
	(0.305)	(1.328)
Cohort 8-9	0.556*	2.588*
	(0.317)	(1.385)
Cohort 10-11	0.429	2.091
	(0.311)	(1.352)
Cohort 12	0.621**	2.951**
	(0.310)	(1.357)
Cohort 13	0.438	2.195
	(0.323)	(1.408)
Cohort 14	0.818***	3.896***
	(0.311)	(1.367)
Cohort 15	0.912***	4.254***
	(0.315)	(1.392)
Cohort 16	0.450	2.197
	(0.328)	(1.435)
Cohort 17	0.836***	3.876***
	(0.320)	(1.414)
Cohort 18	0.826***	3.956***
	(0.318)	(1.403)
Cohort 19	1.018***	4.799***
	(0.315)	(1.392)
Cohort 20	0.691**	3.342**
	(0.326)	(1.433)
Cohort 21	0.857***	4.078***
	(0.323)	(1.426)
Cohort 22	0.827**	3.981***
	(0.323)	(1.426)
Cohort 23	0.746**	3.680***
	(0.317)	(1.397)
Cohort 24	0.837**	4.053***
	(0.328)	(1.449)
Cohort 25	0.892***	4.225***
	(0.339)	(1.507)
Cohort 26	-0.003	-0.368
	(1.282)	(5.633)
Cohort 27	0.004	0.0001
	(0.008)	(0.042)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.D.3: Cost models for $\geq$ 180 days of the customer lifetime.

	Binary model	Tobit model
Constant	-3.310***	-18.222***
	(0.207)	(1.035)
Referral dummy	0.056	0.233
	(0.052)	(0.228)
Tie strength	0.107	0.473
	(0.258)	(1.133)
Previous lifetime referrer	0.082	0.286
	(0.178)	(0.784)
Previous monthly revenue referrer	0.005***	0.025***
	(0.001)	(0.006)
Previous monthly referrals referrer	-0.059	-0.340
	(0.062)	(0.291)
Previous total referrals referrer	-0.017	-0.075
	(0.011)	(0.047)
Tie strength x previous lifetime referrer	0.329	1.529
	(0.202)	(0.936)
Tie strength x previous monthly revenue referrer	0.091	0.373
	(0.221)	(1.015)
Age	0.041***	0.191***
	(0.002)	(0.011)
Female	-0.063	-0.274
	(0.061)	(0.267)
Wealth index	-0.003	-0.012
	(0.002)	(0.008)
Percentage customers in neighborhood	0.043	0.157
	(0.069)	(0.286)
Percentage referrers in neighborhood	-0.010*	-0.042*
	(0.005)	(0.022)
Average revenue per customer in neighborhood	-0.013	-0.048
	(0.021)	(0.097)
Number service calls in neighborhood	0.107	0.509
	(0.162)	(0.804)
Number existing customers contacted	0.021***	0.104***
	(0.002)	(0.012)
Duration contact with existing customers (in sec)	0.016***	0.084***
	(0.003)	(0.014)
Observations	45.700	45,700
Log Likelihood	-6,703.839	-10,752.260

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.D.4: Cost models cohort dummies for $\geq$ 180 days of the customer lifetime.

	Binary model	Tobit model
Cohort 4-5	0.463**	2.209**
	(0.204)	(0.945)
Cohort 6-7	0.421**	1.989**
	(0.204)	(0.944)
Cohort 8-9	0.236	0.985
	(0.220)	(1.012)
Cohort 10-11	0.232	1.089
	(0.213)	(0.978)
Cohort 12	0.148	0.776
	(0.220)	(1.005)
Cohort 13	0.094	0.545
	(0.228)	(1.038)
Cohort 14	0.142	0.771
	(0.226)	(1.030)
Cohort 15	0.281	1.394
	(0.230)	(1.051)
Cohort 16	-0.023	0.022
	(0.238)	(1.079)
Cohort 17	0.169	0.873
	(0.236)	(1.076)
Cohort 18	-0.251	-1.055
	(0.244)	(1.099)
Cohort 19	-0.205	-0.794
	(0.243)	(1.093)
Cohort 20	-0.459*	-1.834
	(0.258)	(1.145)
Cohort 21	-0.421	-1.672
	(0.257)	(1.142)
Cohort 22	-0.664**	-2.641**
	(0.263)	(1.157)
Cohort 23	-0.704***	-2.764**
	(0.249)	(1.105)
Cohort 24	-0.881***	-3.561***
	(0.274)	(1.198)
Cohort 25	-1.221***	-4.891***
	(0.318)	(1.351)
Cohort 26	0.268	0.007
	(1.078)	(4.772)
Cohort 27	-0.008	-0.040
	(0.009)	(0.042)

Note: *p<0.1; **p<0.05; ***p<0.01

4

The role of weak ties for customer referral programs

4.1 Introduction

The marketing literature has been paying increasing attention to the structure of customer networks. Research has repeatedly shown the importance of considering social networks for a variety of marketing applications (Benoit & Van den Poel, 2012; Hill et al., 2006; Martens et al., 2016; Van Vlasselaer, Eliassi-Rad, Akoglu, Snoeck, & Baesens, 2016; Verbeke et al., 2014). One specific marketing practice that is gaining renewed prominence is customer referral programs, in which the firm rewards existing customers for bringing in new customers (Berman, 2016). Previous research has shown that referred customers are more valuable to a firm than non-referred customers (Armelini et al., 2015; Schmitt et al., 2011; Villanueva et al., 2008). They spend more money, have a longer lifetime and are less costly to serve, resulting in higher total customer lifetime value (Garnefeld et al., 2013; Roelens, Van den Bulte, Baecke, & Benoit, 2018; Schmitt et al., 2011; Van den Bulte et al., 2018). Hence, customer referral programs are a useful tool for marketing managers to attract valuable new customers and therefore merit attention from researchers and practitioners.

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Previous research has also shown that among referred customers, those who have a strong social connection with their referrer provide higher value to the firm (Roelens et al., 2018). They have higher revenue, a longer lifetime and a lower cost to serve. This insight leads to the recommendation for marketing managers to mainly incentivize referrals over strong ties. Practically, this implies that customers are asked to bring in close family members, friends or colleagues as new customers.

However, such focus on referrals over strong ties ignores an important theory, called “the theory of the strength of weak ties” that was put forth in the study by Granovetter (1973), one of the most cited papers in sociology. This theory argues that there is particular value in weak social connections due to their increased likelihood of being bridges across social communities. Weak social connections are more likely to access new communities compared to strong social connections. Accessing new communities implies that a new group of potential customers is reached. Thus, while customers who are referred over strong ties are more profitable themselves, customers who are referred over weak ties might provide more value to the company in terms of the number of new customers acquired. This idea was also presented by Kumar et al. (2010). They argued that some customers have a high value due to long lifetime and high profitability, while others have a high value due to their potential to grow the customer base through referrals. Yet, to this day only a limited set of research has considered this aspect of customer value. The objective of this study is to empirically examine the value of weak ties for customer referral programs. In particular, we investigate the effect on customer network growth. We do this using a data set of a European telecom provider that includes both call and text data as well as customer referral data.

The present study contributes to both theory and practice. It adds to the insights on value creation through customer referral programs and advances the state-of-the-art by providing a first large-scale empirical test of the theory of the strength of weak ties for customer referral programs. By leveraging data on actual customer referrals and social connections we are able to trace customer network growth as a result of referrals. Our study provides useful insights for organizations seeking quick growth through referrals. This might be of interest for start-ups or public campaigns that aim to reach a large audience.

We organize the rest of the paper as follows. Next, we situate this research in previous literature and highlight the theoretical foundations. Then, we document the model development and analysis, after which we present and discuss our empirical results. Finally, we highlight theoretical and practical implications of our work.

4.2 Research foundations and previous literature

Our study draws on literature from several backgrounds such as marketing, sociology and economics. The current Section will first discuss the relevant literature of customer referral programs. Next, we discuss an important sociological theory that is relevant to our research, namely the theory of the strength of weak ties. In the last subsection we will discuss the impact of this theory on referral marketing.

4.2.1 Customer referral programs

Previous research has shown that referred customers are more valuable to a firm than non-referred customers (Armelini et al., 2015; Schmitt et al., 2011; Villanueva et al., 2008). This value gap is perceptible in all aspects of customer lifetime value: referred customers spend more money (Roelens et al., 2018; Schmitt et al., 2011; Van den Bulte et al., 2018), are more loyal (Garnefeld et al., 2013; Roelens et al., 2018; Schmitt et al., 2011; Van den Bulte et al., 2018) and are less costly to serve (Roelens et al., 2018). Schmitt et al. (2011) quantified the difference in revenue and lifetime between referred and non-referred customers for a bank to be between 16% and 25%. Roelens et al. (2018) estimated the total difference in CLV (also considering costs) to be 28% in a telecom context. These findings show that customer referral programs are an effective tool for marketing managers to attract valuable new customers.

A recent study details theory-driven phenomena that explain the difference in value between referred and non-referred customers (Van den Bulte et al., 2018). One of these phenomena is better matching. It implies that customers who have been with the company for a longer time know the company better and have a better understanding of the offerings and values. As a result, of all customers, they are best positioned to assess whom of their social connections would fit best with the company. Therefore, the referrals made by customers who have a strong relation with the company are more valuable compared to referrals made by customers who have less experience with the company (Van den Bulte et al., 2018).

It was further shown that the quality of matching varies with the relationship between the referrer and the referred customer (Roelens et al., 2018). If the referrer and referred customer have a stronger relationship, the latter is more valuable to the company. Consequently, the most valuable referred customers are those who are referred by a customer who has a strong relationship with the firm *and* a strong connection with the referred customer. Based on these insights, one would advise marketers to design their customer referral programs as follows: encourage mainly referrals from customers who have been with the firm for a long time and incentivize them to bring in new customers with whom they have a strong relationship. However, this might not give sufficient credit to referrals over weak ties. As Kumar et al. (2010) pointed out, it is important to consider two facets of customer value, namely customer lifetime value and customer referral value. While referrals over strong ties might directly lead to highly valuable customers, referrals over weak ties might provide value by accessing new communities and as a result reaching new groups of potential customers, which can be beneficial in the long term.

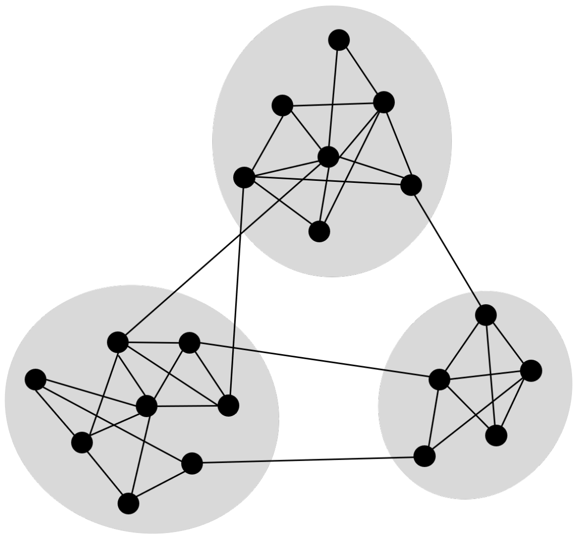
4.2.2 The strength of weak ties

Social networks typically consist of multiple communities, as visualized in Figure 4.1. While within such communities there are typically many strong connections, across communities there are only few weak connections (Granovetter, 1973; Onnela et al., 2007). Without bridging ties, a social network would consist of disjointed closely knit communities that are unable to reach each other (Granovetter, 1973; Onnela et al., 2007). (Granovetter, 1973) theorized that strong social connections typically connect people who move in the same social circles and therefore share access to the same resources and knowledge. Strong connections are also typically formed between people with similar characteristics (McPherson et al., 2001) who are thus likely to possess the same information. Weak social connections on the other hand generally exist between people who reside in different social communities and therefore receive different information and resources. Thus, weak ties are more likely to be sources of novel and non-redundant information (Granovetter, 1973; Levin & Cross, 2004). A related sociological phenomenon, called structural holes, also highlights the importance of bridging gaps between social communities (Burt, 1992). Individuals who can span a gap between communities with their social connections have control over information diffusion and have access to novel information. Such position in the network has been shown to be a factor in differences in social capital (Burt, 2000) and a correlate of idea creativity (Burt, 2004).

4.2.3 The strength of weak referral ties

Extending these ideas to customer referral programs, we argue that some referrals over weak links could be powerful in reaching new social communities and therefore facilitating significant customer network growth. Although previous research on referral programs argues that referrals over strong links lead to highly valuable customers (Roelens et al., 2018), based on sociological theory, one can hypothesize that referrals over weak ties might play a crucial role in accessing new communities and thereby facilitating network growth in the long run. The main idea is that some customers might not have a long lifetime and high revenue themselves, but provide great value through their social connections and referral capacity, as was also argued by Kumar et al. (2010). The same idea has been shown to hold in churn settings (Benoit & Van den Poel, 2012). Some customers might not be the most profitable themselves, but are worth retaining because

Figure 4.1: Social communities.



their presence is associated with and possibly aids the retention of other customers who are more profitable.

Only a very limited set of studies have tried to investigate the effect of referral dyad connectivity on referral outcomes. Reingen and Kernan (1986) first proposed social network analysis as a method for researching referral behavior. By surveying people about their social network and referrals, they constructed a network of 128 individuals. Unfortunately this network only had one bridging link between communities which prevented them from testing the weak tie hypothesis. Interestingly, the one weak link they had in their social network actually resulted in the longest referral path. However, this single observation is insufficient to draw generalizable conclusions from. Brown and Reingen (1987) studied the role of social connections in a customer referral network. They confirmed Granovetter's idea that a higher proportion of weak ties are bridges compared to strong ties, but were unable to investigate the effect of these bridging links in terms of additional referrals or monetary value.

Our study differs significantly from previous work on customer referral programs in two ways. First, whereas previous research on the value of referred customers focused on the acquired customer, the present study measures the long-term referral cascade resulting from a particular referral dyad. Hence, our study captures the effect on long-term growth rather than the value of the one newly referred customer. Second, the studies of Reingen and Kernan (1986) and Brown and Reingen (1987) relied on survey data to construct the - limited - social network as well as the referral paths. In contrast, our study uses large-scale data on actual social connections and customer referrals. Such large-scale data set is crucial for empirically investigating bridging effects, since there are typically fewer bridging links that within-community links in social networks (Onnela et al., 2007).

A very recent study investigated the quantity-quality trade-off for referrals (Viswanathan, Tillmanns, Krafft, & Asselmann, 2018). This is highly relevant to our study as they too aimed to explore the interplay between attracting more customers and attracting valuable customers. However, whereas that study mainly focuses on behavioral characteristics such as extraversion and opinion leadership of customers, our study aims to understand the impact of the social network.

4.3 Research setting and data

4.3.1 Research setting

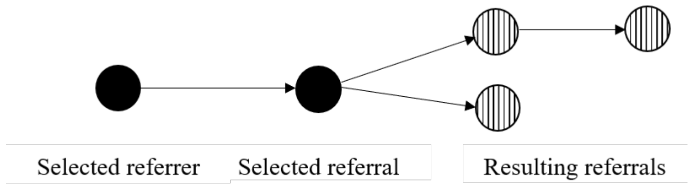
We use a data set from a fast-growing European telecom provider. This telecom operator has been running the same customer referral program, including the same reward, for multiple years as the major element of their marketing mix. Of all customers 57% was referred by mid 2013, indicating the importance of the referral program for the business. The operator provides several pre-paid packages at different price levels. In addition to the referral program, another important part of the business, setting it apart from the competition is that customers can call each other for free. These free in-network calls and texts are valid for a period of 30 days after the last purchase, thus stimulating customers to frequently re-purchase. On top of that, it provides a great incentive for customers to refer friends and family as it will increase their benefit of these free in-network calls.

4.3.2 Data description

We have access to customers' call and text data, referral data, purchase data and some socio-demographics. This data is available for a period of 34 months (October 2010 until July 2013) and hence allows us to assess the long-term effect of a referral. Given that customers can join the provider at different times, we apply the following filters to select valid customers for analysis: (1) customers who were acquired between January and December of 2011, (2) customers who have used their phone at least once, (3) customers who have a valid postal code. Given our focus on evaluating long-term customer network growth, the selection period of 12 months leaves us with sufficient data to assess network growth. After applying these filtering steps, we are left with a sample of 23,908 referred customers.

For each selected referral dyad, we measure the network growth as a result of subsequent referrals, as visualized in Figure 4.2. We use the terms *selected referrer* and *selected referral* to denote the referrer and referral of a dyad we want to investigate. We use the term *resulting referrals* to denote the referrals that are part of the referral tree initiated by the selected referral. For every selected referrer-referral dyad, we record the resulting referrals cascade for 18 months following the acquisition date of the selected referral. It is

Figure 4.2: Referral cascade.



important to note that the selected referral, which has been the subject of previous literature (Armelini et al., 2015; Meyners et al., 2017; Roelens et al., 2018; Schmitt et al., 2011; Van den Bulte et al., 2018) is not part of the resulting network growth in this study. The present study focusses on the subsequent growth after the acquisition of selected referral.

Dependent variables

Resulting referral behavior Our analysis is at the referral dyad-half yearly level. To ensure comprehensive analysis, we define two dependent variables, namely the size of the resulting referrals cascade and the total revenue generated by the resulting referrals. The first is computed as the total number of resulting referrals in the referral cascade. The second dependent variable is measured as the revenue generated by these referrals.

Selected referral revenue To provide a complete picture of the value of referred customers, we also conduct an analysis into the revenue generated by the selected referral him- or herself, rather that that of the resulting referrals cascade (See Figure 4.2). The dependent variable in this analysis is the revenue generated only by the selected referral. We use exactly the same operationalization as for the revenue of the referral cascade to ensure comparability.

Referral dyad variables

To measure local network structure, we define two variables that each capture a different but complementary aspect of referral tie characteristics. The main focus of the sociological theories of weak ties (Granovetter, 1973) and structural holes (Burt, 1992) is on redundancy of information and connecting otherwise disjoint communities. We operationalize this by referral dyad tie strength and network overlap.

Tie strength There may be relationships that are in between strong and weak ties. Therefore, we define tie strength as a continuous variable. Specifically, we measure tie strength, in accordance with previous research, as the ratio of the communication volume between the referrer and referral and the total communication volume of the referrer (Meyners et al., 2017; Nitzan & Libai, 2011; Onnela et al., 2007; Roelens et al., 2018). The communication volume refers to the sum of the minutes called and the number of text messages sent. We consider a text message equivalent to a one minute call (based on Nitzan and Libai (2011)). Representing the total communication volume between customer i and neighbor j by Comm_{ij} and the total communication volume of customer i by Comm_i, we compute the tie strength between customer i and neighbor j as:

$$\text{Tie strength}_{ij} = \frac{\mathrm{Comm}_{ij}}{\mathrm{Comm}_i}$$

Network overlap Network overlap measures the proportion of common neighbors in the direct networks of the referrer and referral. It is computed as in Koroleva and Štimac (2012) as the ratio of the number of common neighbors relative to the absolute number of neighbors of the referrer and referral. The network overlap between two individuals reflects how interconnected they are. If network overlap is high, the proportion of common neighbors is high, indicating that it is likely that the two individuals reside in the same community (Onnela et al., 2007). The lower the overlap between each other's connections, the more likely the information will be non-redundant. By defining network overlap in addition to tie strength we also capture the cohesion of the local networks.

Representing the set of neighbors of customer i and j by respectively n_i and n_j, we define network overlap as:

$$\text{Network overlap}_{ij} = \frac{\mathrm{n}_i \cap \mathrm{n}_j}{\mathrm{n}_i \cup \mathrm{n}_j}$$

Tie strength is measured in the three months prior to the selected referral's acquisition date (Nitzan & Libai, 2011). Network overlap is measured in the three months after the referrals's acquisition date because communication behavior can only be observed after acquisition. Similar to Meyners et al. (2017), we assume that a person's social network remains stable 3 months before and 3 months after joining the provider. This is a reasonable assumption given that previous research has shown that social networks remain the same while the telecom provider changes (Eagle, Pentland, & Lazer, 2009).

Individual network variables

To further capture effects due to local network structure specific to the selected referral, we define two referral-level network variables.

Degree Degree measures the number of unique individuals with whom the selected referral communicated. Individuals with many social connections, and thus a high degree, are considered opinion leaders who are influential (Iyengar et al., 2011). Therefore, seeding a marketing campaign to high-degree individuals is highly effective in generating a high number of referrals (Hinz, Skiera, Barrot, & Becker, 2011). The degree of customer

i is defined as:

$$\text{Degree}_i = \text{n}_i$$

Structural embeddedness Structural embeddedness in general is often referred to as the degree to which a person is connected to other people in the network (Granovetter, 1985; Grewal, Lilien, & Mallapragada, 2006; Ransbotham, Kane, & Lurie, 2012). The structural embeddedness of a selected referral captures the extent to which this person is entrenched in the firms' customer network. It is given by the proportion of the connections that are also a customer with the provider[1]. If a customer has a high degree, this person is more likely to make more referrals (Hinz et al., 2011), however when most of the neighbors already are a client with the provider there is less referral potential left. We thus expect a saturation effect to take place in the network. By including structural embeddedness in our model, we control for referral potential.

Representing the set of connections of customer i by n_i and the subset of those connections who are also a customer with the firm by n_i^c, we define structural embeddedness as:

$$\text{Structural embeddedness}_i = \frac{\text{n}_i^c}{\text{n}_i}$$

Similar as to network overlap, we observe these variables in the three months after the referral's acquisition since we want to capture the referral's full network, which is only possible after acquisition.

Individual variables

In addition to the referral dyad variables and individual network variables, we also control for any effects due the selected referral's age and gender. We further control for neighborhood-related characteristics, captured by wealth index, the percentage of customers in the referral's neighborhood the week before acquisition and the percentage of those customers who are referrers in the referral's neighborhood. A continuous variable is included that captures the time since the acquisition of the selected referral as well as six-monthly dummies to capture any time-specific unobserved shocks.

[1]Note that some literature uses the term *embeddedness* to denote the number of common connections of two individuals (e.g., Aral & Walker, 2014; Muller & Peres, 2018), which is denoted by the term *overlap* in other studies (e.g., Koroleva & Štimac, 2012; Onnela et al., 2007). In addition to network overlap, we capture structural embeddedness consistent with previous research (Grewal et al., 2006; Ransbotham et al., 2012).

4.4 Model development

Before we present the main model of this study, we discuss how we differentiate social effects from confounding factors. Following some recent studies (Aral, Muchnik, & Sundararajan, 2009; Datta, Foubert, & Van Heerde, 2015; Van den Bulte et al., 2018), we use a matching technique to ensure accurate analyses.

4.4.1 Customer matching

Motivation

It is known that individuals who have a strong connection, on the one hand are likely to have similar opinions and views through homophily and on the other hand influence each other's decisions, including purchasing decisions (Aral et al., 2009; Hill et al., 2006; McPherson et al., 2001). Additionally, the theory of the strength of weak ties builds on the idea that individuals with a weak social connection are likely to reside in different social communities. Therefore, weak social connections are less likely to share similar opinions and are less likely be exposed to similar stimuli. If weak and strong tie referrals experience different local and social stimuli, any difference that we find between the two groups could potentially be due to these differences in stimuli. To accurately examine the effect of referral tie connectivity, we exclude other effects that could potentially interfere or affect the one we wish to study.

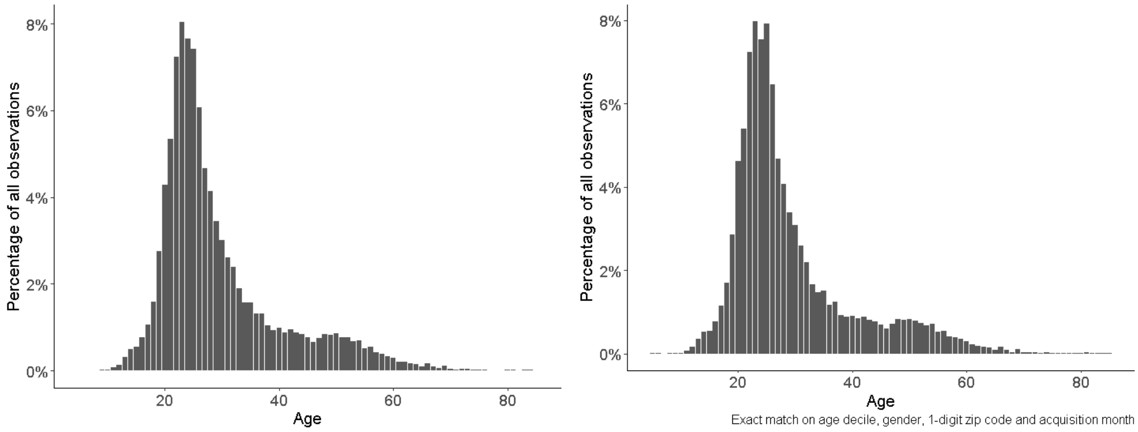
In order to strengthen the confidence that any effects we find are attributable to being referred over a strong or weak tie, we perform a customer matching technique. This reduces imbalance between the two groups and ensures that the two groups are as alike as possible on observables. By doing this, we control for potentially confounding effects of observed and unobserved characteristics. After matching, we can be confident that any difference we find between the two groups is due to differences in referral dyad characteristics and not due to other factors related to the matching variables.

Procedure

To perform the matching, we dichotomize the continuous tie strength variable (King, Blackwell, Iacus, & Porro, 2010) using the median as a cut-off value (i.e. 0.038). This results in 11,954 observations (i.e., dyads) in both the strong and weak referral tie group.

Next, we select the variables to match the two groups (customers referred over strong and weak ties) on. These variables are likely confounders of the studied effect, resulting referral behavior. The first two matching variables are age and gender of the selected referral because the data show that older and female customers are less likely to make referrals. By including age and gender as matching variables, we prevent that the number

Figure 4.3: Age histograms of both referrers and referrals.



(a) Histogram of population age. (b) Histogram of matched set age.

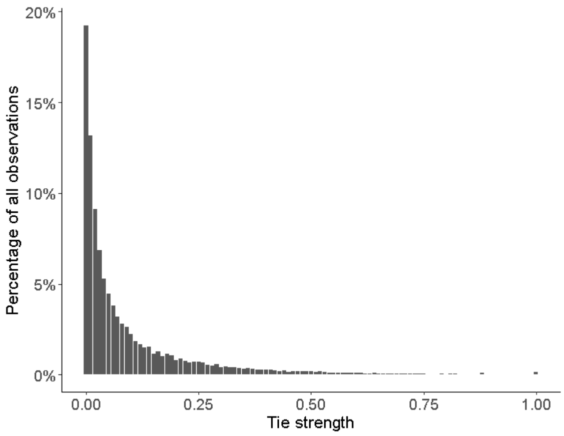
of resulting referrals is confounded by these variables. Second, the density of customers per neighborhood varies significantly. Differences in customer density can impact how many referrals can be made in a customer's area. By matching on area of residence of the selected referral, we ensure that any difference in referrals being made between strong and weak tie referral groups is not affected by neighborhood. Lastly, the number of customers who joined the provider increases steadily over time. Hence, customers who were acquired earlier have more opportunities to refer new customers, while for customers who joined later, more of their social connections might already have joined the operator which limits their opportunity for making referrals. To avoid the number of resulting referrals being confounded by acquisition time, we match customers on acquisition month.

We use exact matching to match customers on age decile, gender, province and acquisition month. Exact matching is chosen over propensity score matching as it reduces imbalance by approximating fully blocked randomization (King & Nielsen, 2016). After matching, 17,886 matched customers are selected. We decide on these levels of granularity for the matching variables by trading off the number of matched customers with controlling as best as possible for (un)observables and reducing imbalance. The selected matched set represents 75% of all referred customers and retains the characteristics of the population well as visualized in Figures 4.3 and 4.4. Table 4.1 reports descriptives of the variables measured for the population and the two matched groups.

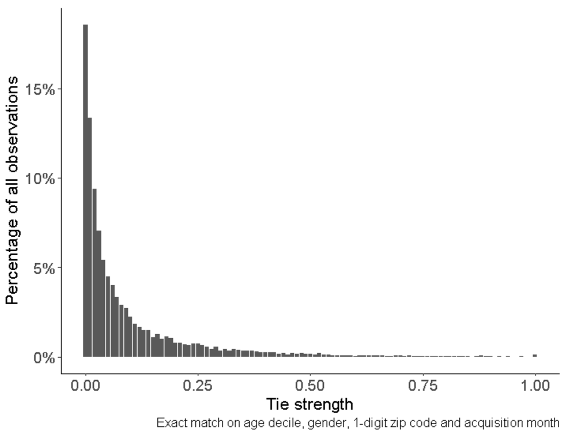
4.4.2 Model specification

Our primary focus in this research is to understand the role of the referral dyad between a referrer and a referred customer on the resulting network growth and value. In this Section, we develop two dynamic models each modelling a different dependent variable, namely the size of the resulting referral cascade and the revenue generated by the result-

Figure 4.4: Tie strength histograms.



(a) Histogram of population tie strength.



(b) Histogram of matched set tie strength.

Table 4.1: Descriptive statistics for weak and strong referral link customers.

	Population			Weak tie referrals			Strong tie referrals		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Dependent variables									
Resulting referral cascade size	1.017	0	2.191	1.070	0	2.310	0.997	0	2.100
Resulting revenue	75.868	0	184.166	79.101	0	192.170	74.749	0	180.251
Resulting revenue selected referral	89.627	90	69.596	85.512	75	66.363	95.024	90	72.048
Network structure variables									
Tie strength	0.094	.038	0.14	.012	0.009	.011	0.173	.113	0.157
Network overlap	0.055	.045	0.047	.045	0.034	.043	0.064	.056	0.048
Embeddedness	0.051	.037	0.066	.049	0.034	.071	0.055	.041	0.063
Degree	58	53	37	57	52	38	61	55	36
Control variables									
Female	0.3	0	0.5	.3	0	.5	0.3	0	0.5
Age	29	26	11	29	26	11	29	26	11
Percentage customers in neighborhood	0.099	.069	0.097	.104	0.074	.097	0.105	.077	0.098
Percentage referrers in neighborhood	77.0	74.0	41.2	76.7	73.8	39.3	77.9	74.6	39.4
Wealth index	104	105	15	104	105	15	104	105	14
Number of customers		23,908			8,943			8,943	

ing referrals. We use a Negative Binomial model for the size of the resulting referrals cascade and a Tobit Type I model for the resulting revenue because there are many observations with value zero. To control for customer-specific referral behavior, we include individual-level random effects in both models that will capture any individual unobserved heterogeneity specific to the selected referral.

The behavior of making referrals typically occurs rather sparingly. As a result, structuring the data at the monthly level results in many months having no referral behavior. This hinders computational effectiveness and any modelling attempts at the monthly level were unsuccessful. To mediate this, we structure the data at a slightly higher aggregation level, namely at the six-month level rather than at the monthly level. By doing this, we retain enough variability in the data and prevent overparametrization.

Consider $i = 1, 2, ..., I$ referred customers making referrals that result in a cascade of new referrals as visualized in Figure 4.2. We employ the same variable specifications, including random effect, in the Negative Binomial model for the resulting number of referrals as in the Tobit Type I model of the resulting revenue. This prohibits any confounding factors to enter the analysis so that comparability with the analysis of the resulting cascade is ensured. We define customer i's resulting revenue y and the latent outcome y^* in six-month term t as:

$$y_{it} = \begin{cases} y_i^* & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{cases} \tag{4.1}$$

where

$$\begin{aligned} y_i^* = \beta_0 &+ \beta_1 \text{ Tie strength}_i + \beta_2 \text{ Overlap}_i \\ &+ \beta_3 \text{ Degree}_i + \beta_4 \text{ Structural embeddedness}_i \\ &+ \beta_5 \text{ Customer lifetime}_{it} \\ &+ \beta_6 \text{ Age}_i + \beta_7 \text{ Female}_i + \beta_8 \text{ Wealth index}_i \\ &+ \beta_9 \text{ Perc customers in neighborhood}_i + \beta_{10} \text{ Perc referrers in neighborhood}_i \\ &+ d_i^k + u_t^k + e_{it}^k \end{aligned} \tag{4.2}$$

and d_i^k is a customer-specific random effect, u_t^k are time fixed effects at the six-month level and e_{it}^k is the error term associated with the model. We refer the reader to Section 4.3.2 for more details on the variable operationalizations. We mean-center and standardize all continuous variables so that their effects represent the effect corresponding to the "average" customer.

4.5 Results

4.5.1 Model-free analysis

Before presenting the results of the proposed model, we provide model-free evidence to explore the first premise of the theory of the strength of weak ties, namely that weak ties are more likely to be bridging links between communities.

We explore whether weak referral links in our data set are indeed more likely to be bridges to other communities compared to strong ties. To test this, we construct the full social network of the customer base at multiple points in time to allow for dynamic network changes. More specifically, we construct 12 different snapshots of the social network at different points in time. For each acquisition month, we construct a snapshot of the social network of the 15th to 18th month after the acquisition month. We use a three month window consistent with the operationalizations of the network variables used in the model. Then, for each snapshot of the network we identify communities using the multi-level modularity optimization algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008)[2]. For each selected referrer-referral dyad, we check whether it is located within a community or across communities (as a bridge). Using a Chi-squared test for trends, we explore whether there are proportionally more bridging referral links in the lower quartiles of tie strength than in the higher ones. The Chi-squared test is significant (χ^2 = 297.29, p-value $< 2.2E^{-16}$), indicating that there are significantly more bridging referral links in the lower values of tie strength. Figure 4.5 shows the proportion of bridging referral links per tie strength quartile, illustrating that the proportion of bridging links decreases with tie strength. This is in accordance with the theory of the strength of weak ties that states that weak ties are more likely to be bridges compared to strong ties.

Additionally, we use the same approach to investigate whether referral links with limited network overlap are more likely to be bridging links to other social communities. The Chi-squared test is significant (χ^2 = 2986.5, p-value $< 2.2E^{-16}$), suggesting that there are significantly more bridging referral links in the lower values of network overlap. This finding is also visible in Figure 4.6 showing a decreasing proportion of bridging links for increasing network overlap. This indicates that if a referral is made between a referrer and referral who have limited network overlap, chances are higher that new social communities are reached.

[2]This method is shown to outperform other known community detection methods in terms of computation time, while performing well in terms of community detection as measured by the modularity (Blondel et al., 2008).

Figure 4.5: Proportion of bridging referral links for each quartile of tie strength.

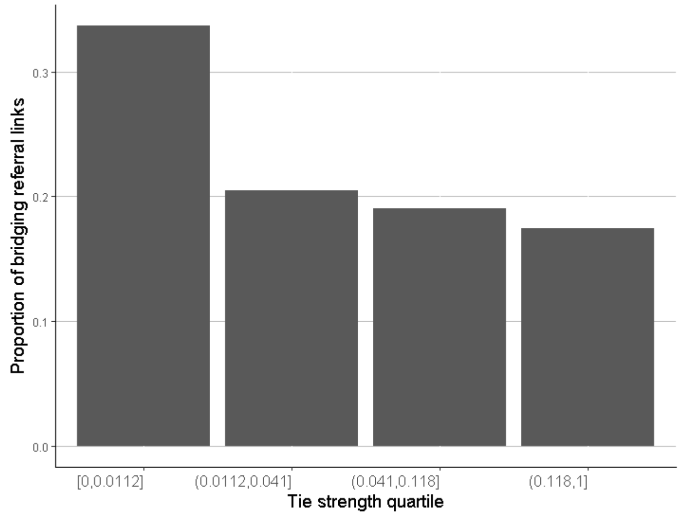
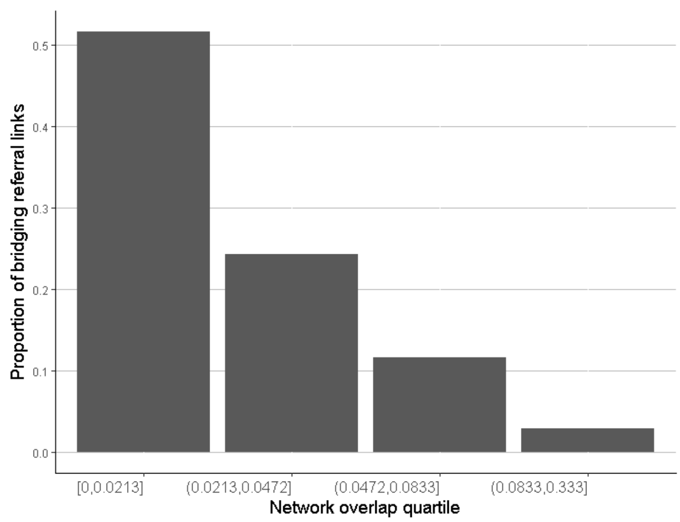


Figure 4.6: Proportion of bridging referral links for each quartile of network overlap.



4.5.2 Results of the resulting referrals cascade models

Table 4.2 reports the results of the two referral cascade models. The estimates for the time fixed effects are not included in Table 4.2 as they are not relevant for interpretation of the studied effects. We do report them in Appendix 4.B for comprehensiveness and notice that most of them are significant, indicating that they absorb some time-specific shocks. Additionally, Appendix 4.D reports the results of the models alternately excluding tie strength and network overlap. These models estimate the effects of the covariates independent of any confounds due to the slight correlation between tie strength and network overlap (the correlation is 0.17, as documented in Appendix 4.A). We discuss the results of the resulting referrals cascade size and revenue models separately in the following.

Referral cascade size model

The results confirm the theoretical expectation that customers who are referred over a weak referral tie trigger a larger cascade of subsequent referrals (β_1 = -.059, $p < 0.01$). The same conclusion holds for referrals who have limited network overlap with their referrer (β_2 = -.079, $p < 0.01$). This provides support for the theory of the strength of weak ties (Granovetter, 1973) and the theory of structural holes (Burt, 1992). It suggests that weakly connected referral dyads indeed might be involved in accessing new communities and transmitting non-redundant information.

The results of tie strength and network overlap hold even when controlling for degree and structural embeddedness that capture much of the referral potential. The degree of a referred customer has a positive effect on the size of the resulting referral cascade (β_3 = .411, $p < 0.01$). This suggests that having a larger personal network increases the opportunities for making referrals. This is in line with literature on opinion leadership that suggests that individuals with more connections are typically more influential (Iyengar et al., 2011; Nair, Manchanda, & Bhatia, 2010). The results further show that customers who are more embedded in the customer network make fewer subsequent referrals (β_4 = -.131, $p < 0.01$). This makes sense as a larger proportion of their social connection is already a customer with the provider and thus leaves these customers with fewer opportunities for making referrals.

Controlling for structural embeddedness in fact provides a more stringent test for the tie strength and network overlap effects. This is true, conditional on having the same level of structural embeddedness, which implies the same level of referral potential, we still find that weak referral ties and referral ties with limited network overlap attract a larger resulting referral cascade. Appendix 4.E shows the estimates of the model without controlling for structural embeddedness. The results indicate that the main effects are stronger, particularly network overlap. Hence, this further confirms that weak referral ties and referral ties with limited network overlap succeed in reaching and attracting more potential customers[3].

Lastly, some control variables have significant and face valid effects. Female customers and older customers are less likely to trigger referrals. The likelihood of a customer bring about referrals increases with the time since the referral acquisition. This could imply that customers take some time to convince others to join the company. It also captures the effect that cascades that are larger are more likely to grow more.

Revenue model

The results of the revenue model demonstrate that the revenue of the resulting referrals cascade is not *significantly* associated with the referral tie strength. This is surprising as we could expect revenue to follow similar patterns as the size of the referral cascade. However, tie strength does not seem to effect the value of the resulting referrals but only the number of the resulting referrals (reported in cascade size model). The results further show that the resulting revenue is higher when the referrer and referral have limited network overlap. This implies that network overlap is a more important covariate for the revenue of the resulting cascade than tie strength is.

However, the results of the models reported in Appendix 4.D show that tie strength is significant when network overlap is excluded from the model. Hence, tie strength does have an effect on the resulting revenue, but this is also partly captured by network overlap, taking away the significance from tie strength in the full model. These findings thus provide support for the theory of the strength of weak ties stating that weak referral links and mainly referral links with limited network overlap lead to significantly more resulting revenue.

Further, the degree of a selected referral is positively associated with the revenue of the resulting referrals cascade ($\beta_4 = 47.018$, $p < 0.01$). In contrast, the results indicate that higher structural embeddedness is associated with lower revenue of the resulting referrals cascade (β_5 = -20.774, $p < 0.01$). Appendix 4.E documents the results of the model that does not include structural embeddedness. We see that the effect of tie strength becomes slightly significant and network overlap becomes even more significant in this model. Thus, when we do not control for structural embeddedness, and therefore let the referral potential be fully captured by tie strength and network overlap, we find even more support for the theory of the strength of weak ties. This indicates that weak referral ties and referral ties with limited network overlap indeed have higher referral potential. This is likely due to their capacity to reach untapped communities as put forth in the theory of the strength of weak ties.

The results of the control variables suggest that women and older customers lead to

[3]We decide to include structural embeddedness in the main model since this provides in a better model fit as demonstrated by the lower Log-Likelihood in the full model.

lower revenue of the referral cascade.

To validate the robustness of our results to the modelling decisions, we performed additional robustness checks. Appendix 4.C.1 contains the results of the resulting cascade models on the customer set without performing matching. We find that the results are robust to the decision to perform matching. Appendix 4.C.2 reports the results of the revenue model with a log-transformed dependent variable. Here too, we find that the same conclusions are drawn and the results are robust. Finally, Appendix 4.C.3 shows the results of the resulting cascade models where we aggregate the dependent variables to one observation per customer[4]. More specifically, we sum the number of resulting referrals and revenue over the observation period of 18 months. The results are in line with the results of the models where we accounted for variations over time. In sum, the robustness checks confirm that the conclusions drawn from the analyses are robust to the modelling decisions made.

4.5.3 Results of the selected referral model

As discussed in Section 4.2.1, previous literature investigated what drives the value of referred customers (Armelini et al., 2015; Roelens et al., 2018; Schmitt et al., 2011; Van den Bulte et al., 2018). Van den Bulte et al. (2018) showed that referred customers are more valuable to a firm when the referrer has a strong connection with the firm. Roelens et al. (2018) extended this insight by showing that the same effect is at play for the connection with the referrer. Thus, if a customer is referred over a strong referral tie, the referred customer is shown to be more valuable to the firm.

To confirm consistency with these previous findings, we run an identical Tobit Type I model on the revenue of the *selected referral* rather than on revenue of the resulting referral cascade[5].

Table 4.3 reports the results of the Tobit model. The results support the findings of previous research that referrals who were referred over a strong referral tie have higher revenue (β_1 = 5.315, p < 0.01). The results further show a similar but less significant effect of overlap in the referrer and referral's social connections (β_2 = 1.098, p < 0.05). More network overlap implies that the referrer and referral have a closer connection due to the presence of common connections, which has been show to increase trust (Uzzi, 1997). This could lead to increased goodwill for making good referrals, which is in line with the better matching theory proposed by Van den Bulte et al. (2018).

[4]Note that these results are based on the matched customer set.

[5]Additionally, to maintain consistency within this dissertation, we also perform an ordered logit model at the monthly level with the same binning as was used in the pseudo-contractual revenue model in Chapter 3 of this thesis. The results lead to the same conclusions as the Tobit model. We refer the reader to Appendix 4.F for the results.

Table 4.2: Results of the referral cascade models.

	Coeff	St error
Resulting cascade size model		
Intercept	-1.293***	.065
Tie strength	-0.059***	.017
Network overlap	-0.079***	.018
Degree	0.411***	.017
Structural embeddedness	-0.131***	.021
Female	-0.449***	.038
Age	-0.322***	.019
Customer lifetime	0.593***	.027
Percentage customers in neighborhood	-0.020	.020
Percentage referrers in neighborhood	-0.022	.017
Wealth index	0.013	.017
Individual-level variation (σ_d)	3.304	1.818
Negative Binomial shape parameter	403.43	.003
Log-Likelihood	-55,053.7	
Resulting cascade revenue model		
Intercept	-154.046***	8.703
Tie strength	-3.524	2.307
Network overlap	-11.775***	2.478
Degree	47.018***	2.746
Structural embeddedness	-20.773***	3.827
Female	-47.409***	5.735
Age	-37.131***	3.876
Customer lifetime	113.604***	3.585
Percentage customers in neighborhood	-2.633	2.583
Percentage referrers in neighborhood	-1.638	2.030
Wealth index	-1.928	2.318
Individual-level variation (σ_d)	351.075***	2.721
Log-Likelihood	-153,953.7	

Note: *p<0.1; **p<0.05; ***p<0.01

The results further suggest that customers who have a high degree spend more money (β_3 = 6.389, $p < 0.01$). Calling a higher number of people thus leads to making more purchases. On the other hand, customers who are more embedded in the customer network spend less (β_4 = -17.893, $p < 0.01$). This makes sense as the telecom operator in this study offers each active customer a certain number of free calls and texts to other existing customers. Hence, customers whose social connections are also customer with the same provider spend less money on buying credits.

In conclusion, these results confirm findings of previous research that customers referred over strong ties have higher revenue themselves.

Table 4.3: Results of the selected referral model.

	Coeff	St error
Intercept	92.713***	1.757
Tie strength	5.315***	.454
Network overlap	1.098**	.483
Degree	1.098***	.483
Structural embeddedness	-4.807***	.477
Female	1.375	1.030
Age	5.252***	.457
Customer lifetime	-7.595***	.747
Percentage customers in neighborhood	1.121**	.557
Percentage referrers in neighborhood	1.117**	.456
Wealth index	0.088	.476
Individual-level variation (σ_d)	51.316**	2.735
Log-Likelihood	-272,422.6	

Note: *p<0.1; **p<0.05; ***p<0.01

4.6 Conclusion and implications

Customer referral programs have received increasing attention of marketing scholars and is an often-used marketing tool by practitioners. Although previous research on customer referral programs has investigated the value of referred customers (Roelens et al., 2018; Van den Bulte et al., 2018), no research has examined the long-term contribution of referred customers to the customer base growth. Based on sociological theory, our study investigates the role of referral dyad connectivity for customer network growth. Using a Negative Binomial model and a Tobit model, we model the total contribution that was made by a referred customer in terms of the number of subsequent referrals and revenue generated by those referrals. We find that customers who were referred over a weak social connection are responsible for larger referral cascades. The same is true for customers who have limited network overlap with their referrer. These two findings together provide support for the idea that referrals over weak ties are more likely to be bridges to other communities, which is the key premise of the theory of the strength of weak ties.

4.6.1 Theoretical implications

The social connections between individuals determine how and where information flows through a social network. Consequently, network characteristics such as tie strength and network overlap affect the transmission of information. Our study investigates the effect of these characteristics on the growth of the network size and value. To do so, we integrate the marketing literature on customer referral programs and the sociological literature on social networks. We extend the literature stream on customer referral programs and show that it is beneficial for firms to encourage referrals over a diverse range of tie strengths. Whereas previous research has shown that customers acquired over strong tie referrals are more profitable, the present study highlights the valuable role of weak tie referrals for stimulating network growth. We further extend the sociological literature on the theory of the strength of weak ties by providing an empirical test of the theory on a large-scale customer referral data set. In doing so we answer the call by Aral (2016) for a deeper understanding of the effects of weak ties, social cohesion and structural holes. We provide an answer to his observation that "Access to new large-scale, micro-level data presents a tremendous opportunity to modernize and improve the explanatory power of the weak tie theory." (Aral, 2016, p. 1935) Similarly, our study contributes to the literature on structural holes by empirically assessing the value of spanning structural holes for customer referral program effectiveness.

4.6.2 Practical implications

Our results show that referrals over weak ties can result in significant growth of the customer network size and value. Hence, the present study complements previous research on the value of referred customers. While referrals over strong ties generally lead to more profitable referrals, referrals over weak ties can result in increased value through customer base growth. Thus, it is important for marketing managers to realize that stimulating a referral over a specific strength of tie can help them in reaching different goals.

The managerial question is how marketing managers can stimulate referrals over weak ties. One could imagine that customers turn first and more frequently to their close social connections to recommend a product or service. Hence, the first few referrals made by a customer are likely to be strong tie referrals. It is likely that only later referrals will be made over weak ties. A possibility to stimulate weak tie referrals would be to increase the referral incentive as customers make more referrals. In that way managers would pay less for initial strong tie referrals that are more likely to occur anyway and pay some more to encourage customers to keep making referrals - also over weak ties. This idea was also put forward in Ryu and Feick (2007). They found that information transmission through weak ties can be improved with incentives, which was later confirmed by Barrot, Becker, and Meyners (2013). Hence, offering higher incentives can in fact increase the occurrences of referrals over weak ties and consequently the network size and value.

Finally, it is also important to note that the rise of online social networks allows individuals to maintain many weak ties for long periods of time. Whereas people used to get out of touch, now people stay connected through online social networks. Facebook in particular has been shown to help convert latent ties to weak ties and to easily and cheaply maintain weak ties (Ellison, Steinfield, & Lampe, 2007). This could enhance the importance of weak social ties and increase the possibilities for marketing managers to leverage these ties.

4.6.3 Limitations and directions for future research

The results of our study are based on data of only one company. To boost confidence in these findings and enable practitioner adoption, we urge researchers to further explore these effects in other settings and contexts. Additionally, ideally further research would be conducted in settings with different characteristics compared to previously researched contexts such as riskiness of the product or online compared to offline communication. We acknowledge however that it is not straightforward to collect the necessary data as multiple data sources (social network and referral data) need to be collected over a long period of time.

The results of this study show that referrals over weak ties result in larger resulting referral cascades compared to referrals over strong ties. However, we do not see this significant difference in the revenue generated by the referral cascade. Note that this finding is only true for tie strength and not for network overlap. A possible explanation of this finding with respect to tie strength might be that the attracted customers generate less-than-average revenue. Alternatively, some of the resulting referrals could potentially be fraudulent or cases of reward scrounging. Unfortunately, we do not have detailed insights in such behavior in this data set. It could however be an interesting avenue for future research. Only one previous study has investigated opportunistic behavior in the context of referral programs (Meyners et al., 2017).

Another possibly interesting area of future research is the application of self-excitation to referral marketing. Self-excitation implies that the occurrence of one event increases the short-term probability of another event happening (Hawkes, 1971). Self-exciting processes (also called Hawkes processes) are stochastic processes that model events happening in continuous time where the occurrence of one event increases the chances of another event happening. This makes sense in the context of customer referrals and customer behavior in general, where self-excitation or contagion behavior is shown to be at play. Porter and White (2012) used a self-exciting hurdle model to model terrorist activity. Manzoor and Akoglu (2017) used a self-exciting model to model customers' purchasing behavior. Whereas the present study focuses more on the effects driving customer referral program effectiveness in general, such a self-excitation model would be more focused on modelling the arrival of referrals and the time dimension. Admittedly, these models are often limited in the number of covariates they can incorporate, which makes it a less suited approach for research investigating the various drivers of customer behavior such as the present study.

In addition to other methodologies for tackling this research problem, extending the insights further by investigating the decay from first to second order referral, from second to third order and so on could also prove interesting (Christakis & Fowler, 2013). Future work could also investigate whether there is an optimal combination of referrals over strong and weak ties for maximizing the customer base value and growth. A few studies have aimed to explore the complementarity of weak and strong ties in other contexts such as innovation-seeking alliances (Ozcan & Eisenhardt, 2009; Tiwana, 2008) and organizational performance (Uzzi, 1997). These studies found that organizations derive different value from both weak and strong ties with other players. However, this idea has not been investigated with respect to customers.

We hope our study and these suggestions can inspire other scholars to continue this literature stream.

Appendix

4.A Correlation table of variables

Table 4.A.1: Correlations of the model variables.

	1.	2.	3.	4.	5.	6.	7.	8.
1. Tie strength	1							
2. Network overlap	0.17	1						
3. Structural embeddedness	0.02	0.16	1					
4. Degree	0.01	0.07	-0.18	1				
5. Age	0.02	-0.14	-0.04	-0.16	1			
6. Perc customers in neighborhood	0.01	0.02	0.07	-0.01	-0.02	1		
7. Perc referrers in neighborhood	-0.01	0	0	0.01	-0.01	-0.1	1	
8. Wealth index	-0.01	0.05	0.04	0	-0.05	.23	0.04	1

4.B Estimates of the calendar time fixed effects

Table 4.B.1: Estimates of the calendar time fixed effects.

	Coeff	St error
Referral cascade size model 4.2		
Half year 2	29.312	6.053
Half year 3	33.266***	9.164
Half year 4	7.905***	12.850
Half year 5	-44.422***	16.853
Referral cascade revenue model 4.2		
Half year 2 .054	0.039	
Half year 3	-0.061	.068
Half year 4	-0.258***	.098
Half year 5	-0.593***	.129
Selected referral revenue model 4.3		
Half year 2	-3.298***	1.128
Half year 3	-3.849**	1.854
Half year 4	-7.168***	2.677
Half year 5	-10.810***	3.558

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.C Robustness checks

4.C.1 Results of the resulting cascade models without matching

Table 4.C.1: Results of the referral cascade models without matching.

	Coeff	St error
Resulting cascade size model		
Intercept	-2.423***	.078
Tie strength	-0.065***	.021
Network overlap	-0.084***	.021
Degree	0.473***	.020
Structural embeddedness	-0.103***	.024
Female	-0.763***	.045
Age	-0.377***	.022
Customer lifetime	0.545***	.031
Percentage customers in neighborhood	0.053*	.024
Percentage referrers in neighborhood	-0.001	.020
Wealth index	0.075	.020
Individual-level variation (σ_d)	5.957***	2.441
Negative Binomial shape parameter	403.43	.00003
Log-Likelihood	-58,466.3	
Resulting cascade revenue model		
Intercept	-156.000***	1.900
Tie strength	-4.353**	2.140
Network overlap	-16.450***	2.229
Degree	53.760***	2.310
Structural embeddedness	-24.660***	2.962
Female	-56.700***	4.982
Age	-51.260***	3.114
Customer lifetime	111.000***	3.276
Percentage customers in neighborhood	-2.429	2.392
Percentage referrers in neighborhood	0.416	1.768
Wealth index	-3.854**	2.063
Individual-level variation (σ_d)	336.640***	1.007
Log-Likelihood	-202,380.5	

Note: *p<0.1; **p<0.05; ***p<0.01

4.C.2 Results of the resulting revenue model with log transformed dependent variable

Table 4.C.2: Results of the resulting revenue model with log transformed dependent variable.

	Coeff	St error
Intercept	0.213**	.071
Tie strength	0.013	.018
Network overlap	-0.035**	.017
Degree	0.329***	.017
Structural embeddedness	-0.082***	.023
Female	-6.845***	.058
Age	-0.120***	.020
Customer lifetime	1.236***	.029
Percentage customers in neighborhood	-0.020	.020
Percentage referrers in neighborhood	-0.024	.016
Wealth index	-0.026	.017
Individual-level variation (σ_d)	1.850***	.006
Log-Likelihood	-67,303.12	

Note: *p<0.1; **p<0.05; ***p<0.01

4.C.3 Results of the resulting cascade models with one observation per customer

Table 4.C.3: Results of the referral cascade models with one observation per customer.

	Coeff	St error
Resulting cascade size model		
Intercept	0.496***	.015
Tie strength	-0.028***	.013
Network overlap	-0.052***	.013
Degree	0.341***	.015
Structural embeddedness	-0.099***	.017
Female	-0.340***	.029
Age	-0.236***	.015
Percentage customers in neighborhood	-0.082***	.013
Percentage referrers in neighborhood	-0.003	.013
Wealth index	-0.017	.013
Negative Binomial shape parameter	0.474	.008
Log-Likelihood	-29,527.6	
Resulting cascade revenue model		
Intercept	-62.060***	8.267
Tie strength	-16.570**	6.793
Network overlap	-33.590***	6.984
Degree	175.600***	6.710
Structural embeddedness	-46.040***	8.471
Female	-169.700***	15.050
Age	-100.800***	7.307
Percentage customers in neighborhood	-32.080***	6.859
Percentage referrers in neighborhood	-7.738	6.570
Wealth index	8.509**	6.762
Log-Likelihood	-76,483.34	

Note: *p<0.1; **p<0.05; ***p<0.01

4.D Results of referral cascade models without tie strength and network overlap

Table 4.D.1: Results of the referral cascade models without tie strength and network overlap.

	Model without tie strength		Model without network overlap	
	Coeff	St error	Coeff	St error
Resulting cascade size model				
Intercept	-1.269***	.065	-1.299***	.065
Tie strength	-	-	-0.071***	.017
Network overlap	-0.088***	.017	-	-
Degree	0.411***	.017	0.407***	.017
Structural embeddedness	-0.131***	.021	-0.149***	.021
Female	-0.456***	.038	-0.464***	.038
Age	-0.324***	.019	-0.311***	.018
Customer lifetime	0.594***	.027	0.588***	.027
Percentage customers in neighborhood	-0.020	.020	-0.021	.020
Percentage referrers in neighborhood	-0.021	.017	-0.021	.017
Wealth index	0.014	.017	0.011	.017
Half year 2	0.053	.039	0.060	.039
Half year 3	-0.064	.068	-0.051	.068
Half year 4	-0.262***	.098	-0.242**	.098
Half year 5	-0.598***	.129	-0.572***	.129
Individual-level variation (σ_d)	3.307	1.818	3.310	1.819
Log-Likelihood	-55,059.6		-55,063.8	
Resulting cascade revenue model				
Intercept	-154.0 ***	8.693	-152.0 ***	8.584
Tie strength	-	-	-4.935**	2.285
Network overlap	-12.240***	2.460	-	-
Degree	46.620***	2.741	45.340***	2.756
Structural embeddedness	-20.800***	3.750	-22.650***	3.618
Female	-47.670***	5.728	-46.240***	5.524
Age	-37.070***	3.838	-33.460***	3.432
Customer lifetime	113.600***	3.579	114.300***	3.537
Percentage customers in neighborhood	-2.708	2.574	-2.748	2.564
Percentage referrers in neighborhood	-1.555	2.028	-1.248	1.996
Wealth index	-1.968	2.320	-1.928	2.297
Half year 2	29.090***	6.049	28.380***	6.010
Half year 3	33.050***	9.152	31.430***	9.054
Half year 4	7.597	12.830	5.238	12.680
Half year 5	-44.300***	16.820	-47.840***	16.620
Individual-level variation (σ_d)	1.768	.011	1.769	.010
Log-Likelihood	-153,954.9		-153,965.4	

Note: *p<0.1; **p<0.05; ***p<0.01

4.E Results of referral cascade models without structural embeddedness

Table 4.E.1: Results of the referral cascade models without tie strength and network overlap.

	Coeff	St error
Resulting cascade size model		
Intercept	-1.280***	.065
Tie strength	-0.059***	.017
Network overlap	-0.099***	.017
Degree	0.432***	.017
Structural embeddedness	-	-
Female	-0.438***	.038
Age	-0.313***	.018
Customer lifetime	0.599***	.027
Percentage customers in neighborhood	-0.026	.020
Percentage referrers in neighborhood	-0.023	.017
Wealth index	0.010	.017
Half year 2	0.046	.039
Half year 3	-0.077	.068
Half year 4	-0.281***	.098
Half year 5	-0.623***	.129
Individual-level variation (σ_d)	3.312	1.820
Log-Likelihood	-55,074.4	
Resulting cascade revenue model		
Intercept	-152.3 ***	8.538
Tie strength	-3.997*	2.230
Network overlap	-13.450***	2.372
Degree	48.670***	2.663
Structural embeddedness	-	-
Female	-43.22***	5.454
Age	-34.010***	3.520
Customer lifetime	113.700***	3.504
Percentage customers in neighborhood	-4.222*	2.544
Percentage referrers in neighborhood	-1.805	1.988
Wealth index	-2.796	2.279
Half year 2	28.800***	5.978
Half year 3	32.750***	8.965
Half year 4	7.340	12.540
Half year 5	-44.170***	16.410
Individual-level variation (σ_d)	1.770	.010
Log-Likelihood	-153,959.9	

Note: *p<0.1; **p<0.05; ***p<0.01

4.F Results of the ordered logit model on the revenue of the selected referral

Table 4.F.1: Results of the selected referral ordered logit model.

	Coeff	St error
Ordered logit model		
Intercept level 3	6.314***	.343
Intercept level 2 or 3	9.695***	.343
Tie strength	0.109***	.013
Network overlap	0.128***	.013
Degree	0.928***	.013
Structural embeddedness	-0.133***	.014
Female	0.174***	.028
Age	-0.019	.013
Customer lifetime	-0.509***	.007
Percentage customers in neighborhood	-0.034***	.016
Percentage referrers in neighborhood	0.018	.012
Wealth index	0.058***	.013
Individual-level random intercept	2.446	.032
Log-Likelihood	-274,483.4	

Note: *p<0.1; **p<0.05; ***p<0.01

5

Conclusion, contributions and future research

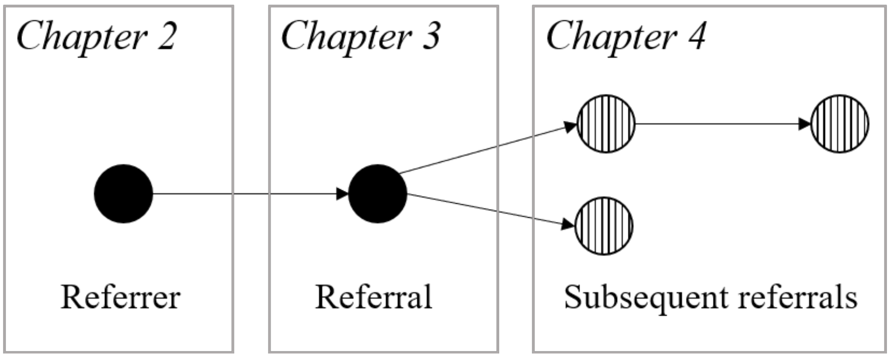
Recent literature has documented the power of social influence traversing customer networks. The topic of leveraging social connections for spreading brand awareness and stimulating product adoption has received considerable attention. It is known that people put more trust in the recommendations of close social connections than those of others - including marketing messages (Nail, 2004). Hence, referral marketing provides a fitting tool for stimulating customer acquisition while leveraging social influence (Trusov et al., 2009). While many companies have already adopted customer referral campaigns, academic research is still rather scarce. The effect of the consumer behavior and choices on that of social connections has received much attention (Christakis & Fowler, 2013; Godes & Mayzlin, 2004; Hill et al., 2006). Also the presence and role of word-of-mouth (WOM) (Benoit & Van den Poel, 2012; Godes & Mayzlin, 2004; Trusov et al., 2009; Verbeke et al., 2014) and eWOM (e.g., Steffes & Burgee, 2009) has been well researched. However, natural WOM might still differ from firm-stimulated WOM in the context of a formal referral program. Recently, some research has started to investigate the value of referred customers and the mechanisms behind it (Van den Bulte et al., 2018). This dissertation aims to add to this literature by investigating the usefulness of referral data as well as the value created by referral programs.

In what follows, we first recapitulate the structure and foundations of this dissertation. Next, we summarize the findings of each of the empirical chapters, after which we discuss the theoretical and practical implications. Finally, we highlight some interesting avenues for future research.

5.1 Composition of this dissertation

This dissertation consists of three studies each of which investigates a distinct facet of the mechanisms of referral marketing. These facets can easily be understood when visualizing the interactions involved in customer referral programs as in Figure 5.1 (recap of Figure 1.1). Figure 5.1 illustrates the referrer who convinces a social connection, the referral, to join the company's services, after which the referral in turn becomes a referrer by passing on the word and convincing two other social connections to join the company. The research in this dissertation is based on the referral behavior and the social network of the customers of a European telecom provider.

Figure 5.1: Structure of this dissertation based on the social interactions in customer referral programs.



As Figure 5.1 illustrates, the first study of this thesis, presented in Chapter 2, focuses on identifying those customers who are best suited to be referrers in a customer referral program. It investigates how to identify a group of customers (referrers) who are most influential and can affect the largest number of potential customers through word-of-mouth. The research in this thesis then continues in Chapter 3 by an investigation of which referrals provide most value to the company. It is important to not only try to identify the most influential customers who can attract as many new customers as possible, rather the actual value generated by those new customers should also be considered. That is the focus of Chapter 3, in which we identify factors that underlie the acquisition of highly valuable referrals in terms of three aspects of customer lifetime value (CLV) (revenue, lifetime, cost). Whereas Chapter 3 only takes into account the value created by referrals themselves, Chapter 4 extends these insights by exploring the value generated by subsequent referrals. Some referrals might not have a long lifetime and represent a high revenue themselves, but provide great value through their subsequent referrals that result in many new - profitable - customers joining the company.

5.2 Summary of the findings

One of the steps to take when setting up a marketing campaign is selecting the target audience (Berman, 2016). Also for customer referral programs, marketers need to decide which customers to target. In the case of a customer referral program, it is in the interest of the success of the program to target customers that are most influential. This is true, targeting those customers who are most influential will lead to the largest cascade of word-of-mouth, optimizing the costs for launching and maintaining the program. In Chapter 2, we focused on how data on customer referrals can help identify the most influential customers. Previously proposed approaches to this problem typically use simulation-based methods to approximate referral flow over a social network because data on real influence flow is not easy to observe or gather. We use a game-theoretic approach to compare how well such simulation-based methods perform compared to actual referral behavior. As detailed in Chapter 2, we find that using such simulations leads to an overestimation of the actual influence spread and resulting product adoption. A better identification of influencers is attained when referral data is used. However, since such data is not straightforward to gather, based on our study we propose that companies can enhance such simulation-based methods in two ways. First, we found that incorporating a measure of tie strength between individuals to obtain a weighted version of the network leads to a better identification of influencers. Second, looking beyond the targeted customer by incorporating the influence of their connections further improves the results. This makes intuitive sense, if the connections of the most influential customers are not willing or able to spread the message, the influence will not spread very far, which clearly is a suboptimal outcome. These results show that selecting the customers based on referral data allows companies to identify their most influential customers who will trigger the largest cascade in product adoption. It is thus useful for companies to invest in collecting data on their customers' referral behavior.

Research related to Chapter 2 focuses on maximizing the number of people who are influenced by the social contagion of a set of seed individuals. However, not all individuals are equally valuable for a firm to convert to customers. Customers differ in terms of generated revenue, lifetime and cost-to-serve. Since customer referral programs aim to help in customer acquisition, the value of the customers acquired through these programs is an important metric for success (Schmitt et al., 2011). Previous studies show a sizeable value gap between referred and non-referred customers in a banking context (Armelini et al., 2015; Schmitt et al., 2011; Van den Bulte et al., 2018). In Chapter 3, we assess the difference in value between referred and non-referred customers in a telecom setting, where trust is potentially less important than in banking. On top of that, we add to previous findings by examining this value gap with respect to all facets of CLV, namely revenue, lifetime and cost-to-serve. We find that the increased value of referred customers is perceptible in all facets of CLV. Hence, referred customers not only account for more revenue and stay longer with the firm, but are also less costly to serve. Overall, we quantify the difference in total CLV between referred and non-referred customers to be 28%. This is in line with previous research that documented the difference only due to revenue and lifetime to be between 16% and 25% (Schmitt et al., 2011).

After establishing that a sizeable difference in value exist, we investigate where these differences stem from. We use both pseudo-contractual models as well as a Hidden Markov Model to model the factors influencing the three aspects of referred customer value. We find that a stronger relationship between the referrer and the referral is associated with higher profitability, longer lifetime and lower cost-to-serve of the referral. This implies that the most valuable referred customers are those who have a strong connection with their referrer. We further corroborate findings from previous research that referrers who have been with the company for a long time make more valuable referrals (Van den Bulte et al., 2018). Thus, we find that the most valuable referred customers are those who have a strong relationship with their referrer, who in turn has a strong connection to the firm. This study thus provides insights in what drives the value of referred customers. It further provides guidance for companies to decide who to include in the referral program so that the value of the referred customers is maximized.

While some customers might be highly profitable themselves and thus appealing to attract with a referral program, other customers might not provide great value through their personal profitability but rather through their referral capacity, influencing other - potentially more profitable - customers to join the firm (Kumar et al., 2010). Based on the sociological theory of the strength of weak ties (Granovetter, 1973), we argue that there might be particular value in weak referral ties due to their ability to reach untapped communities of potential adopters. Therefore, in Chapter 4 we analyze the long-term growth in the customer network that results from referrals. More specifically, we measure the size of the referral cascade and the revenue generated by those referred customers in the cascade. The results show that referrals over weak ties generally lead to larger growth in the network. This provides evidence for the theory of the strength of weak ties that states that weak ties are more likely to be bridges across social communities and can therefore access new groups of potential customers (Granovetter, 1973). Chapter 4 thus extends the insights of Chapter 3 by showing the complementarity of referrals over strong and weak ties. While referrals over strong ties lead to immediate profitable referrals, referrals over weak ties contribute more to indirect long-term growth by accessing new groups of potential customers.

In conclusion, based on the interactions involved in customer referral programs as visualized in Figure 5.1, this dissertation provides various theoretical and practical advances for referral marketing using insights from the underlying social network.

5.3 Theoretical contributions

This dissertation contributes to the literature stream on referral marketing by shedding light on the role of social network insights for customer referral programs.

Chapter 2 contributes to the literature stream on influence maximization by illustrating the value of referral data. Specifically, we contribute by assessing the quality of the often-used simulation-based methods and comparing their performance to observed referral behaviour. Therefore, this study responds to the need for simulations that can quantitatively be compared with specific social phenomena, as pointed out by Conte et al. (2012). This study further bridges design-oriented information systems research and empirical marketing research. As such, Chapter 2 contributes to what Probst et al. (2013) propose as a necessary addition to influence maximization literature in their comprehensive literature study.

This dissertation also provides substantive new insights in the value creating mechanisms of referral marketing. We show that referred customers are more valuable than non-referred customers and that this difference in value is not only perceptible in revenue and lifetime, but also in cost-to-serve. The study presented in Chapter 3 further extends the current understanding of the theoretical phenomena underlying customer referral programs. The importance and presence of better matching in customer referral programs is confirmed and shown to be at play for all relationships involved in a customer referral program. Customers who are referred over a strong social connection are found to be more valuable to the company, indicating that better matching between the referrer and referral is likely to take place.

The findings of Chapter 4 further extend the state-of-the-art on customer referral programs by showing the capacity of referrals over weak ties to reach untapped communities of potential customers and as such trigger significant customer base growth. The study provides support for the theory of the strength of weak ties in customer referral programs. Hence, this study contributes by providing a large-scale empirical test of the theory of the strength of weak ties in the context of referral marketing.

5.4 Managerial contributions

In general, the findings reported in the empirical chapters of this dissertation (Chapter 2, 3 and 4) provide valuable insights for managing successful customer referral programs.

They also indicate that it is in an organization's best interest to not leave referral marketing to human judgement, but actually take a data-driven approach to launching and managing customer referral programs.

Depending on its marketing strategy, a firm could benefit from different parts of this dissertation. In particular, the respective empirical chapters could serve as a roadmap for company growth and success. One potential use of the chapters as input for firm strategy could be along the lines of the following reasoning:

- As a small company it is important to successfully identify influencers and brand advocates to stimulate positive word-of-mouth.
  $\rightarrow$ Chapter 2 can provide guidance.
- As a next step, increasing and securing profitability is crucial to the small firm's survival.
  $\rightarrow$ Chapter 3 can provide pointers.
- As a growing company, overcoming potential saturation in the customer base can be done by continuing to reach for new customer groups.
  $\rightarrow$ Chapter 4 can be useful.
- As a large player in the market, the knowledge on the influencers should be fine tuned and attracting valuable new customers is key to stay on top of the competition.
  $\rightarrow$ Chapters 2 and 3 could again serve as input here.

However, nowadays we also see successful companies that solely focus on market share and growing the user base and only later figure out how to make the business profitable (many recent technology companies use this strategy). If this is the organizational strategy, then the company could first benefit from finding guidance in Chapter 4 and only later taking pointers from Chapters 2 and 3.

In sum, although this dissertation does not focus on organizational strategy, the findings can potentially contribute to strategic decision making and referral marketing could be a component of firm strategy. In the following, we discuss additional managerial insights derived from the studies in this dissertation.

5.4.1 Referral marketing value and cost

This dissertation shows that referral marketing can create significant value in multiple ways. In our research context, we estimate that the difference in total CLV between referred and non-referred customers is 28%. This is a significant difference, outweighing the referral reward in our research setting. Organizations could keep this finding in mind when deciding on the referral reward. It is crucial that the referral reward does not exceed 28% of the average non-referred customer's CLV to gain benefits of the referral program.

The added value of referred customers confirms that referral marketing is a powerful tool in the marketing manager's toolbox. It could thus be an important part of the marketing strategy and decisions could be motivated based on the expected added CLV, the referral reward cost and the customer acquisition cost incurred otherwise. Ideally, the referral reward is lower than, or at least on par with, the customer acquisition cost in other marketing campaigns. Moreover, the return on investment of a customer referral program can easily be measured (which is not always the case for marketing campaigns) thanks to the explicit assignment of referrer credits.

5.4.2 Customer targeting

It is in the interest of firms wanting to optimize financial gains to selectively target specific customers with a customer referral campaign. Depending on the goal the firm wants to realize different customers could be targeted. For example, when a firm launches a campaign aimed at attracting valuable new customers to boost profitability, it is more effective to stimulate referrals over strong ties. This can be done by asking customers to refer close friends and family. For start-ups working towards user base growth, it will be most efficient to stimulate referrals over weak ties. This could be part of the specifics of the campaign. Firms could for example ask their customers to refer someone who lives in a different postal code or someone who works at a different company. A recent campaign from an American non-profit provides a great example of a campaign benefiting from the ultimate weak tie, namely strangers. The organizers distributed 5,000 "kindness cards" in New York and told people to pass on the card when they witnessed someone else performing a kind act. Each time a new person received the card, a $10 reward was issued. This campaign succeeded in reaching 1.3 million impressions and the cards ended up travelling to 18 different states in the USA[1].

5.4.3 Data requirements

Organizations that have data on their customers' social network such as telecom providers, social media platforms and banks, could use this data to examine tie strength and network overlap in the network. We expect that tie strength is less intensive to compute since it is a dyad-based variable and thus requires limited data input. Network overlap on the other hand is more resource intensive to compute as it needs data on all social connections. While in Chapter 3 we find that tie strength is a powerful measure to identify valuable potential customers, in Chapter 4 we find that network overlap is slightly more important when identifying customers who could potentially access new communities. Hence, companies who have the data and resources to compute network-based measures for their

[1] *Source:* https://kindnessishere.squarespace.com/

customers potentially occupy an advantageous position compared to companies who do not have such information or resources.

As a final note, we highlight how the technological and societal evolution of social media strengthens the potential of referral marketing. Thanks to various online social networking sites, people are now able to keep in touch with others for long periods of time. Whereas people used to get out of touch, now people stay connected through online social networking sites. This has multiple advantages for marketers. Such platforms lower the barrier for people to make referrals to others whom they haven't spoken with for a while and they allow people to share a message with a large group of people. According to a recent study, the average Facebook user has 145 friends, but only 28% of them are considered close friends (Dunbar, 2016). Hence, social media increase the number of acquaintance-like relationships. Specifically for Facebook it was shown that the platform makes it easier to convert latent ties into weak ties and to easily and cheaply maintain weak ties (Ellison et al., 2007). Keeping the value of weak referral ties in mind, as shown in Chapter 4, social media thus likely enhance the potential of referral programs.

5.5 Avenues for future research

Notwithstanding the contributions of this dissertation to the state-of-the-art of referral marketing, there are ample opportunities for further research in this area. In the following section, we discuss some promising avenues for future research.

In Chapter 2 we investigate the influence maximization problem that aims to influence as many potential customers as possible. In Chapter 3, in contrast, we examine the value of referred customers. Future research could further the insights by combining the ideas from Chapter 2 and Chapter 3. Concretely, it would be interesting to evaluate how seed node selection changes when the expected value of potential customers is also incorporated in the influence maximization problem. One could expect that the group of selected influencers changes as a result of this adaptation of the problem. Such future research could shed some light on the subtle nuance between referral quality and quantity. Whereas the influence maximization problem aims to influence as many other people as possible (optimizing quantity), including a measure of expected customer value could result in the conversion of less but potentially more valuable customers (optimizing quality).

5.5.1 Referral marketing value and cost

The process of setting up a customer referral program involves many decisions about the design. For example, which communication channels will be used to communicate the program, what will the reward be for making referrals, what is the process for making referrals and so on. It would be useful for future research to explore the impact of program design factors on the ultimate performance of the referral program.

While Chapter 3 shows the immediate value of making referrals over strong ties, Chapter 4 highlights the long-term benefits of making referrals over weak ties. Clearly both types of referrals provide distinct added value to the firm. Hence, incentivizing referrals over weak and strong ties could be regarded as a sort of exploit-explore trade-off that can be made: (1) exploit the highly profitable current customers and their strong social connections to immediately attract valuable new customers, and at the same time (2) explore potential value in other social communities by leveraging referrals over a weak ties to reach new potential customers. This raises the question of whether there is an optimal ratio of referrals over strong and weak ties to optimize the firm's overall profitability. Future research could investigate whether there exists such an optimal portfolio. Many studies have investigated the complementarity of weak and strong ties in other contexts such as innovation-seeking alliances (Ozcan & Eisenhardt, 2009; Tiwana, 2008, e.g.,) and organizational performance (Uzzi, 1997, e.g.,). Yet, this has not been investigated on the customer-level.

Further, people typically have a range of social connections with differing tie strengths and characteristics. A question that still remains unsolved is whether patterns can be identified in the referral behavior of customers. Do customers typically first refer their closest friends? Previous research has argued that strong connections typically carry more trust towards each other (Levin & Cross, 2004) and that strong connections are more likely to be activated for referrals (Brown & Reingen, 1987). It would be interesting for future research to explore whether a threshold in the number of referrals exists after which there are decreasing returns on investment for the marketer. Building on this, another interesting path for future research is to examine if it is possible to adapt the referral incentive in such a way that the bottom line is always positive.

An alternative avenue for future research could be investigating potential misuse of customer referral programs. The reward that typically comes with customer referral progams might provoke opportunistic behavior from people wanting to reap the benefits without actually making valid referrals. One previous study has looked into this behavior and found that the referrer's degree significantly increases reward-scrounging behavior (Meyners et al., 2017). In Chapter 4, we find that customers with a high degree typically have larger referral cascades. However, the question remains whether these are valid referrals and this is really just an artefact of knowing many people or whether some of these referrals are dishonest referrals. An important area for future research is thus documenting whether such misuse can be detected, what characterizes it and how companies can prevent and detect it.

5.5.2 Customer targeting

A lot of research has been conducted on trying to predict customers behavior and preferences (e.g., Benoit & Van den Poel, 2012; Hill et al., 2006; Verbeke et al., 2014). The marketing field has moved from mass communication to more targeted and personalized approaches to marketing. The same idea could be investigated for customer referral programs. Is it possible to predict when a customer is most likely to make a referral and if so, is it beneficial to provide a personal time-limited incentive? This would enable firms to optimize the contact with each customer by only contacting each person at the right time.

These are some suggestions for future research that would further enhance the insights in the value drivers of customer referral programs and the opportunities for marketing managers to leverage them. In sum, this dissertation answered some unexplored research questions on the role of social networks for referral marketing and in doing so laid the foundation for interesting future research.

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