Profitability as a criterion in key account selection
-Evidence from a professional services organization

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-Evidence from a professional services organization

**Abstract:**

Business-to-business companies within the professional services sector tend to encounter fierce competition when aiming to win over the most distinguished customers. To avoid unprofitability, these companies need to put much consideration into prioritizing the right type of customers. However, there is not much academic literature published on customer prioritization, i.e. key account (KA) selection.

The aim of the study is to measure the relationship between KA selection and customer account profitability when taking to account other KA selection criteria in a professional services organization. The study uses internal and external customer data that is obtained from a professional services organization.

Several quantitative tests such as ANOVA and binary logistic regression were utilized in the study. Furthermore, AIC, BIC and likelihood ratio tests are used in order to make valid comparisons between models.

The results show that there is a relationship between profitability and KA selection when profitability is measured in monetary terms. However, no relationship could be found when profitability is measured as a percentage. Further tests even indicate that profitability has not been used as a KA selection criterion, but instead is a by-product of the fact that KAs have bigger contracts and therefore provide higher account revenues. Furthermore, customer size, higher account revenue and a higher number of sales opportunities increase the odds of being selected as a KA, whereas a long business relationship does not.

**Keywords:** B2B, Key Account Management, Strategic Account Management, Key Account Selection, Profitability, Customer Profitability, Professional Services.
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1 INTRODUCTION

The business-to-business landscape has been changing rapidly during the last two decades. One of the most critical changes has to do with the complexity of business-to-business relationships. These relationships have become more complex due to the increased expectations of the customer and the cost pressures of the seller (Jones et al. 2005). The required technical know-how, communication skills, industry knowledge and response-time of sellers have increased the need for active account management (Jones et al. 2005).

There are many types of interpretations of the nature of account management, which have resulted in a variety of definitions, account management (AM) roles and AM programs (Ojasalo 2001a). For instance, key account management (KAM), which refers to managing the most important customers, is commonly used in organizations where confidentiality and trust are essential for a functioning business relationship (Skaates & Seppänen 2002; Nätti & Palo 2008). Also, KAM is utilized by companies that have to do business with large customers that usually expect special treatment and a considerable time investment (Pels 1992; Ojasalo 2001a). However, a large customer does not necessary indicate that it is more profitable for the seller, due to the fact that larger customers require more of a seller’s time and resources (Sharma 1997; Piercy & Lane 2006). Therefore, the challenge is to find ways to prioritize accounts not only based on sales volumes but also profitability and future outlook.

Many companies, especially professional services organizations, are operating in an extremely competitive environment (Nätti & Palo 2012). In this type of business environment there is a tendency of being easily forced to a price war when aiming to win over the biggest and most distinguished customers (Piercy & Lane 2006). As a result, the seller may win the customers’ business but suffer from the unprofitable business relationship in the long term. This may lead to worsening business relationships and bad service quality, which affects the seller’s reputation (Piercy & Lane 2006). Therefore, an unprofitable business relationship cannot continue in the long term.

Consequently, it is essential for the sellers to not only prioritize large customers that expect to be prioritized, but to also to prioritize customers that are actually contributing the seller’s profitability and thereby increasing the seller’s financial performance. (Sharma 1997).
1.1 Research problem

The role of key account management is a widely discussed topic by practitioners and academia. Since the topic is widely discussed, there are a lot of definitions and interpretations of what constitutes KAM. Early academic literature characterizes KAM as special treatment in areas of service, marketing and administration to specific customer groups (Barett 1986; McDonald 1997). On the other hand, a more recent and widely referred definition is presented by Ojasalo (2001a) that defines KAM as identification and analysis of key accounts in order to create strategic and operational capabilities to enhance customer relationships. To avoid confusion in the interpretation of terminology, Homburg et al (2002) have simply described KAM as all activities that have to do with managing the most important customers.

Table 1 Findings of Guesalga and Johnston (2010) literature review

<table>
<thead>
<tr>
<th>Topic</th>
<th>In Numbers</th>
<th>In percentages (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SAMA</td>
<td>Academic</td>
</tr>
<tr>
<td>Organizing for KAM</td>
<td>20</td>
<td>12</td>
</tr>
<tr>
<td>Adaptation of KAM approaches</td>
<td>17</td>
<td>11</td>
</tr>
<tr>
<td>Success factors in KAM</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>Global account management</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>Role and Characteristics of KA managers</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>Customer relationships</td>
<td>11</td>
<td>14</td>
</tr>
<tr>
<td>Team selling</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Selection of key accounts</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Reasons to adopt KAM</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>Elements of a KAM program</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>107</td>
<td>102</td>
</tr>
</tbody>
</table>

In order to have a better understanding of the available KAM literature, Guesalga and Johnston (2010) made a literature review that takes into account research from both academics and practitioners. The results from the literature review in question are summarized in table 1. The sample that represented the practitioners was taken from the Velocity magazine, published by the Strategic Account Management Association. The members of the association are executives and consultants working with KAM. The results of the study are presented in figure 1. They indicate that the most researched KAM topics amongst academics and practitioners are: how to organize KAM, how to adapt KAM processes and success factors in KAM. Other interesting insights from Guesalga and Johnston (2010) literature review are for instance that KAM research
have clearly evolved during the past two decades. Also, most of the KAM research has utilized qualitative methods, but there has been a notable increase in the use of more complex quantitative methods in later years (Guesalga & Johnston 2010).

However, one of least researched topics in KAM according to Guesalga and Johnston (2010) is the selection of key accounts. The studies that Guesalga and Johnston (2010) refer to when discussing the selection of key accounts are Pels (1992) and Sharma (1997). Both of the studies can be considered relatively old, especially if the statement that the KAM literature has evolved is correct. Furthermore, most on the studies of KAM is focused on production companies despite that Nätti and Palo (2012) have clearly recognized that KAM is widely used in professional services organizations.

Consequently, there is a clear need to address the question of how to select and prioritize customers from a KAM point of view. The lack of KA selection literature is evident per se, but lack is even more apparent in the service literature.

### 1.1 Aim of the study

The aim of the study is to measure the relationship between KA selection and customer account profitability when taking to account other KA selection criteria in a professional services organization.

The following research questions are addressed:

- **Rq1**: Does customers’ account profitability significantly differ between a key account and other accounts in a typical professional services organization?

- **Rq2**: Is customer account profitability a significant predictor of a customer to be selected as a KA when other probable KA selection criteria are taken to account?

### 1.2 Limitations of the study

This study uses the assumption made by Homburg et al (2002), which suggests that KAM involves all activities that have to do with managing the most important customers. As a result, the study focuses only on different KA selection criteria/metrics and not on other KAM related activities. The customer profitability measures used in the study describes only current profitability and is utilized as KA selection criteria. Therefore, no estimates of the future customer profitability are made. Also, the study
utilizes data from a company that have several key account selections based on its customers’ geographical location. Consequently, this study has its focus on the Nordic key account selection, which consists of companies that have its headquarters in the Nordic region.

1.3 Research approach

The study in question consists of both a theoretical discussion and an empirical study. The theoretical framework is built upon four themes that are relevant to the empirical study. The latest and the most relevant literature are presented and discussed within each of the themes in order to get a holistic view of the various aspects of the study.

The empirical study is based on data acquired from a global professional services organization. The company is referred in this study as company X. The focus of this study is on analyzing the KA selection of company X quantitatively, by utilizing internal and external customer data. The variables used in the analysis consists of both customer profitability related data and other data that have been recognized as relevant criteria for KA selections by earlier academic literature. This data is analyzed with the help of several quantitative analysis methods. Lastly, the result from the empirical study is discussed and compared with the earlier literature.
2 THEORETICAL FRAMEWORK

As mentioned in the research approach, this chapter consists of four main themes. The first theme introduces KAM from several points of views in order to get a better understanding of the phenomenon itself. The second theme of this chapter revolves around professional services organizations, and how these types of organizations utilize KAM, since the empirical study has its focus on a professional services organization. The third theme addresses the most important topic of the empirical study, which is the actual KA selection process. As KA selection is a crucial part of KAM, it is important to get a holistic view of KAM before discussing the KA selection literature. Lastly, the role of profitability in KAM and KA selection is discussed due to the fact that the empirical study focuses on the customer profitability.

2.1 Introduction to KAM

From the introduction it could be concluded that there is variety of definitions of KAM. The underlying reason for this has to do with the fact that KAM is not a straightforward process and it is often tailored in accordance with customer expectations and wishes. However, there are a large variety of theories of what constitutes KAM. Therefore, this chapter intends to give a brief explanation to the evolution of KAM, what kinds of activities do KAM include and what can be considered successful KAM.

2.1.1 Evolution of KAM

During the late 1950’s and the 1960’s there could be observed a clear shift in business-to-business selling strategies due to changes in the business landscape (Weilbaker & Williams 1997). There started to emerge a trend where a few bigger companies usually accounted for most of a seller’s revenues (Weilbaker & Williams 1997). Up to this point, sales responsibilities were usually dived by geographical grounds, which led to variations in price, quality and service. Bigger buyers, with business operations in several locations and countries started to question this type of business model and demanding clearer communication and more uniform delivery. (Coletti & Tubidy 1987; Weilbaker & Williams 1997).

Consequently, many sellers responded by naming a single person to be responsible of a specific customer (Shapiro & Wyman 1981). This person was given the responsibility to take care of the communication with the customer and to manage the internal
coordination of activities and costs, which were related to the customer in question (Shapiro & Wyman 1981). This type of behavior started to be recognized by academics, and themes such as relationship management, international account coordination and national account management started to emerge in the journals (Shapiro & Wyman 1981). In more recent literature, most of the scholars have used the term “key account management” when referring to the actual phenomenon and term “account” when referring to a customer (Ojasalo 2001a).

KAM literature evolved a lot during the last decades according to Guesalga and Johnston (2010) and took influence from many research fields such as relationship marketing, sales management and supply chain management (McDonald et al. 1997). To get a better understanding of the essence of KAM, Ojasalo (2001a) identified various characteristics of KAM, which are illustrated in Figure 1.

**Figure 1  Characteristics of KAM (Ojasalo 2001a)**

<table>
<thead>
<tr>
<th></th>
<th>Emphasis</th>
<th>Equally emphasized</th>
<th>Emphasis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transactional marketing/ short-term approach</td>
<td></td>
<td></td>
<td>Relationship marketing/ long-term approach</td>
</tr>
<tr>
<td>Strategic</td>
<td>•</td>
<td></td>
<td>Operational</td>
</tr>
<tr>
<td>Theoretical/descriptive</td>
<td></td>
<td></td>
<td>Managerial/normative</td>
</tr>
<tr>
<td>Consumer market</td>
<td></td>
<td></td>
<td>Business-to-business market</td>
</tr>
<tr>
<td>Goods</td>
<td></td>
<td>•</td>
<td>Services</td>
</tr>
<tr>
<td>Goals: Profitability and shareholder value</td>
<td>•</td>
<td></td>
<td>Goals: Sales volume, market share, margin, etc.</td>
</tr>
</tbody>
</table>

According to Ojasalo (2001a) KAM is strongly relationship orientated and focuses on long-term value creation. The strong relationship orientation is the clearest difference between a standard account and a key account. KAM consist of both strategic marketing and operational involvement to ensure that a relationship with a key account is developed in the right direction. Furthermore, the academic KAM literature is not only theoretical but also aims to create value for practitioners. Most of the literature is focused on the business-to-business landscape and are applicable for both services and goods industries. Lastly, the ultimate goal of KAM is long term profitability and increasing shareholder value. (Ojasalo 2001a)
There has also evolved an alternative, or more of a complementary, way of understanding KAM, which is based on the notion of service-dominant logic introduced by Vargo & Lusch (2004). S-D logic is based on the several foundational premises, but the main point is that companies in business relationships should aim to co-create value together and not separately take advantage of one another (Vargo & Lusch 2004). Storbacka (2012) has discussed the role of KAM from an S-D logic perspective and suggest that key account selling or management is not the same thing as strategic account management. According to Storbacka (2012) SAM “focuses on co-creation of value and is both ‘inside – out’, that is implements strategy in order to achieve agreed corporate goals, and ‘outside-in’, that is identifies business and renewal opportunities by deeply understanding the customer’s value-creating process, and influences the firm’s strategic process.” In other words, SAM can be considered as creating and maintaining relationships with the most important stakeholders in a way which resembles partnerships, whereas KAM focuses more how to create and maintain long lasting and profitable relationships with the most important customers. However, some academics do not see a substantial difference between these two views and therefore do not categorize them separately (Davies & Ryals 2014).

### 2.1.2 The role of KAM

As argued in the last section, KAM can be seen from several perspectives. The same applies when discussing about what KAM is in practice. Because of this, Homburg et al. (2002) conceptualized four dimensions of KAM; activities, actors, resources and formalization.

According to Homburg et al. (2002) model, the activities perspective answers the question: what is done? There are activities such as customized pricing, customized services and products, tailored customer service, information sharing, joint coordination of workflow and taking over functions outsourced by the customer (Homburg et al. 2002). All of these KAM activities are supposed to increase customer loyalty, customer satisfaction and share of wallet (Homburg et al. 2010). Share of wallet refers to the expense percentage of a customer’s total expenses that a company could potentially spend on the seller’s products or services (Homburg et al. 2010).

The actor perspective answers the question: who does it? There are KAM involvement both on horizontal level, which quantifies time spent on KAM, and vertical level, which focuses on hierarchical aspects (Homburg et al. 2002). From a horizontal point of view,
there are staff members that work with KAM full-time and staff that have a KAM role in addition to their main duties (Homburg et al. 2002). From a vertical point of view, there are both top level management and entry level work force involved in KAM (Homburg et al. 2002). The combination of vertical and horizontal level contribution depends largely on the business and industry in question. However, it is noted that top level management involvement is important due to the strategic nature of KAM ((McDonald 1997; Guesalga 2014). Also, KAM is in most cases a coordinated effort between formal or semi-formal teams (McDonald 1997).

The resources perspective answers to the question: with whom is it done? This question is closely linked to the previous one. Hence, one of the most important success factors of KAM is that the right people get access to relevant information (McDonald 1997; Homburg et al. 2002; Salojärvi et al. 2010). The access to information requires collaboration, not only between sales and marketing, but also between IT, logistics, manufacturing, finance and accounting (Homburg et al. 2002). Collaboration is also required between industry branches/service lines, multiple countries and cultures (McDonald 1997). Therefore, it is crucial that the staff responsible of KAM have the necessary authority to coordinate internally within the organization (McDonald 1997; Salojärvi et al. 2010).

Lastly, the formalization perspective answers the question: how formalized is it? Companies KAM programs tend to differ from each other in both complexity and intra-organizational acceptance (Homburg et al. 2002). Therefore, the level of formality of a KAM program is an important factor to consider when analyzing a company’s KAM processes (Homburg et al. 2002). In some companies there are global standards on how KAM is applied, reported and evaluated (Homburg et al. 2002). On the other hand, KAM may also be a very informal and approached with a case-by-case mentality (Wengler et al. 2006). Many companies even admit that they do not utilize KAM, but still informally give special treatment to the most important customers (Wengler et al. 2006). Wengler et al. (2006) calls this type of behavior as “hidden key account management”.

2.1.3 Success factors in KAM

There are several studies that discuss what makes KAM successful (Guesalga and Johnston 2010). The success factors vary a lot depending on culture and industry specific contexts. However, there are some success factors that have been cited and
confirmed frequent times by several academics and practitioners, which can be applied to nearly every KAM case.

One of the most important success-factors is directly related to the knowledge and capabilities of the key account manager (McDonald 1997; Abratt & Kelly 2002; Guesalga 2014). A KA manager should be highly skilled in areas such as negotiation, managing relationships, marketing and finance (Abratt & Kelly 2002). To exemplify the role of the KA manager, McDonald (1997) draws a parallel - “The key account manager conducts the orchestra”. Also, the KA manager should have a formal or semiformal team. The team should be cross-functional, because it has been recognized that cross-functionality increases the awareness of the value of KAM practices internally, especially of efforts that is hard to measure in monetary terms (Abratt & Kelly 2002).

Another important success-factor is to truly understand a key account’s business and what creates value for it (Abratt & Kelly 2002). To succeed, the KAM team needs to have tools by which they can gather and store customer information and to be able to distribute it to the relevant people (Salojärvi et al. 2010). Thus, an integrated CRM system is necessary for sufficient internal coordination and information distribution (Salojärvi et al. 2015).

Furthermore, successful KAM usually requires a culture that encourages the pursuit of customer satisfaction in all company levels (Abratt & Kelly 2002). It is important that even top management should have customer satisfaction as a top priority, and even be involved in KAM activities (Guesalga 2014). However, it has been noted that the senior leadership needs to understand that their involvement should only be limited to support the underlying KAM strategy (Guesalga 2014). Otherwise there is a risk that the message to the customer will not be uniformed (Guesalga 2014).

However, it is impossible to succeed in KAM without recognizing which customers should be selected as KAs. Therefore, a KA selection process is essential for successful KAM (Abratt & Kelly 2002). Key accounts should be identified in accordance with clear guidelines (Abratt & Kelly 2002). Also, the selection should be done based on several financial and nonfinancial criteria that are aligned with the company’s strategic oversight (Abratt & Kelly 2002; Tzempelikos & Gounaris 2013). The benefits of KAM will be marginal if the KA selection is done based on the wrong criteria. According to Piercy and Lane (2006) KAM can become a serious liability if it the companies enrolled in KAM programs are not in a position where they benefit from a strong relationship
with the seller. In these types of situations there is a great risk that the customer will react negatively to any KAM related activities. Thus, KAM cannot be successful without appropriate KA selection methods.

Summary: The KAM literature has evolved considerably during the last decades. Traditionally, KAM has been perceived more as a support function whereas today it is seen as a strategic choice that influences how a business-to-business company should operate. Consequently, the KAM literature has become more complex and is strongly linked with relationship marketing. Companies that utilize KAM needs to have certain features embedded throughout the organization to benefit from KAM. Thus, companies need to understand that KAM is a strategic choice and select key customers with caution. As a result, an efficient KA selection process is considered as a very important success factor of KAM.

2.2 KAM in professional services organizations

Most of the KAM literature has focused on business-to-business supplier and buyer relationships, despite the fact that the business-to-business services industries have been adopting KAM for a long time. KAM is especially relevant to knowledge intensive service industries, were trust and confidentiality are considered extremely important (Skaates & Seppänen 2002; Nätti & Palo 2012). The following section discusses what a professional services organization constitutes in order to get a better understanding of how KAM should be applied and what kind of KA selection criteria is typical in professional services organizations.

2.2.1 The definition of professional services

Knowledge intensive services, which are performed by professional services organizations, usually are referred to as professional services (Nätti & Palo 2012). However, it is not entirely clear which services can be considered as professional services (Thakor & Kumar 2000). Thakor and Kumar (2000) aimed to clarify the notion of professional services, both theoretically and empirically, in order to have a better understanding of which professions are by definition considered as professional. According to Thakor and Kumar (2000) there is not a universal understanding of the definition of professional services - it is a matter of perception. Generally, white-collar professions, which require expertise and credentials, are seen as more professional than services that are performed with hands (Thakor & Kumar 2000). Also, services
are considered professional when they are seen as homogenous, complex and critical (Thakor and Kumar 2000).

Services are not traditionally considered homogenous (Dahringer 1991), but when compared with other types services, a certain type of homogeneity, or replicability, can be seen as a sign of professionalism (Thakor & Kumar 2000). For instance, a brain surgeon needs to be able to replicate a specific type of clinical engagement on several patients. Also, the notion of a professional service being critical in this case refers to the fact that the service should have an impact on the society (Thakor & Kumar 2000).

However, the clearest differentiator between services in general and professional services, especially from a business-to-business perspective, has to with the complexity of the service offerings. The complexity of professional services offerings not only requires a high level of expertise from the service provider itself, but usually even from the buyer (Lian & Laing 2007). It is typical that the buying company approaches a professional services organization with fuzzy, implicit or unrealistic expectations, because they do not have the expertise needed to make a realistic assessment of the situation (Ojasalo 2001b). According to Ojasalo (2001b) fuzzy expectations refer to a situation where a customer does not clearly know what it wants from a service provider, whereas implicit or unrealistic expectations are expectation misalignments. These situations arise when the customer recognizes a problem and is confused about how to solve it (Ojasalo 2001b). Hence, the fuzzy expectations and misalignments of specific knowledge between the buyer and seller highlight the value of customer references. Customer references works as proof-of-concept to the buyer and therefore increases the credibility of the service provider (Skaates & Seppänen 2002). Consequently, professional services organizations put a lot of effort to build a strong reputation.

Furthermore, the complexity and intangibility of professional services makes continual interactions between the buyer and service provider a necessity (Lian & Laing 2007). Usually several interactions occur before, during and after the service provided (Skaates & Seppänen 2002). Therefore, there is a substantial human element involved in the service delivery, which require a strong relationship orientation. Ojasalo (2001b) suggests that professional services organizations should focus on establishing long lasting relationships. He implies that on the short term, customer satisfaction levels vary a lot due to expectations misalignments and lack of trust.
The strong relationship orientation of professional services can also be perceived by how professional services organizations develop their competences. According to (Awuah 2007) market-based learning is as critical for internal competence development. Professional services firms learn from their customers, competitors and other actors that are in the reach of their network (Awuah 2007).

2.2.2 Characteristics of KAM in professional services organizations

There is little research on specific characteristics and challenges of KAM in professional services organizations (Nätti et al. 2006). Therefore, Nätti et al. (2006) conducted a explorative qualitative case study were two professional services organizations were studied; one that had been utilizing KAM for a long time, called Factor, and one that had just started, called Auctor. The results of the case study supports earlier KAM literature presented in earlier sections, but also highlight specific KAM actions that are particularly relevant for professional services organizations.

Case Factor had been implementing KAM for years and had a strong culture of highly prioritizing the pursuit of customer satisfaction. Metrics to measure KAM performance and incentives had been established to support collaboration within sales and other internal divisions. The KA managers had been recruited internally and made up of persons with wide internal networks. Furthermore, KA managers had KAM teams that consisted of persons from different expertise areas to enhance internal collaboration. The KA managers were considered the linking pin between the key customers and the organizational expertise areas. Account specific information gathered from customer interactions and external sources were stored in detail in an internally shared IT system. Clear account plans were serially initiated based on the account information gathered and by involving partly the customer in the planning process. (Nätti et al. 2006)

On the other hand, case Auctor had just adopted KAM. The company had an individualistic culture and a functional structure with several subgroups. Incentives and metrics were designed to create competition internally. KA managers were few and were recruited outside the organization and thus lacked internal network within the organization. No official KAM teams were initiated. The KA managers did not have a linking role internally and was more focused on integrating IT tools in the account management process. However, customer specific knowledge was not gathered in a
common shared system and the communication and cooperation between experts involved in the same account was weak. (Nätti et al. 2006)

Consequently, case Factor felt that applying KAM deepens the relationships with their important customers and creates value creation opportunities; whereas case Auctor had experienced problems already during KAM implementation and did not achieve noteworthy customer relationship improvements (Nätti et al. 2006). As can be seen for case Auctor, KAM implementation is not an easy task and can in many cases be a substantial risk (Piercy & Lane 2006). An organization should not implement KAM if the structures of the organization do not show elements of “KAM fit” (Piercy & Lane 2006). Furthermore, the success factors of case Factor are clearly in accordance with the elements of successful KAM, presented in the earlier sections, by i.e. Abratt & Kelly (2002), Guesalga (2014) and Salojärvi et al. (2015).

However, compared to other types of organizations, professional services organizations seem to be reliant of effective internal and customer orientated knowledge transfer. As Nätti et al. (2006) puts it; “The key issue in customer-relationship management (and in KAM) is to find a match between the customer’s needs and the competence of the professional organization.” Therefore, it is crucial that KAM practices in professional services organizations have a strong focus on enhancing information sharing and collaboration between internal functions, or areas of expertise, to facilitate value creation opportunities (Nätti & Ojasalo 2008).

Nevertheless, Nätti and Ojasalo (2008) argue that issues related to knowledge transfer are very common in professional services organizations, due to the fact that they have a tendency of suffering from loose coupling. According to several literature summarized by Nätti and Ojasalo (2008), loose coupling refers to mismatches in communication, collaboration, ideas between people, subgroups or even functions. In other words, a company suffering from the before mentioned mismatches can be considered loose coupled. Some level of loose coupling is nearly unavoidable in professional services organizations due to the nature of the business itself, which purpose is to create monetary gains from scarce knowledge (Nätti & Ojasalo 2008).

Thus, the most important function of KAM in business-to-business professional services organizations is to organize and select the KAs in way that enables seamless coordination internally, in order to achieve the account specific goals (Nätti & Palo 2012). If the goal is to increase account revenue, the KA plan should focus on cross-
selling, which requires internal collaboration between cross-functional functions (Storbacka et al. 2011). The KA selection should in this case be organized in a way that increases the cross selling opportunities. Or if the goal is to increase account profitability, the KA team needs to assess the reasons behind the unprofitability and address them (Sharma 1997).

From a professional service point of view, Nätti and Palo (2012) argues that it is not enough to have management support, sufficient resources and clear metrics, but also a balance between coordination and local flexibility. Because professional services are based on trusted, and even confidential, relationships (Skaates & Seppänen 2002; Nätti & Palo 2012), it is crucial to have a bit of discretion in KAM implementation (Nätti & Palo 2012). Relationships between professionals and customers should be addressed in situations-specific contexts (Nätti & Palo 2012). For instance, parties that can be critically affected of a specific decision should be involved in the decision-making process (Nätti & Palo 2012). On the other hand, there is a substantial risk when involving parties that do not have the same agenda or the “KA management mind-set”, due to contradicting short term incentives and goals (Piercy & Lane 2006).

Summary: Professional services are seen as homogenous, complex and critical in nature. This type of business is usually built upon trust and confidence, which makes the business relationship oriented. Thus, there is a lot of interaction between a professional services provider and its customers. Internal and external coordination is very important for professional services organizations, due to the fact that they in many cases suffer from loose coupling. Loose coupling makes KAM practices challenging to implement and therefore can be considered a risk if not implemented correctly. Also, a coordinated and centralized key account selection process may prove challenging in this type of organization, due to loose coupling, which can cause contradicting short term incentives and goals.

2.3 Selection of key accounts

As mentioned in the research problem section, selection of key accounts is not a widely studied topic. The topic cannot be considered “new” or “emerging”, based on the enormous amount of KAM literature that has been written during the last decades. However, the importance of key account selection is constantly increasing due to the rising competition and emergence of new technologies (Gosselin & Bauwen 2006).
Therefore, this section is intended to elaborate on why KA selection is a crucial part of KAM and what kind of criteria should the selection be based on.

### 2.3.1 Relevance of key account selection

The whole notion of key account selection is bound to the idea that some customers are better than others. This perception is inherited from the world famous Pareto Principle, which assumes that 80 percent of specific effects come from 20 percent of causes (Brynjolfsson et al. 2011). For instance, 80 percent of all sales come from 20 percent of customers (Brynjolfsson et al. 2011). While this notion is not true in all cases (Brynjolfsson et al. 2011), it is still used quite widely as an assumption when dealing with uncertainties.

According to Pels (1992) there are two reasons why a seller would choose to work with a limited amount of customers:

1. The seller has no choice but to have a restricted amount of customers
2. The seller has on purpose chosen to do business with only a few customers.

The first reason is directly linked to the seller's own resources and capabilities. A seller can only attain as many customers as it is capable to provide for. Therefore, it is quite usual that sellers find themselves in a position where they become financially dependent on a few customers (Pels 1992). These customers understand their power position and thus require a substantial amount of attention from the seller. Piercy and Lane (2006) call this phenomenon as the “KAM trap”. They argue that KAM practices are in many cases destructive because KAM strategies drive businesses towards this unbalanced power relationship between the buyer and seller (Piercy & Lane 2006).

On the other hand, the situation is different if the seller has deliberately chosen to work with a restricted amount of customers. In these cases the power balance between the buyer and seller is neutral, sometimes even opposite. The seller may have obtained a competitive advantage; such as scares resources, valuable patents or other expertise (Azzam 1996).

The two cases above illustrate situations where not much efforts have been put to create a structural KA selection process, since these companies have either deliberately or been forced to work with a restricted amount of customers.
Still, in most cases sellers tend to take all the business they are able to handle, due to the pressure from shareholders to grow. Sellers usually have various types of customers, which all require different amount of attention. In this case a KA selection process becomes necessary in order to meet the requirements of the more demanding customers. Consequently, seller needs to understand the customers’ expectations and how to exceed them (Parasuraman et al. 1991). According to McDonald (1997) a buying company chooses a supplier based on how easy it is to do business with the supplier, the quality of the product or the service provided and culture match. Furthermore, Sharma (1997) have recognized that buyers that are multifunctional and have a multi-layered decision making process tend to prefer KAM practices. The same tendency can also be seen in large for-profit companies (Sharma 1997).

Despite the buyers’ preferences, the seller needs to make an own evaluation on which companies is fit for being a key account based on own strategic priorities (Sharma 1997). According to Ojasalo (2002) sellers should ask themselves: “Which existing or potential customers are important to us now and in the future?” and “What criteria determine important customers?” These criteria should be based on a selection that takes to account both non-financial and financial criteria (Pels 1992; Jones et al. 2009).

Nevertheless, there are not any widespread methods available to do this kind of selection (Wengler et al. 2006); despite the fact that tracking and storing data have never been easier than today (Salojärvi & Sainio 2015). There are some selection criteria that are used by sellers, yet in a relatively primitive way (Wengler et al. 2006).

However, according to Homburg et al. (2010), a key account selection does not necessary work despite of a well-motivated key account selection procedure. Their study indicates that if a seller lacks the prerequisite of successful KAM, such as senior level executive involvement, customer information and the right type of incentives, a key account selection would not correspond with the marketing and resource allocations in the daily work. In other words, a strategic key account selection will stay as an intention if the prerequisites for a successful KAM are not met (Homburg et al. 2010). Consequently, a firm has to earnestly evaluate its capabilities before trying to implement a formal key account selection process.
2.3.2 Selection criteria

As earlier mentioned, there are both financial and non-financial KA selection criteria (Pels 1992; Jones et al. 2009). These selection criteria should not be used singly, but rather as a mixture, including both nonfinancial and financial once (Pels 1992; Piercy & Lane 2006; Tzemeplikos & Gounaris 2013). Some of the criteria can also be considered less important than others, if their impact towards the seller or the customer seems unnoticeable (Wengler et al. 2006).

Financial KA selection criteria

The most common financial criterion is the current sales volume to an account (Wengler et al. 2006). Approximately 80 percent of sellers applied the criteria in question, according to a study by Wengler et al. (2006) focusing on the German business-to-business market. This measurement is used to prioritize customers based on how much money the customer is paying to the seller. On the other hand, Pels (1992) suggest focusing on the future by calculating present and future sales gaps. The present sales gap refers to the difference between actual sales and potential sales to the customer, whereas the future sales gap is linked to the estimated growth of the sales potential (Pels 1992). The present sales gap resembles the term “share of wallet” that refers to the expense percentage of a customer's total expenses that a company could potentially spend on the seller’s products or services (Homburg et al. 2010), which is more commonly used term by practitioners. However, according to Sharma (1997), sales volume related criteria are not good for KA selection, because these measurements does not take to account the costs associated with the customer. In other words, it does not take to account the actual contribution of a customer, i.e. customer profitability (Sharma 1997).

A less used by practitioners (Wengler et al. 2006), but even more important (Sharma 1997; Piercy & Lane 2006), financial criterion is customer profitability (McDonald et al. 1997). To measure effectively customer profitability it is important that the seller have adequate reporting systems, since it requires continues revenue and cost monitoring per customer (Mulhern 1999). Particularly interesting is that the role of customer profitability seems to be undermined by practitioners (Wengler et al. 2006), despite the fact that a high customer profitability rate is one of the most essential metric for a healthy businesses (Narver & Slater 1990). There are several variations of customer
profitability, which are more thoroughly discussed in section 2.4 The role of profitability in KAM.

Other financial criteria are for example market share, market cap (Wengler et al. 2006) and the overall turnover of the customer (Czinkota & Wesley 1983). These measurements are not linked to the seller, but rather explain the size of the customer. A large market share and big market cap can be considered as indicators of a strong position in the market, which makes the company “worth knowing”, whereas a higher overall turnover indicates that a customer have the means to acquire more costs (Czinkota & Wesley 1983). In other words, these measurements measures how large a customer actually is (Czinkota & Wesley 1983).

**Nonfinancial KA selection criteria**

Nonfinancial selection criteria are in reality at least as important to business-to-business companies as financial ones (Tzemeplikos & Gounaris 2013). After all, a substantial portion of the benefits of KAM are nonfinancial.

Status and image related selection criteria are the most common nonfinancial criteria (Pels 1992; McDonald 1997; Wengler et al. 2006). These criteria are intangible in nature (McDonald 1997). According to the study by Wengler et al. (2006) 35 percent of business-to-business companies admittedly utilize these types of measurements. The purpose of these criteria is to quantify a customer’s reputation. The selling company is usually more willing to give special treatment, such as KA status, to customers that can affect the seller’s reputation positively. For instance, reference value is a very usual measurement when measuring a customer’s status or image (Tzemeplikos & Gounaris 2013). A seller is prepared to invest more in a customer that can be used as a reference (Skaates & Seppänen 2002). As earlier mentioned, quality references bring credibility to a seller, which helps to acquire new customers and attract talent (McDonald 1997; Skaates & Seppänen 2002). According to Andreassen and Lindestad (1997) corporate image is a better predictor of customer loyalty than customer satisfaction, when studying services providers that provides complex services. Therefore, the value of status and image related selection criteria should not be undermined.

Another nonfinancial criterion is something that Pels (1992) has named as the network effect. This criterion is linked to the selling companies’ strategic goals. For instance, if a seller wants to enter a specific new market or get a better position in a certain
segment, it can prioritize customers that have the power or the network to positively influence the targets set (Pels 1992). However, the network criterion should be combined with other criteria, which are not as intangible in nature (Pels 1992).

Furthermore, selection criteria such as know-how development, relationship length and geographical location are used by business-to-business companies (Pels 1992; Wengler et al. 2006; Tzemeplikos & Gounaris 2013). Yet, they are considered less useful compared to status and image related criteria (Wengler et al. 2006).

Know-how development is used as a criterion when the seller acts within a technologically advanced market, from which the seller has to continuously learn from in order to maintain its competitive advantage (Pels 1992). Also, Ojaslo (2002) recognizes know-how developments as an important selection criterion for knowledge intensive service companies that do business with buyers with high level of expertise.

Moreover, relationship length is a criterion that is used in businesses that rely on strong personal relationships between the buyer and seller. Basically, the customers that have loyally been in business with the seller for a long period of time are enrolled to the KAM program. This type of selection is very widely used in business-to-consumer services industry, such as in retail, aviation and hospitality (Meyer-Waarden et al. 2007). Business-to-business companies seem to more seldom use relationship length as a selection criterion (Wengler et al. 2006).

Lastly, geographical location as a KA selection criterion is not as relevant today as it was a few decades ago. Customers that acted in several geographical locations usually had to be enrolled in some kind of KAM program, due to the fact that these customers required more internal and external coordination from the seller. However, the ICT technology available today has made companies less dependent on geographical selection (Gosselin & Bauwen 2006).

Summary: KA selection is based on the notion that some customers are better than others. Therefore, the purpose of a KA selection is to prioritize customers in according to specific guidelines that are aligned with the seller’s strategy. These guidelines should consist of both financial and nonfinancial criteria. A financial criterion might be the sales volume to the customer, customer profitability, market share, market cap and turnover. In contrast, a nonfinancial criterion might be customer image, network effect, know-how development, geographical location and relationship length. The most
commonly used criteria are sales volume and customer image, while academics argue that customer profitability is overlooked.

2.4 The role of profitability in KAM

The role of profitability in KAM is a discussed topic by academics. Many academics have recognized that profitability should be one of the prime goals of KAM (Jones et al. 2009). However, studies such as Wengler et al. (2006), Piercy and Lane (2006) and Sharma (1997), denotes that KAM practitioners tend to focus more on nonfinancial measurements and other financial determinants, such as sales volume, when selecting key accounts. To enhance the understanding behind this phenomenon, it is crucial to understand what drives profitability. Therefore, this section is dedicated to elaborate on what profitability constitutes, how KAM affects profitability and what does this imply for the KA selection process.

2.4.1 The effect of KAM on profitability

As explained in the “role of KAM” section, all KAM activities are supposed to increase customer loyalty, customer satisfaction and the customer share of wallet (Homburg et al. 2010). These measurements are supposed to affect positively the financial performance of the seller (Homburg et al. 2010). Therefore, it crucial to discuss how these measurements is actually linked to profitability.

There is a common saying, which indicates that it is five times more costly to win a new customer as it does to retain an existing one (McDonald et al. 2000). This saying refers to the fact that there are acquisition costs related with acquiring a new customer, which do not reoccur after a successful sale (Rust & Zahorik 1993). The retention costs, which are costs that are associated with retaining a customer, are much less compared the acquisition costs (Reichheld & Sasser 1990). Therefore, it is important for a seller to not only win new customers, but to also make sure that the old ones stay. Sellers that have a good retention rate, i.e. have many customers that continue to use the seller’s product or service, have a lot of loyal customers (Reichheld & Sasser 1990). The measurement this for type of activity is called customer loyalty. Companies with loyal customers can outperform financially companies with less loyal customers, due to the fact that they have a better retention rate (Reichheld & Sasser 1990). Thus, customer loyalty usually indicates better profitability. In other words, companies that have a substantial amount of loyal customers have a less heavy cost burden compared to similar companies with
less loyal customers, which affects profitability. However, Reinarz and Kumar (2000) consider this type of rationale as an oversimplification. They argue that the effect of customer loyalty to profitability is not as strong in non-contractual relationships. But, Reinarz and Kumar (2000) agree that customer loyalty has a significant effect on profitability in contractual relationships, which ultimately all business-to-business relationships are based on. To elaborate, contractual relationships refer to business relationships that rely on a business contract, usually in a form of a written document (Reinarz and Kumar 2000).

Moreover, a study by Anderson et al. (1994) on the Swedish business-to-business market has found a positive correlation with customer satisfaction and financial returns. In other words, companies that have more satisfied customers enjoy better profitability. The study also noted that customer satisfaction has a lagged effect on financial returns (Anderson et al. 1994), which means that positive financial returns due to increased customer satisfaction do not appear immediately. Therefore, a long term approach is essential when analyzing the economic benefits of customer satisfaction.

Lastly, the share of wallet refers to a percentage or a sum that a customer pays compared to what the customer could pay if the seller would win all the customers’ business that the seller can handle (Homburg et al. 2010). The effect of share of wallet to profitability has somewhat the same rationale as customer loyalty. By having already acquired a customer, an increase in sales to the same customer would only increase the retention costs a fraction of what acquiring new business would (Rust & Zahorik 1993). But from a financial point of view, there is a risk that the additional business would incrementally increase other costs due to additional resource allocation. But, the resource issue is more a question of effective pricing, which can be done effectively with relevant customer information (Ryals 2006). By having a customer relationship already in place means that the seller most likely has a better access to information in relation to the buyer than companies without an established business relationship. As earlier mentioned, one the most crucial requirements of successful KAM was access to customer information (Salojärvi et al. 2010).

Consequently, all of these measurements are not independent of one another. It is well known that there is a clear correlation between customer satisfaction and loyalty, which most likely also affects the share of wallet. However, the link between these measurements and profitability is ultimately quite vague. Therefore, a company should
not only focus on increasing the customer satisfaction, customer loyalty and the share of wallet separately but also take the profitability of the customer to account when selecting KAs.

2.4.2 Profitability as a measurement

A business cannot continue without being profitable in the long term (Narver & Slater 1990). That is why profitability is the essence of business. However, there are alternative ways of understanding and measuring profitability. It is important to understand the difference of profit and profitability (Goodman 1970). Profit is a static historical term that is used for reporting purposes, whereas profitability is a dynamic term that is calculated to support decision making (Goodman 1970). Alternatively, some argue that profitability is just a historical measure that explains which customers are not making a loss for a company. In other words, profitability can be viewed as measurement that is calculated from historical profit data but used for predicting the future, or alternatively, just as another historical measurement.

Still, profitability measurements are used by decision makers, especially marketers, to motivate and quantify specific types of actions or activities (Goodman 1970). For instance, a foundation in relationship marketing theory is that it is more beneficial to establish long-term customer relationships than short-term (Reinarz and Kumar 2000). The term “beneficial” in this case ultimately refer to increased profitability.

Profitability can be measured in many ways depending on the context. Therefore, it is crucial to understand the context form which a specific profitability measure is used for. Generally, measures such as profit margin, return on equity (ROE) and return on assets (ROA) are appropriate if someone is interested to measure profitability from a very high level (Kaplan & Atkinson 1998). These measurements measure the overall health of a company. However, if someone is interested of the profitability of specific projects, customers or segments; the unit of measurement has to be defined (Mulhern 1999). Thus, when addressing the question of key account selection, the relevant unit of measurement should be the profitability of a customer, i.e. an account (Sharma 1999). However, measuring customer profitability is not necessary an easy task, due to the complex level of reporting it requires from a seller (Mulhern 1999).

The most primitive and typical way of the measuring the current profitability of a customer is to calculate the gross margin (Johnson et al. 2009). Gross margin can be
calculated by subtracting the total sales revenue from the cost of goods sold or costs of services provided, and by dividing the sum with the total sales revenues (Kaplan & Atkinson 1998). Gross margin is expressed as a percentage and calculated for a specified period of time (Kaplan & Atkinson 1998). This measurement can be easily applied to a specific customer (Johnson et al. 2009). However, the measurement is not taking into account indirect costs of individual transactions, such as marketing expenses or distribution costs (Johnson et al. 2009). Thus, this measurement can be problematic if there are a substantial amount of indirect costs related to individual transactions or that the indirect costs varies a lot between customers (Johnson et al. 2009). There is a risk that this measurement of profitability does not represent the actual profitability of a customer (Johnson et al. 2009).

Another alternative according to Johnson et al. (2009) is to calculate something called “pocket margin”. Pocket margin is a calculation based on cost-to-serve data from each individual transaction (Johnson et al. 2009). By applying this method, a seller can by the end of a specified period check “what is left in the pocket”. Yet, this method can be considered challenging because it requires monitoring and analysis of individual transactions, which can be considered problematic for a seller with multiple revenue sources (Johnson et al. 2009). However, data and reporting tools advance constantly, thanks to the rapid technology advancements, which make measurements such as pocket margin easier to implement.

Furthermore, the customer profitability measures presented earlier focus on current customer profitability, whereas several academics have also suggested various mathematical models that aim to estimate the future profitability of a customer. These methods have been referred to as “lifetime value of customer”, “customer valuation”, “customer relationship value” and “customer equity” (Mulhern 1999). These models vary in nature, but usually are based on calculating a value for a customer by utilizing historical data and estimating the likelihood of additional purchases and customer continuity. However, these models have got several critiques for being too complicated for practical use. For instance, Blattberg et al. (2009) have recognized conceptual issues with customer lifetime value functions. These types of measurements are not relevant to this study since the focus in this study is on measuring the current customer profitability as a KA selection criterion.

To conclude, the method of customer profitability analysis depends on the context of the analysis. Generally, it is better to utilize as much information as possible in order to
get more accurate results. However, a primitive profitability analysis is better than no profitability analysis at all. If resources are limited, it is better to use the methods available and keep in mind the limitations during the analysis.

Summary: KAM is supposed to increase the seller’s profitability in the long term by increasing customer satisfaction, customer loyalty and the customer share of wallet. Thus, KA selection process should be designed in a way that ultimately supports the purpose of KAM. This goal can be reached by increasing and securing the customer profitability of each customer account. Current customer profitability can be measured with measures such as gross margin, pocket margin, whereas future customer profitability can be measured with customer lifetime models. The method should be chosen based on the context of the analysis and available data.

2.5 Summary of the theory and literature

It is crucial to get a holistic view of KAM to fully understand the powers that drives it. One has to understand that KAM is a long term process with many elements linked together. Without the right elements linked together, KAM can become a cost burden that does not create any value for a seller (Piercy & Lane 2006). Therefore, this section summarizes the theoretical concepts introduced and discusses what this implies for a company’s KA selection.

Earlier sections have introduced KAM and its success factors, discussed KAM from a professional services organizations viewpoint, presented the importance of KA selection and noted the role of profitability in KAM and in KA selection process. These topics are strongly linked to one another and therefore needs to be theoretically conceptualized. This conceptualization is visually presented as figure 2. Figure 2 illustrates how KA selection and other KAM elements are intertwined.

The illustration starts from a KA selection. The key account selection should be done based on both nonfinancial and financial criteria. The criteria should be chosen strategically – so that the customers that would be enrolled in a KA program would benefit from it, while increasing the seller’s profitability. Also, due the strategic nature of the KA selection, it is important to keep in mind industry specific challenges in KAM when preparing for a selection. For instance, successful KAM in professional services organizations require efficient internal and external coordination, due to loose coupling.
When the customers have been chosen, they are entitled for specific actions such as: customized pricing, customized services and products, tailored customer service, information sharing, joint coordination of workflow and taking over functions outsourced by the customer. These actions are special treatment that only the customers in question are allowed to have. This special treatment is designed to increase customer satisfaction, customer loyalty and the share of wallet from the customer, since these three elements have a positive relationship with financial
performance in the long run. In other words, they increase customer profitability for the seller.

Yet, the success of the whole journey is dependent on the fact that the seller is fit for a KAM program. A seller is fit for a KAM program when it has competent KA managers that can utilize diverse teams, tools for information sharing, a culture that encourages the pursuit of customer satisfaction and involvement of top management.

The main point in the figure 2 is to illustrate that KAM are supposed to ultimately increase the seller’s profitability. In order to so, each individual customer should become as profitable for the seller as possible. Therefore, KA selection should be organized in a way that maximizes the profitability of customers that are strategically and financially important for the seller. However, sometimes for strategic reasons a seller may tolerate an unprofitable KA for a short period of time, but ultimately, it needs to become profitable. As a result, a seller simply should not have unprofitable customers as key accounts in the long run.

2.5.1 Effects on KA selection

As the figure 2 implies, the key account selection process has a critical role in the KAM. Without a functioning KA selection process the goals of KAM will not likely be fulfilled. Furthermore, when the role of profitability is such an important factor in the KAM, it is essential to understand in more detail the relationship between profitability and the KA selection process.

As earlier discussed, the KA selection is typically done based on several criteria, as figure 3 implies. The theory implies that customer profitability seems to be overlooked as a KA selection criterion by practitioners despite the fact that the literature argue that customer profitability should have a notable role in the KA selection.

However, the problem with customer profitability as a measurement is its complexity. There are so many different customer profitability measurements available. Also, customer profitability can be presented in various ways, such as in percentages and in monetary terms. Therefore, it is crucial to understand in more detail the relationship between customer profitability and KA selection and how customer profitability stands in relation to other KA selection criteria.
Thus, this study aim to measure the relationship between KA selection and customer account profitability when taking to account other KA selection criteria in a professional services organization. No specified hypotheses are set due to the fact that the earlier literature have not taken any clear stance on the relationship in question, especially when taking other KA selection criteria to account.

Figure 3  The KA selection process

However, two research questions are set, which are:

Rq1: Does customers’ account profitability significantly differ between a key account and other accounts in a typical professional services organization?

Rq2: Is customer account profitability a significant predictor of a customer to be selected as a KA when other probable KA selection criteria are taken to account?

Conclusions regarding the relationship between customer account profitability and KA selection can be drawn by answering the research questions above.
3 DATA

This chapter introduces the data used in the empirical part of the study. First, the data description is presented, which includes the data sampling strategy, detailed description of the data sample and the data timeframe. Second, the variables that are compiled based on the data sample are presented. Third, relevant descriptive statistics of the data is presented and discussed.

3.1 Data description

The data of the study is mostly gathered from the case company’s internal databases. External company data, such as client companies’ financial figures, have been gathered from both ORBIS and ODIN databases. As mentioned in the introduction chapter under the research approach subsection, the company of focus is a multinational professional service organization. The company, which in this research is called company X, has willingly provided the necessary internal customer data for this research on the condition that the company can stay anonymous. Furthermore, any sensitive data such as customer specific information cannot be disclosed in the paper. Consequently, the data is only used to analyze and to discuss the KA selection phenomenon in relation to customer account profitability and other KA selection criteria without going into detail on a single customer group.

The data sample used in the study consists of cross sectional data and was gathered based on a stratified sample technique. This type of sample technique divides the studied population to relevant subgroups based on specific requirements from which the samples are gathered (Wooldridge 2012). The subgrouping of the sample was made based on company X KA selection. The first subgroup consists of the customer accounts that company X prioritized. This group of customer accounts is referred in this study as key accounts (KA). All of the KAs have assigned KA teams and are entitled to special treatment that other customer accounts are not entitled to. Company X has several KA selection processes based on the customers’ geographical location. The customer sample acquired represents the Nordic KA selection, which includes customer accounts that have its parent company headquarters located in Finland, Sweden, Denmark or Norway. The KA lists were obtained from fiscal years 2016, 2015, 2014. The fiscal years in company X are from 1.7 – 30.6. For instance, fiscal year 2015 is from 1.7.2014 – 30.6.2015.
The second customer subgroup consists of customer accounts that have not been prioritized in the KA selection but have a business relationship with company X. This group is referred in this study as other accounts (OA). The sample for the OAs has been gathered based on specific criteria. The criteria have been applied for each FY separately.

The criteria for OA sample is as follows:

(1) The parent company headquarters are located within the Nordic region
(2) The relationship with the customer has to have started before FY13
(3) The customer has paid Company X more than 50,000 USD from relationship start

The first criterion is set so that the OAs sample fulfils the same geographical requirement as the KAs have. The second criterion is set because the customer should already have had an ongoing customer relationship with company X for the researcher to be able to obtain the necessary data variables for the study. For instance, if a customer has started a business relationship with company X for the first time one week before the data for a certain FY is gathered, there would not be any historical customer data available for the customer in question for the same period of time. The third criterion is set based on the fact that sufficient or reliable customer data is not available under the thresholds in question. Also, all sampled customer accounts from the KA subgroup can be fitted under the same criteria as the OA sample.

Table 2 illustrates in more detail the customer sample sizes of each customer subgroup. Yet, it is important to note that the OA subgroup does not include customers that are part of the KA selection, since that would distort the data. For instance, the KAs for fiscal year 2016 (FY16) are not included in the OAs total sample of same FY.

The FY customer sample that has the least amount of missing data or errors is used in the study. As table 2 shows, FY16 has the least amount of unusable data, since 91% of the data sample of the FY in question is usable. Thus, the FY16 combined customer sample consist of customers that are chosen based on the criteria presented earlier and have been customers of company X on 1.7.2015, i.e. from the start of FY16. As earlier mentioned, each fiscal year starts 1.7 and end 30.6.
Table 2  Information of the customer sample

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<th>Subgroup KA</th>
<th>Subgroup OA</th>
<th>Combined</th>
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<td>Sample used</td>
<td>Non-missing data</td>
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<td>113</td>
<td>87 %</td>
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Used in the study

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3.1.1 The data timeframe

As mentioned earlier, the aim of the study is to measure the relationship between KA selection and customer account profitability when taking to account other KA selection criteria in a professional services organization. To be able to measure the relationship in question, the data has been arranged in a manner that emulates the KA selection process of company X.

Hence, a timeframe of how the data is used is illustrated in figure 4. The timeframe consist of three different levels: FY t, FY t-1 and FY t-2. The FY t represents the year of which the KA selection is predicted. In other words, FY t represents the actual outcome of the KA selection, which in this case is the FY16 combined customer sample of KAs and OAs. In addition to the customer sample with KAs and OAs, other data is gathered to act as KA selection criteria by which the KAs are chosen. These criteria are based on both internal and external customer data.
The FY t-1 represents the fiscal year when the decision of next fiscal year's KA selection is made, i.e. the KAs for FY t. Also, all the variables that are based on internal customer data are collected from FY t-1. The reason for this is that, this type of data can be considered accessible in real-time since company X has full control over it. Thus, company X can look up the newest internal customer data when deciding the KA selection for the next FY.

In contrast, the external customer data, which is controlled by the customer, is collected from FY t-2. External data consist of variables that can be accessed only after the customer has made the information public. For example, financial information of a customer company that the customer itself publishes annually is regarded as external customer information. This type of information is not available in real-time for the decision makers of company X. Therefore, the decision makers have no choice but to utilize external customer information from FY t-2.

![Figure 4 Illustration of the data timeframe](image)

Consequently, the data for this empirical study is gathered from FY14, FY15 and FY16. However, both the internal and the external customer data are based on information that is related to the customers of FY16, which consist of KAs and OAs.

### 3.2 Variables used in the study

The variables used in this study have been gathered based on the customer sample introduced in the 3.1 “Data description” subsection. These additional variables act as KA selection criteria by which the KA selection is based on. Therefore, the variables
represent both financial and nonfinancial criteria that the earlier literature has recognized to be important in KA selection processes. The variables that are used as the KA selection criteria in this study are described as follows:

**Financial criteria**
- Account revenue (AR)
- Gross profit (GP)
- Gross margin in percent (GMP)
- Total assets of the customer (TA)

**Nonfinancial criteria**
- Customer relationship length (RL)
- Sales opportunities identified (SOI)
- Publically traded (PT)

The variable that separates the customers to KAs and OAs is named “KA priority status: KA vs. OA (KPS). Furthermore, the data is controlled with customer industry (CI) and customers headquarter country (HQ).

Figure 5 illustrates from which FY each of the variables have been gathered. As mentioned in the 3.1. “Data timeframe” subsection, the variable that divides the customers to either KAs or OAs is from FY16.

**Figure 5 Illustration of the data timeframe with all variables included**

<table>
<thead>
<tr>
<th>FY t-2</th>
<th>FY t-1</th>
<th>FY t</th>
</tr>
</thead>
<tbody>
<tr>
<td>FY14:</td>
<td>FY15:</td>
<td>FY16:</td>
</tr>
<tr>
<td>TA, PT</td>
<td>AR, GP, GMP,</td>
<td>KPS</td>
</tr>
<tr>
<td></td>
<td>RL, SOI</td>
<td></td>
</tr>
</tbody>
</table>

The variables that are gathered from FY15 are account revenue (AR), gross profit (GP), gross margin in percent (GMP), customer relationship length (RL) and sales opportunities identified (SOI). These variables are gathered from FY t-1 since they consist of company X internal customer data, which is accessible for the decision makers of company X in real-time. In other words, company X can utilize this type of data on the same FY as the decision of the next fiscal year’s KA selection is made, which is on FY t-1.
However, the variables total assets of the customer (TA) and publically traded (PT) are gathered from FY14 since the data consist of external customer related data. As mentioned earlier, external customer data cannot be accessed by company X in real-time, and is based on information published by the customers themselves. This type of data is usually published by companies on annual bases, which means that company X has to rely on historical data until new information is published. Thus, external customer related data is gathered from FY t-2.

Next, each of the variables are presented individually in order to explain in more detail what type of data the variables actually consists of and how the variables are related to the KA selection literature.

3.2.1 KA priority status: KA vs. OA (KPS)

The priority status variable is categorical with two groups and therefore is coded as a dummy variable. In other words, the variable is assigned a value of either 0 or 1 (Wooldridge 2012). If the customer account has been chosen as a KA the variable takes value 1. Consequently, if the customer is chosen as an OA the variable takes the value 0. The group of interest should be coded with the higher value (Wooldridge 2012), which in this case represents the KAs.

3.2.2 Account revenue (AR)

Account revenue in this case represents the sum of money that a customer account has paid to company X during a specified FY. A customer account may consist of several entities such as affiliate companies. Thus, the account revenue may consist of payments from several customer entities, which then are relocated under a specific account that in most cases is named by the parent entity. The account revenue is continues and currency used is USD. Continues variables are variables that are not restricted to any specific value (Wooldridge 2012). Also, it is important to note that no expenses have been deducted from this payment.

From a theoretical point of view, this variable is used in the study to measure the current sales volume of company X to each customer. In other words, this measurement is used as KA selection criterion that prioritizes customers based on how much money a customer is paying to company X. The variable is important to include in the study since Wengler et al. (2006) noted that the current sales volume is the most
commonly used KA selection criterion in the German business-to-business market. Also, Pels (1992) highlights the role of sales volume in her study.

### 3.2.3 Gross profit (GP)

The gross profit is one of the customer profitability measures that are used in this study. The variable is continues and measured in USD. The measurement is calculated by subtracting the direct expenses from the account revenue during a specified FY. In other words, gross profit represents the sum of money that is left after deducting all direct expenses related to the services company X provides in a specified FY. This type of profitability measurement is commonly used to measure current customer profitability (Johnson et al. 2009). However, does not take to account indirect expenses, such as costs associated to sales or marketing (Johnson et al. 2009). However, company X has very small indirect costs that can be related to the customer since everything from administration to the actual service delivery is billed hourly from the customer. Therefore, this measurement can considered as a valid indicator of customer profitability in this type business setting.

### 3.2.4 Gross margin as a percentage (GMP)

The second customer profitability measure used in this study is gross margin as a percentage. This variable is derived from the same calculations as gross profit, but is presented as a percentage. This measurement can be calculated by dividing gross profit with the account revenue of a specified FY. However, there is a notable difference between gross profit and gross margin of a customer account despite they derive from the same measurement type. Gross margin expressed as a percentage does not focus on the amount of money that company X has obtained. Instead the measurement takes to account how big of a portion is left of the revenue after the expenses. Therefore, it is crucial to take both the gross profit and gross margin calculations to consideration in the study.

### 3.2.5 Total assets of the customer (TA)

The total asset of the customer is one of the variables that are not obtained through company X internal databases. This measure is from the customer’s own balance sheet and obtained through external databases. Total assets or turnover are usually used to determine the size of a company (Czinkota & Wesley 1983). KAM literature, such as
Sharma (1997), states that large customers prefer KAM and therefore it is common for companies to select that type of customers as key accounts. This study uses total assets instead of turnover due to the fact that the turnover measurement is not comparable between financial industry and other industries (Brooks 2008). Furthermore, the total assets variable is transformed with the natural logarithm. This is common procedure in studies that uses size related variables, since it makes the variable distribution less skewed (Brooks 2008). However, it is important to recognize that the logarithmic transformations changes how the results are interpreted (Brooks 2008).

3.2.6 Customer relationship length (RL)

The customer relationship length is continues and indicates how long company X have had a business relationship with the customer. The variable is expressed in number of years. Relationship length has been recognized for example by Meyer-Waarden et al. (2007) and Wengler et al. (2006) as a possible criterion for enrolling a customer to a KAM program, which is reason why the variable is used in the study. Due to the fact that a customer account may consist of several entities, the relationship has been counted to start from the point of time when the first business relationship with company X started for any entity within the account. By applying the same relationship start principle for the every customer account the distortion of the data can be minimized.

3.2.7 Sales opportunities identified (SOI)

Sales opportunities identified is a continuous variable that is measured per FY. The variable basically measures the quantity of sales opportunities that have emerged for a specific account. This data have been obtained from the company X CRM system. The employees at company X have to document every sales possibility that can be verified, such as formal invitations to tender and other sales pursuits. The variable is used to indicate the future potential of the business relationship. For example, a lot of recognized sales opportunities indicate that there are a lot of cross selling opportunities within the account. This means that the customer account may be seen as strategic account by the company X. According to Sharma (1997) KAs should be chosen based on the selling company’s strategic priorities. Furthermore, Nätti & Ojasalo (2008) noted that the most crucial challenge for professional services organizations is to be able match the customer’s needs with the competence of the professional organization.
Consequently, these selling opportunities represent possible matches between the customer needs and the competence of the organization. The fact that company X keeps track on the selling opportunities indicate that this type of criteria might be utilized in the KA selection process. However, there is a risk that a big proportion of the opportunities that emerge are not documented, either on purpose or accidentally.

### 3.2.8 Publically traded (PT)

The publicly traded variable is a categorical variable. The variable separates between the customers that are publicly traded and the customer that are not. In this study, a customer company is considered publically traded if any entity within a specific customer account is listed in the main stock exchange of Finland, Sweden, Denmark or Norway. The variable takes the value 1 if the customer is listed and value 0 if it is not listed in any of the before mentioned stock exchanges.

The variable is used in the study since publically traded companies are considered to have a good customer reference value. The logic behind this argument is that publically traded companies have to be more transparent than privately owned ones and therefore needs to choose more carefully their service providers in comparison with non-public companies. Moreover, a high reference value of a customer is strongly linked with a customer's image (Tzemeplikos & Gounaris 2013). Customer image or status is according to Wengler et al. (2006) the most used nonfinancial KA selection criteria. Thus, company X might have used this type of criteria as a measurement of customer image in the KA selection.

### 3.2.9 Customer industry (CI)

The customer industry variable explains what industry the customer operates within. The variable is categorical with 19 categories. When the study contains more categories than two, individual dummy variables have to be included (Wooldridge 2012). For instance, if the number of categories is g amount of groups, the amount dummy variables should be g-1 and one intercept that act as the comparison group (Wooldridge 2012). However, differences in the dummies will not be analyzed since they only act as control variables in this study. The costumer industries consist of the following categories:
AM: Wealth & Asset Management
AU: Automotive & Transportation
BK: Banking & Capital Markets
CO: Telecommunications
CP: Consumer Products & Retail
DI: Diversified Industrial Products
GO: Government & Public Sector
IN: Insurance
LS: Life Sciences
ME: Media & Entertainment
MI: Mining & Metals
OG: Oil & Gas
PC: Health
PH: Private Households
RE: Hospitality & Construction
SE: Professional Firms & Services
TB: To Be Determined
TE: Technology
UT: Power & Utilities (intercept)

To be more specific, a dummy variable have been created for each industry categories except from the last one. The last industry category acts as the intercept, i.e. as the comparison group.

3.2.10 Customer headquarter country (HQ)

The customer HQ country variable clarifies in which country the headquarters of the customer accounts are located. If an account has several identities, the parent entity headquarter of the customer account is used. The variable is categorical with 4 categories. Consequently, the same principle is used to set up the HQ country categories as used for the customer industry variable. As in the case of the customer industries, customer HQ categories have only a controlling function. The customer HQ countries consist of the following categories:

DK: Denmark
FI: Finland
NO: Norway
SE: Swedish (intercept)

Thus, dummy variables have been created for Denmark, Finland and Norway whereas Sweden acts as the intercept.
3.3 Sample and other possible data biases

A big portion of the data has been gathered by company X employees themselves and handed to the researcher based on requirements set by the researcher. Due to the fact that the data is company X specific and customer related, the researcher cannot confirm that the data is fully accurate. However, there is no reason to believe that company X would try to distort the data. It has been made clear for company X that it and its customers are anonymous in the study. Therefore, company X does not have any incentive to provide the researcher with false information.

Another issue is that some of the customers lack total asset data. Most of the missing total asset data are from the GO (Government & Public) sector customers. Approximately 84 percent of the observations that belong to the industry category in question lack total asset data. The reason why the total assets data cannot be found for government customers is that they do not have a proper company identity. These types of customers are for instance small towns, cities and governmental organizations. Thus, the customers that lacked the total assets data are not used in the analyses that require the customer total asset variable (TA) or in the analyses that require the same amount of observations to make reliable comparisons. The analysis method that uses a reduced sample of 610 customers is noted in chapter 4 “Analysis methods”. An average of the total assets values was not used for the missing total assets values since the data that was not missing varied considerably between the government and public sector customers. Moreover, the government and public sector companies that did not lack the total assets information were categorized to the industry category in question only because these companies were owned by the government. Thus, these types of companies cannot be assumed to have similar asset structure as cities or other similar governmental instances.

3.4 Descriptive statistics

This subsection presents some descriptive statics for continues and categorical variables.

3.4.1 Continues variables

Table 3 presents some descriptive statistics of the continuous variables. The number of valid observations is 798 for all observations if not taking to account total asset variable
As mentioned earlier, a notable portion of the customers that is part of the government & public sector industry category lack total assets data.

Table 3  Descriptive statistics of continuous variables

<table>
<thead>
<tr>
<th>FY 16 List</th>
<th>AR FY15 (USD)</th>
<th>GMP FY15 (%)</th>
<th>GP FY15 (USD)</th>
<th>TA FY14 (ln)</th>
<th>SOI FY15 (quantity)</th>
<th>RL FY15 (year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>798</td>
<td>798</td>
<td>798</td>
<td>610</td>
<td>798</td>
<td>798</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>-228 %</td>
<td>-291 368</td>
<td>11.79</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Maximum</td>
<td>12 572 813</td>
<td>140 %</td>
<td>5 803 002</td>
<td>27.56</td>
<td>67</td>
<td>31</td>
</tr>
<tr>
<td>Mean</td>
<td>496 751</td>
<td>32 %</td>
<td>192 288</td>
<td>19.61</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>1 053 645</td>
<td>26 %</td>
<td>480 238</td>
<td>2.47</td>
<td>8</td>
<td>6</td>
</tr>
</tbody>
</table>

The minimum and maximum observation values indicate that no errors are left in the sample. The minimum observation value of the account revenue (AR) variable cannot be negative since it does not take to account any expenses. However, the minimum value for both gross margin USD (GMU) and gross margin in % (GMP) is negative since these measurements take to account expenses. In other words, it can be concluded that the sample has at least some unprofitable customers. However, the mean of the observations of GMP inclines that the average customers have a gross margin of 32%, which can be considered an indicator of a healthy business. Furthermore, the high std. deviation compared to the mean of variables AR and GP signals that some customers account for a much bigger portion of the account revenue and of the gross profit for company X.

On the other hand, the TA variable contains fewer observations than rest of the variables since total assets data could not be found of all the customer companies. The fact that many institutions within the government & public sector do not need disclose total asset information is the main reason for the data loss. This issue has been discussed in the subsection 3.3 “Sample and other possible data biases”.

Furthermore, the OI variable can be considered interesting. If looking at the minimum, maximum and std. deviation of the variable, it becomes clear that some observations are radically different from others. The mean is 3 but the maximum value is 67. Also, the std. deviation is more than twice bigger than the mean.
Lastly, the relationship length (RL) between company X and the customer vary from 3- to 31 years. The minimum value is obvious due to the fact that one of the criteria for the sample was that they have been customers since FY13.

### 3.4.2 Categorical variables

The categorical variables are presented in individual tables. In table 4 the distribution between the KAs and the OAs within the priority status variables are presented. The KA represents 11% of the total FY16 customer sample. This is as expected since the whole point of a KA selection is to prioritize some customers over the others. It can also be concluded that both of the groups within the variables are independent from each other, i.e. not a single observation is included in both of the groups.

#### Table 4  Descriptive statistics of the KA priority status (KPS) variable

<table>
<thead>
<tr>
<th>KA priority status (KPS)</th>
<th>Listed</th>
<th>KA/OA</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>KA</td>
<td>89</td>
<td></td>
<td>11%</td>
</tr>
<tr>
<td>OA</td>
<td>709</td>
<td></td>
<td>89%</td>
</tr>
<tr>
<td>Total</td>
<td>798</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

The descriptive statistics of the publically traded variable is presented in table 5. Only 26 percent of the customer accounts can be considered to be listed in Nordic stock exchanges.

#### Table 5  Descriptive statistics of the publically traded (PT) variable

<table>
<thead>
<tr>
<th>Publically traded (PT)</th>
<th>Listed</th>
<th>Yes/No</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>206</td>
<td>26%</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>592</td>
<td>74%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>798</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

As mentioned earlier in the variable descriptions, the customer industry (CI) dummies acts as control variables. From table 6 can be seen that the number of observation between each industry varieties quite drastically. Some of the industries, such as mining & metals (MI) and life sciences (LS), have very few observations. In contrast,
the biggest category of 133 customers consists of government and public (GO) sector customers. However, it have to be noted that in the reduced sample of 610 customers, which is used in some of the analysis methods, the number of government and public (GO) sector customers is only 12. Furthermore, other big industry categories are hospitality & construction (RE), professional firms & services (SE) and consumer products & retail (CP).

Table 6  Descriptive statistics of the customer industries (CI) control variable

<table>
<thead>
<tr>
<th>Customer industry (CI)</th>
<th>Industry</th>
<th>Per industry</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM</td>
<td>59</td>
<td>7 %</td>
<td></td>
</tr>
<tr>
<td>AU</td>
<td>39</td>
<td>5 %</td>
<td></td>
</tr>
<tr>
<td>BK</td>
<td>49</td>
<td>6 %</td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>10</td>
<td>1 %</td>
<td></td>
</tr>
<tr>
<td>CP</td>
<td>75</td>
<td>9 %</td>
<td></td>
</tr>
<tr>
<td>DI</td>
<td>55</td>
<td>7 %</td>
<td></td>
</tr>
<tr>
<td>GO</td>
<td>133</td>
<td>17 %</td>
<td></td>
</tr>
<tr>
<td>IN</td>
<td>21</td>
<td>3 %</td>
<td></td>
</tr>
<tr>
<td>LS</td>
<td>9</td>
<td>1 %</td>
<td></td>
</tr>
<tr>
<td>ME</td>
<td>17</td>
<td>2 %</td>
<td></td>
</tr>
<tr>
<td>MI</td>
<td>6</td>
<td>1 %</td>
<td></td>
</tr>
<tr>
<td>OG</td>
<td>20</td>
<td>3 %</td>
<td></td>
</tr>
<tr>
<td>PC</td>
<td>8</td>
<td>1 %</td>
<td></td>
</tr>
<tr>
<td>PH</td>
<td>18</td>
<td>2 %</td>
<td></td>
</tr>
<tr>
<td>RE</td>
<td>90</td>
<td>11 %</td>
<td></td>
</tr>
<tr>
<td>SE</td>
<td>92</td>
<td>12 %</td>
<td></td>
</tr>
<tr>
<td>TB</td>
<td>34</td>
<td>4 %</td>
<td></td>
</tr>
<tr>
<td>TE</td>
<td>35</td>
<td>4 %</td>
<td></td>
</tr>
<tr>
<td>UT</td>
<td>28</td>
<td>4 %</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>798</td>
<td>100 %</td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, table 7 presents the distribution of customer accounts headquarters between the Nordic countries. Finland has the smallest representation of the sample (14%) and Sweden the biggest representation (37%).
Table 7  Descriptive statistics of the Customer HQ country (HQ) control variable

<table>
<thead>
<tr>
<th>Customer HQ country (HQ)</th>
<th>Per country</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>DK</td>
<td>175</td>
<td>22 %</td>
</tr>
<tr>
<td>FIN</td>
<td>114</td>
<td>14 %</td>
</tr>
<tr>
<td>NO</td>
<td>214</td>
<td>27 %</td>
</tr>
<tr>
<td>SE</td>
<td>295</td>
<td>37 %</td>
</tr>
<tr>
<td>Total</td>
<td>798</td>
<td>100 %</td>
</tr>
</tbody>
</table>
4 ANALYSIS METHODS

The aim of the study is to measure the relationship between KA selection and customer account profitability when taking to account other KA selection criteria in a professional services organization. To be more specific, two research questions were set. Two main quantitative methods are used to answer the research questions. The methods used are analysis of variances (ANOVA) and binary logistic regression.

The following chapter introduces the methods used in the study in more detail. The methods are presented in accordance with the research questions that specify the aim of the study.

4.1 Research question one

The first research question of the study is: Does customers’ account profitability significantly differ between a key account and other accounts in a typical professional services organization?

To answer this research question series of one way ANOVA tests are utilized. A one way ANOVA, also called one factor ANOVA, measures the difference of means between groups or within groups by utilizing variances (Weiss 2006). The dependent variable (DV) needs to be continuous, i.e. a numerical variable, whereas the independent variable (IV) must be categorical with two or more groups (Weiss 2006). In this study, the one way ANOVA measures the differences in the means of the dependent variable between two groups of a single independent variable.

The one way ANOVA model can be described as:

\[ y_{ij} = \mu_j + \varepsilon_{ij} \]

where \( y_{ij} \) represent the observations, \( \mu_j \) the mean of the observations of the jth group and \( \varepsilon_{ij} \) the error term (Weiss 2006).

Three one way ANOVAs are tested in this particular analysis as follows:

- ANOVA 1: DV: Account revenue (AR), IV: Priority Status (KPS)
- ANOVA 2: DV: Gross profit (GP), IV: Priority Status (KPS)
- ANOVA 3: DV: Gross margin in % (GMU), IV: Priority Status (KPS)
The dependent variable in ANOVA 2 and ANOVA 3 are measurements that measure the current customer profitability of the customer accounts of company X. ANOVA 1 has as the dependent variable a metric that measures the current sales volume to each customer account. The independent variable is in each of the analyses is the variable KA priority status (KPS). The purpose of performing the one way ANOVA tests in this study is to get an understanding of the differences in the means of the profitability related measures between KA and OA. The ANOVA 1, which has account revenue (AR) as the dependent variable, is added to enhance the understanding of how a metric that does not take to account customer related expenses act in comparison to customer profitability metrics that takes to account these types of expenses.

If there is not a difference between the means of the profitability related measures, it indicates that the measurements in question have not acted as KA selection criteria when company X has decided the next fiscal year's KAs. As illustrated in figure 5 in the subsection 3.2. “Variables used in the study”, the variables account revenue (AR), gross profit (GP) and gross margin in % (GMP) are from FY15, whereas the KA priority status (KPS) variable is from FY16. Consequently, if a significant difference cannot be found, it would strongly indicate that the measurements in question are bad predictors for a customer to be selected as a KA.

The hypotheses for the ANOVA tests are:

H0: Means are equal for all groups
H1: At least one group mean differs

Since the independent variable consists in this case of only one independent variable with only two categories, the hypothesis for each analysis can be stated as:

HO: $\mu_1 = \mu_2$
H1: $\mu_1 \neq \mu_2$

4.2 Research question two

The second research question of the study is: Is customer account profitability a significant predictor of a customer to be selected as a KA when other probable KA selection criteria are taken to account?
This research questions is much more complicated than the first one. To answer this question it is not enough to measure if there are differences in profitability related measurements between KAs and OAs, since other possible selection criteria has to be taken to consideration. Consequently, the method used to answer this question is a series of binary logistic regressions. By utilizing this type of approach the other KA selection criteria can be taken to account when analyzing the predictive value of a specific profitability measure. Furthermore, by running several binary logistic regressions separately, and by utilizing nested models, the predictability of each profitability measure can be compared to each other.

Binary logistic regression is a model that is commonly used when the dependent variable is binary, i.e. categorical with two categories. There are also other models that can apply a categorical dependent variable such as the probit model, which give very similar, if not identical, results as the logit model (Brooks 2008). These models fit binary data well due to the fact that they do not follow the assumptions as linear models do (Brooks 2008; Wooldridge 2012). In contrast to linear regression models, the models uses functions that effectively transform the regression model into values that are bounded to fit within 0 and 1 (Brooks 2008). However, the log of the odds ratios, which are used to estimate the probabilities of being in 0 or 1, goes from $-\infty$ to $+\infty$ (Gujarti 2011). The logit model uses the maximum likelihood estimation technique instead of ordinary least squares that is used in linear models (Gujarti 2011). Thus, the logit model \( L_c \), the log of the odds ratio, estimates probabilities (Gujarti 2011).

The logit model is based on following function:

\[
L_c = \ln(P_c/1-P_c) = BX_c + u_c
\]

where \( c \) is the customer, \( P_c \) is the probability that goes from value 0 – 1, \( BX_c \) represents the combination of independent variables, \( u_c \) the error term (Gujarti 2011).

In other words, \( BX_c + u_c \) can be described as:

\[
BX_c + u_c = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots \beta_n x_n + u_c.
\]

Consequently, the \( L_c \) function is the probability of customer to be chosen as a KA. If the customer is chosen as a KA, the customer take the value of 1 and if not the value 0. The independent variables, i.e. predictive and controlling variables, are introduced in the data chapter. The variables have been setup in accordance with the data timeframe illustrated in figure 4 and 5.
To be able to compare the models to each other, three different model comparison measurements are used. These measurements are Akaike information criterion (AIC), Bayesian information criterion (BIC) and likelihood ratio test (LRT). The measurements can be expressed as:

\[
AIC = 2[l(\theta_2) - l(\theta_1)] - 2(p_2 - p_1). \text{ (Akaike 1973)}
\]

Or alternatively: \( AIC = -2 \log L + 2k \)

\[
BIC = 2[l(\theta_2) - l(\theta_1)] - \log n(p_2 - p_1). \text{ (Schwarz 1978)}
\]

Or alternatively: \( BIC = -2 \log L + \log(n)k \)

\[
LRT = -2*L(\text{null model}) - (-2*L(\text{fitted model})). \text{ (Cramer 1986)}
\]

The k represents the number of parameters in the model with the intercepts included and n the number of observations. In the LRT test the null model refers to the model with no added parameters and fitted model to the model with added parameters (Cramer 1986).

Both the AIC and BIC measurements aim to identify how good a certain model is. However, AIC and BIC does the estimation of the model differently (Kuha 2004). BIC tries to identify the models with the highest probability of being the true model for the data, with the assumption that one of the models under consideration is the true one (Kuha 2004). On the other hand, AIC does not expect there to be a true model, but alternatively uses expected prediction of future data as a benchmark to estimate the effectiveness of the model (Kuha 2004). The model that has the lowest AIC and BIC can be considered as the most effective model (Kuha 2004). Kuha (2004) argues also that the best way to use the AIC and BIC measurements are to use them together.

However, AIC and BIC is not capable of giving a p-value for model comparison in the same way that LRT does. The LRT measurement can be used to compare a nested model from another fitted model that uses the same data (Cramer 1986). A nested model is a model that utilizes the same data but have a reduced number of parameters compared with the original model (Cramer 1986). The LTR ratio can be distributed as a chi-square with degrees of freedom in accordance with the number of reduced parameters between the nested and original model (Cramer 1986). This means that a P-value can be contained and a hypothesis can be set between the nested model and the model of comparison as follows:
H0: The nested model is true
H1: The comparison model is true

Consequently, four main binary logistic regressions are conducted, from which one acts as the nested model and the other three as the comparison models. As in the ANOVA tests, each of the profitability measures is added to the nested model in a separate binary logistic regression. Furthermore eight alternative binary logistic regressions are conducted in the same manner. One of the eight alternative models acts as the nested model including only the control variables customer industry (IC) and customer HQ country (HQ). To each of the seven additional models one separate parameter is added that represents a possible KA selection criterion. By doing this, and calculating the AIC, BIC and LRT, it can be concluded what kind of effect a criterion by itself can add to a model that does not otherwise have prediction power. The results of the main models are explained in detail whereas the focus of the alternative models is on the AIC, BIC and LRT comparisons. Furthermore is important to note that all the binary logistic models used a reduced sample of 610 customers, due the fact that some of the customers lacked total asset data. The same procedure is done for every binary regression model to maintain the comparability of the models.

The models are constructed as follows:

**Main models**

LM (nested): \( L_c = \alpha + \beta_1 \text{OP} + \beta_2 \text{RL} + \beta_3 \text{TA} + \beta_3 \text{PT} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LM 1 (L1): \( L_c = \alpha + \beta_1 \text{AR} + \beta_1 \text{OP} + \beta_2 \text{RL} + \beta_3 \text{TA} + \beta_3 \text{PT} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LM 2 (L2): \( L_c = \alpha + \beta_1 \text{GRU} + \beta_1 \text{OP} + \beta_2 \text{RL} + \beta_3 \text{TA} + \beta_3 \text{PT} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LM 3 (L3): \( L_c = \alpha + \beta_1 \text{GRP} + \beta_1 \text{OP} + \beta_2 \text{RL} + \beta_3 \text{TA} + \beta_3 \text{PT} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

**Alternative models**

LS (nested): \( L_c = \alpha + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LS 1 (L1): \( L_c = \alpha + \beta_1 \text{AR} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LS 2 (L2): \( L_c = \alpha + \beta_1 \text{GRU} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LS 3 (L3): \( L_c = \alpha + \beta_1 \text{GRP} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LS 4 (L4): \( L_c = \alpha + \beta_1 \text{OP} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).

LS 5 (L5): \( L_c = \alpha + \beta_1 \text{RL} + \beta_3 \text{CI} + \beta_3 \text{HQ} + \epsilon_c \).
In addition to AIC and BIC, the Nagelkerke $R^2$ is reported. This measurement interprets the proportion of the unexplained variation of a model (Nagelkerke 1991). As a result, the Nagelkerke $R^2$ is measuring the goodness-of-fit between within a 0 to 1 scale (Nagelkerke 1991). The model fits the data better when the pseudo $R^2$ value is closer to one. However, this measurement only used to see if the pseudo $R^2$ supports the claim of the AIC and BIC measurements.

### 4.3 Model assumptions

One way ANOVA and binary logistic regression are very different in nature and therefore does not have the same assumptions. Therefore, the assumptions that are relevant in this study are discussed for each main method separately.

#### 4.3.1 One way ANOVA

One of the main assumptions of a one way ANOVA analysis is that the variances are assumed to be equal. This assumption is violated for two of the three ANOVA analyses that are conducted. The Levene’s test of equality of variances is used to confirm that ANOVA 1 with the dependent variable AR and ANOVA 2 with the dependent variable GP do not assume equal variances. In other words, the The Levene’s test is strongly significant ($p$-value < 0.01) for ANOVA 1 and ANOVA 2 whereas ANOVA 3 is not significant on a 0.05 significance level. Therefore, the Welsch and Brown-Forsythe are added to the analysis to confirm that that the results from the ANOVA 1 and ANOVA 2 can be considered trustworthy. The Welsch and Brown-Forsythe test are considered robust against heterogeneity between variances (Roth 1983). These results are presented in the empirical results chapter.

Furthermore, as earlier mentioned, the dependent variable in ANOVA should preferably be normally distributed. However, according to the Shaprio Wilk’s test none of the dependent variables, i.e. AR, GRU, GRP, can be considered normally distributed. However, this argument is flawed according to Norman (2010). Norman (2010) argues that the data does not have to be normally distributed; rather the means should be normally distributed. According to the Central Limit Theorem the means are
approximately normally distributed when the sample size is greater than 5 or 10. Hence, normal distribution is not a problem (Norman 2010).

Lastly, outliers may distort the results of the ANOVA. All the dependent variables used in the one way ANOVA analysis have a small amount of outliers when checking the box plots of each variable in SPSS. However, in this study the outliers are actually of great importance because they can be considered as meaningful for company X. Since the study uses a data sample that actually represents to a great deal the actual population within the sample criteria set, deleting the outliers would distort the data. The real winners or losers are therefore of great importance to the analysis. Nevertheless, all the data points that can clearly be considered as errors or other misclassifications have been deleted from customer sample. This was done manually by screening the data for suspicious data values during the sampling process. All suspicious values were noted and double-checked with a financial controller from company X. The data that had been misclassified according to company X was not added to the customer sample presented in subchapter 3.1 “Data description”.

4.3.2 Binary logistic regression

One of the main benefits of using a logistic regression model is that relationship between the dependent and independent variables does not have to be linear (Gujartı 2011). Also, a logistic regression model does not require normally distributed data and homoscedasticity of variances within the independent variables is not an issue (Gujartı 2011).

However, the main independent variables should not suffer from high multicollinearity or have asymmetric relationships (Brooks 2008). One reason why the main models LM1, LM2 and LM3 was modelled separately is the fact that some of the predictor variables would have otherwise suffered from strong multicollinearity. The multicollinearity was measured with the help of a correlation matrix that utilized the Person correlation technique. The correlation matrix is presented and discussed further in the empirical results.
5  EMPIRICAL RESULTS

The empirical results of the study are presented in accordance with the research questions. The results that are related to the research question one is presented first. The research question two is addressed after that.

5.1 Results related to research question one

The results of the ANOVA tests are presented in separate tables. The results of the first test, which had account revenue as the dependent variable, can be seen from table 8.

Table 8  Results of ANOVA 1

<table>
<thead>
<tr>
<th>ANOVA 1 (Dependent: AR)</th>
<th>df</th>
<th>F</th>
<th>( \eta )</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>1</td>
<td>409.71</td>
<td>0.34</td>
<td>0.001</td>
</tr>
<tr>
<td>Welsch</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brown-Forsythe</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>798</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KA (mean)</td>
<td>2 229 220</td>
<td>279 275</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OA (mean)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: significant when \( P < 0.5 \)
Small \( \eta > 0.10 \), medium \( \eta > 0.059 \), Large \( \eta > 0.138 \) (Cohen 1988)

The results from ANOVA 1 is strongly significant (\( P < 0.001 \)) and therefore the Ho hypothesis can be rejected. In other words, there is a highly significant difference between the mean account revenue of KAs and OAs. Both the Welsch and Brown-Forsythe test show the same results, and therefore confirms the results of the one way ANOVA between groups test. The large F-value of 409.71 indicate that there are a lot of variations between the means of the groups. The effect size of ANOVA 1 is large, and shows that 34% of the variance is caused by the KA priority status (KPS) variable. The mean account revenue for KAs is approximately 2,2 mil and for OAs 279 k in USD. Consequently, the means of each group clearly demonstrates that KAs on average brings company X more account revenue than OAs.
Table 9  Results of ANOVA 2

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>F</th>
<th>η</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>1</td>
<td>329,465</td>
<td>0,29</td>
<td>0,001</td>
</tr>
<tr>
<td>Welsch Brown-Forsythe</td>
<td>798</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n KA (mean)</td>
<td>925</td>
<td>197</td>
<td>100</td>
<td>286</td>
</tr>
<tr>
<td>OA (mean)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: significant when P < 0.5
Small η > 0.01, medium η > 0.059, Large η > 0.138 (Cohen 1988)

The ANOVA 2, which has gross profit as the dependent variable, show similar results as ANOVA 1. The one way ANOVA test is strongly significant (P < 0.001). Both the Welsch and Brown-Forsythe tests are also strongly significant and therefore confirm the results of one way ANOVA test. Consequently, the H₀ hypothesis of equal mean gross profits between the groups can be rejected. The F-value is very high as in the case of ANOVA 1. The effect size of ANOVA 2 is large and indicates that 29% of the variance is caused by the dependent variable KA priority status (KPS). The differences in the means of each group are large, but not as large as in the case of ANOVA 1. The mean gross profit for KAs is approximately 925 k and for OAs 100 k in USD.

However, the results of ANOVA 3, shown in table 10, differ from the results of ANOVA 1 and ANOVA 2. As table 10 shows, the one way ANOVA test is not significant with a confidence interval of 95%. The P-value for the ANOVA test is 0.737. The Welsch and Brown-Forsythe are even more conservative and show a P-value of 0.797. Thus, the Ho hypothesis of that the means are equal between KAs and other OAs is not rejected. The F-value is less than 1, which indicate that there is nearly no variations between the means of the groups. The effect size is less than 0.001 (η < 0.001). Furthermore, the mean gross margin as a percentage is for KAs 32.85% and for OAs 31.96%. By looking at the mean gross margin as a percentage of each group, it can be seen that the KAs and OAs means are nearly identical, with a difference of only 0.11 percentage points.
Table 10 Results of ANOVA 3

<table>
<thead>
<tr>
<th>ANOVA 3 (Dependent: GRP)</th>
<th>df</th>
<th>F</th>
<th>η</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>1</td>
<td>0.113</td>
<td>0.001</td>
<td>0.737</td>
</tr>
<tr>
<td>Welsch Brown-Forsythe</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>798</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KA (mean)</td>
<td>32.85</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OA (mean)</td>
<td>31.96</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: significant when P < 0.5
Small η > 0.01, medium η > 0.059, Large η > 0.138 (Cohen 1988)

To summarize, both account revenue and gross profit differs significantly between KAs and OAs, whereas gross margin as a percentage do not differ between the groups in question. Thus, the answer to the first research question is that there is a significant difference in customers’ account profitability between KAs and OAs in a typical professional services organization when the profitability is measured in monetary terms, i.e. as gross profit. On the other hand, there is not a significant difference in customers’ account profitability between KAs and OAs when the profitability is measured as a percentage, i.e. gross margin.

As mentioned in the 4 “Analysis methods” chapter, the account revenue variable was tested in ANOVA 1 to enhance understanding of how a metric that does not take to account customer related expenses act in comparison to customer profitability metrics that takes to account these types of expenses. The result of ANOVA 1 was very similar to ANOVA 2 that had the gross profit (GP) variable as the dependent variable. This indicates that these variables may have a correlation with each other.

5.2 Results related to research question two

As mentioned in the model assumptions subchapter, a correlation matrix with Pearson's correlations is used to detect possible correlation between the predictive independent variables that are used in the binary regression models. The correlation matrix is presented in table 11.
Table 11 Correlation matrix between the predictive independent variables

<table>
<thead>
<tr>
<th>Person’s correlation</th>
<th>AR</th>
<th>GPU</th>
<th>GMP</th>
<th>OI</th>
<th>RL</th>
<th>TA</th>
<th>PT</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>1,000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GP</td>
<td>0,973</td>
<td>1,000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GMP</td>
<td>0,120</td>
<td>0,201</td>
<td>1,000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOI</td>
<td>0,462</td>
<td>0,462</td>
<td>0,091</td>
<td>1,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RL</td>
<td>0,101</td>
<td>0,077</td>
<td>0,001</td>
<td>0,086</td>
<td>1,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TA</td>
<td>0,435</td>
<td>0,384</td>
<td>0,044</td>
<td>0,457</td>
<td>0,063</td>
<td>1,000</td>
<td></td>
</tr>
<tr>
<td>PT</td>
<td>0,125</td>
<td>0,123</td>
<td>-0,029</td>
<td>0,069</td>
<td>-0,031</td>
<td>0,283</td>
<td>1,000</td>
</tr>
</tbody>
</table>

It can be concluded from the correlation matrix that the variables account revenue (AR) and gross profit (GP) have a very strong positive correlation, with a value of 0,973. This value is very near full correlation. Therefore, these predictive independent variables are not utilized in the same logistic regressions. However, the predictive effects of the models are compared with AIC and BIC. Also, despite the fact that the variables gross profit (GP) and gross margin as a % (GMP) do not have a very strong correlation; they cannot be included in the same logistic regression since the variables have an asymmetric relationship with each other, which means that the variables are derived from one another. The rest of the predictive independent variables do not have a high correlation with each other. Furthermore, a moderate or small amount of positive correlation can also be found for instance between TA and AR (0,435), TA and GP (0,384) or TA and SOI (0,457). However, these correlations are not considered strong enough to distort the results of the binary logistic regressions.

The results from the main model regressions are presented in Table 12. The table summarizes the most relevant information in regards to this study for the four main model binary logistic regressions. Each of the models uses the same amount of observations and is controlled by customer industry (CI) and customer headquarter country (HQ). When looking at all the four models together, it becomes apparent that there are both similarities and differences between the results of each model. In all four main models the sales opportunities identified (SOI) variable and the total assets of the customer (TA) variable is highly significant with a P-value < 0,001. Both of these variables have also an Exp(B) > 1, i.e. bigger than one odds ratios, which show that the relationship of both of the independent variables is positive between the dependent variable KA priority status (KPS). Therefore, in all of the models, the odds for a
customer to selected as a KA is higher when there are more identified sales opportunities and more total assets. For instance, in model LM the odds to be selected as a KA is 1.42 times higher when a customer has one more identified sales opportunity. The same applies to total assets but instead as a fold increase due to the ln transformation. In model LM the odds to be selected as a KA is 4.63 times higher for a customer that have a 2.71 (e) fold increase in total assets.

Table 12 Results from the main model binary logistic regressions

<table>
<thead>
<tr>
<th>Variables</th>
<th>LM (Nested)</th>
<th>LM1 (+ AR)</th>
<th>LM2 (+ GMU)</th>
<th>LM3 (+ GMP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOI</td>
<td>1.418 0,001</td>
<td>1.261 0,001</td>
<td>1.275 0,001</td>
<td>1.431 0,001</td>
</tr>
<tr>
<td>RL</td>
<td>0.948 0,337</td>
<td>0.921 0,160</td>
<td>0.939 0,248</td>
<td>0.949 0,357</td>
</tr>
<tr>
<td>TA</td>
<td>4.632 0,001</td>
<td>6.015 0,001</td>
<td>5.363 0,001</td>
<td>4.661 0,001</td>
</tr>
<tr>
<td>PT</td>
<td>3.178 0,050</td>
<td>3.944 0,44</td>
<td>3.330 0,59</td>
<td>2.909 0,72</td>
</tr>
<tr>
<td>AR</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GP</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GMP</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.989 0,131</td>
</tr>
</tbody>
</table>

Note: Controlled for CI: customer Industry (18+1) and HQ: customer headquarter country (3+1). Significant when \( P \leq 0.5 \) (two-sided). Cut value 0.5 for prediction classifications.

However, the publically traded (PT) variable can be considered significant in only two of the models, LM1 and LM2 with a confidence interval of 95%. In other words, in model LM3 and LM4 the fact that a customer company is publically traded does not significantly add prediction power to the models, whereas in LM1 and LM2 it does. The publically traded variable have in all models an Exp(B) > 1 and therefore has a positive
relationship between the dependent variable KA priority status. Thus, only from the models LM1 and LM2 it can be concluded that the odds are higher for a listed company to be chosen as a KA.

In contrast, the variable relationship length (RA) is not significant in any of the models, i.e. the p-value > 0.05. The Exp(B) < 1 would have indicated, if the variable were significant, that an additional year of a business relationship with a customer would lower the odds of being selected as a KA. But, due to the fact that the variable is not significant the Exp(B) is irrelevant.

When looking at the models separately, the added variable account revenue (AR) in LM1 and the gross profit (GP) in LM2 are both highly significant (P-value < 0.001). Also, these variables have an Exp(B) > 1. Due to the fact that account revenue and gross profit are both expressed in dollars, the increment is better to change to 10 000. For instance, in LM1 the odds of being selected as a KA are 1.02 times higher for customer that pays 10 000 dollars more, and in model LM2 the odds are 1.03 times higher for customer contributes 10 000 more in gross profit. On the other hand, the variable gross margin in % is not significant in model LM3 with a confidence interval of 95%. Thus, gross margin in % does not add any predictability to LM3. More detailed information about models can be found in the appendixes as appendix 1.

To conclude, the result presented above gives an indication of the relationship between each variable in each model. However, in order to compare the models with each other; AIC, BIC and the LRT ratio has to be taken to consideration. According to the AIC and BIC scores, model LM1 is the best model in comparison to the other models since it has the lowest scores in both calculations. The Nagelkerke R² confirms the results by having the highest R² value for model LM1. On the other hand, the worst model is according to the AIC score LM, i.e. the nested model, but for the BIC model LM3. However, the differences of both AIC and BIC between the model LM and LM3 is minimal. The LRT test with the P-value of 0.986 confirms that LM3 is not significantly a better model than the nested one, i.e. LM. This result implies that gross margin as a percentage does not work as a good predictor for being chosen as a KA. The LRT test also shows that both LM1 and LM2 are significantly truer than the nested model LM with a high significance of P-value > 0.001. Thus, LM1 and LM2 can be considered better in comparison with the nested model LM.
However, this does not yet describe if LM1 or LM2 is truer. By looking at both the AIC and BIC value of LM1 and LM2 it becomes evident that LM1 is the truer model, due to smaller scores of both AIC and BIC. Furthermore, the Nagelkerke R² implies the same as AIC and BIC by having the higher R² score for LM1. In other words, by adding the gross profit (GP) variable to the nested model, the model does not become as close to the truth as if adding the account revenue (AR) variable instead.

The models have only small differences in the amount of correct predictions between the models. Therefore, from these values it is hard to make generalizations. However, it can be concluded that the amount of correct classifications of both KA and OA is high. Model 1 has the highest rate of correctly classified KA with a percentage of 84.2.

Due to the fact that the odds ratios of the parameters changes when adding either AR, GP or GMA variables to the main nested model, makes it impossible to make conclusions about the predictive capacity of each variable separately. Therefore, the individual KA selection criterion effectiveness can be seen from the alternative model regression table 13. More detailed tables of the alternative models can be found in appendixes as appendix 2. Model LS is containing the control dummy variables, which do not add significantly predictability to the model. The other models consist of one added predictor that represents a possible KA selection criterion. The interpretation of B, which represents the log odds units, is added to the table since it describes if the relationship is positive or negative between dependent variable and the added independent predictor.

Table 13 Results from the alternative model binary logistic regressions

<table>
<thead>
<tr>
<th>Variables</th>
<th>B</th>
<th>-2 Log likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>LRT</th>
<th>Chrd</th>
<th>P (Sig.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS (CI and HQ)</td>
<td>Control</td>
<td>366,510</td>
<td>412,510</td>
<td>430,573</td>
<td>Nested</td>
<td>147,847</td>
<td>0,001</td>
</tr>
<tr>
<td>LS1 (+ AR)</td>
<td>+</td>
<td>218,663</td>
<td>266,663</td>
<td>285,511</td>
<td></td>
<td>129,375</td>
<td>0,001</td>
</tr>
<tr>
<td>LS2 (+ GP)</td>
<td>+</td>
<td>237,135</td>
<td>285,135</td>
<td>303,983</td>
<td>147,847</td>
<td>0,001</td>
<td></td>
</tr>
<tr>
<td>LS3 (+ GMP)</td>
<td>-</td>
<td>366,372</td>
<td>414,372</td>
<td>433,220</td>
<td>0,14</td>
<td>0,710</td>
<td></td>
</tr>
<tr>
<td>LS4 (+SOI)</td>
<td>+</td>
<td>215,160</td>
<td>263,160</td>
<td>282,008</td>
<td>151,35</td>
<td>0,001</td>
<td></td>
</tr>
<tr>
<td>LS5 (+ LR)</td>
<td>+</td>
<td>364,712</td>
<td>412,712</td>
<td>431,560</td>
<td>1,798</td>
<td>0,180</td>
<td></td>
</tr>
<tr>
<td>LS6 (+ TA)</td>
<td>+</td>
<td>175,079</td>
<td>223,079</td>
<td>241,927</td>
<td>191,431</td>
<td>0,001</td>
<td></td>
</tr>
<tr>
<td>LS7 (+ PT)</td>
<td>+</td>
<td>348,641</td>
<td>396,641</td>
<td>415,489</td>
<td>17,869</td>
<td>0,001</td>
<td></td>
</tr>
</tbody>
</table>

Note: Significant when P≤0.5. The nested model refers to the reduced model. The B is the odds unit of the of the added predictor variable. n = 610.
From table 13 it can be concluded that some of the predictive variables makes the nested model significantly better, whereas some variables do not based on the LRT tests. In the LRT tests, the LM model acts as the nested model and the other models as comparison models. Individually, account revenue (AR), gross profit (GP), sales opportunities identified (SOI), total assets of the customer (TA) and publically traded (PT) makes the LM model better with a high significance level (P-value > 0.001). In contrast, gross margin % (GMP) and customer relationship length (RL) does not, even with a confidence interval of 95%. From the LRT tests it can be concluded that by adding the variables gross margin in % (GMP) or customer relationship length (RL) to the nested model does not make the model truer.

Furthermore, the models that is the most and least true can be distinguished by comparing the AIC and BIC scores between the models. The model LS6 has clearly the lowest AIC and BIC scores, which indicate that the model in question is the truest model. This implies that the total assets of the customer are the best predictor when compared with the other predictors. According to B, the relationship of the variable in question is positive. The same relationship was found in all the main models also. In contrast, the least true model that is significant according to the LRT test is model LS7, which has the publically traded (PT) variable as the added predictor. This result may explain why in some main models the PT variable where significant and in some not, when other KA selection criteria was taken to account.

Lastly, table 13 shows that LS1 is a truer than LS2, which implies that the account revenue (AR) variable is a better predictor in comparison with the gross profit (GP) variable. Both AR and GP have a positive relationship with the priority status variable. The main model regressions, which took also other KA selection criteria to account, showed similar results with the same variables in question.

To summarize, the models used to answer the second research question indicate that company X uses measurements such as total assets, account revenue and identified sales opportunities as criteria for KA selection. However, despite the fact that the main and alternative models LRTs implies that gross profit is a significant add-on to the models, it seems that the measurement have not been used as a KA selection criterion. The arguments for this claim are further discussed in chapter 6 “Discussion”. Also, the models show that gross margin as a percentage is not a significant predictor and has most certainly not been used as a KA selection criterion.
6 DISCUSSION

In this chapter the most interesting results of the study are presented and discussed. The results are also compared with the earlier literature. The first part of the discussion focuses on the profitability related criteria of the KA selection, whereas the second part discusses the relationship between KA selection and other possible KA selection criteria. In the third part of the chapter the reliability and validity of the empirical results are discussed.

6.1 Profitability as a KA selection criterion

The results of the empirical study show that the relationship between KA selection and customer account profitability in company X is quite complex. First of all, it can be concluded from the one way ANOVA tests that the customer accounts that have been selected as KAs are in monetary terms on average more profitable than OAs. This statement is valid due to the fact that there is a clear difference between the means of the two groups when account revenue and gross profit are used as the dependent variable. However, the statement is not correct when gross margin as a percentage is used as the dependent variable. Thus, there is not a significant difference in the means of gross margin as a percentage between KAs and OAs.

The results of the ANOVA tests indicate that gross margin as a percentage has most probably not been used as a KA selection criterion during the KA selection process. The ANOVA suggests also that both account revenue and gross profit may have had been used as a KA selection criterion. Nonetheless, the ANOVA tests do not give any indication of how good account revenue or gross profit are as predictors for a customer to be selected as a KA, especially when other possible criteria are taken to account.

The binary logistic regressions confirmed that the gross margin as percentage does not add any predictive value to a model, with or without other possible KA selection criteria. Moreover, account revenue and gross profit makes the models significantly better, according to the likelihood ratio tests. However, account revenue is according AIC and BIC scores a better add-on to a model than gross profit is.

When taking to account the facts that account revenue is a better predictor than gross profit for being chosen as a KA, and the fact that the correlation matrix showed a nearly full positive correlation (0.973) between the variables in question, it can be concluded
that the higher account revenue is most likely the prime criteria for the accounts’ selection as KAs. The fact that there is a relationship between gross profit and KA selection is mostly just due to the fact that gross profit highly correlates with account revenue. Also, since gross margin as a percentage did not differ between the KAs and AOs, but gross profit did, clearly shows that larger account revenue actually drives the profitability. By evaluating these insights together, it seems unlikely that gross profit have been considered as a KA selection criterion. It seems more likely that the higher gross profit is a byproduct of the fact that KAs are being chosen based on criteria that indicate purchasing power, such as account revenue. This analysis would be aligned with Wengler et al. (2006) and Sharma (1997) studies that concluded that profitability are undermined by practitioners. Also, the results of Wengler et al. (2006) study showed that sales volume was the most commonly used KA selection criterion.

Therefore, it can be concluded that the selected KAs are more profitable than other accounts when measured in monetary terms. However, profitability does not seem to have had been used as a criterion in the KA selection. Thus, the reasons behind the higher profitability in monetary terms are most likely merely a consequence of company X prioritizing companies with higher account revenue.

### 6.2 Other KA selection criteria

In addition to the profitability related insights, other interesting results emerged. For instance, the AIC and BIC scores of the alternative models tell us that the best criterion for predicting the KA selection is customer total assets. The results implied that the odds of being chosen as a KA are bigger when the customer has bigger total assets. This result supports the conclusions of Sharma (1997) that stated that large and multifunctional companies are usually preferred as KAs. Since the size of a company seems add the odds of being selected as a KA, it may explain why customer companies that are chosen as KAs have on average more account revenue in comparison to other accounts, due to the fact that larger companies have more purchasing power than smaller ones.

Furthermore, the alternative model that used the opportunities identified variable as the predictive variable had the second best AIC and BIC scores. This result strongly indicate that the odds for a customer to be selected as a KAs for the next fiscal year increases when company X identifies more sales opportunities towards the customer. This result is aligned with Sharma (1997) that states that the KAs should be chosen
based on the selling company strategic priorities. Also, Ojasalo (2002) instructed companies to ask themselves: “Which existing or potential customers are important to us now and in the future?”. It seems that company X may have taken into consideration customers that show future potential in form of additional sales opportunities. The interesting thing is that the sales opportunities identified variable actually is a better predictor than even account revenue according to the alternative model regressions. However, the differences between the AIC and BIC scores between the two alternative models in question are not high. Also, there is the risk that the customers that are prioritized have more identified sales opportunities due to the fact that they already take part of KAM activities. In this case the actual KAM activities might be the reason behind the additional identified sales opportunities. But, the before mentioned scenario does not undermined the fact that additional identified sales opportunities can still be an important KA selection criterion in KA selection process, since sales opportunities may enable additional sales for company X in the future.

Adding the publically traded variable to the alternative nested model made the model significantly better according to likelihood ratio tests. But, in only two of the main logistic regression models the variable in question showed significant results. The main logistic regression model took to account other predictive variables, which clearly showed that the variables predictive value is not as good as for the other significant variables in the same models. Also, the alternative model with the publically traded variable had the worst AIC and BIC scores when comparing the alternative models that had significant results from the likelihood ratio test. Hence, it seems that company X does not at least select KAs only based on the fact that the customer is publically traded or not. Due to the contradicting results of the variable in question, it is impossible to make reliable interpretation of the variable in question.

Lastly, one of the most interesting insights is actually that relationship length does make any model better, either the main model binary logistic regressions or the alternative model binary logistic regressions. This means that that relationship length cannot have acted as a KA selection criterion during the KA selection process. In other words, company X does not prioritize customers based on how long they have been in business together. These results does not contradict the Wengler et al. (2006) study, which mentions that relationship length is not commonly used as a KA selection criterion in business-to-business companies. Meyer-Waarden et al. (2007) argues that
this type of criterion is more widely used in the business-to-consumer service industry, such as in retail, aviation and hospitality sectors (Meyer-Waarden et al. 2007). However, since professional service organizations are thought to be relationship oriented; relationship length actually could have been a reasonable KA selection criterion to consider. Even Ojasalo (2001b) suggests that professional services organizations should focus on establishing long lasting relationships.

6.3 Reliability and validity of the study

The validity and reliability of the results need to be discussed due to the fact that KAM, and especially KA selection, are very complicated topics to measure. The validity of a study refers to how accurately the study measures what it is supposed to measure, whereas reliability focuses on the consistency of the measurement instruments (Crossley et al. 2002). Overall, the tests are conducted on a sample that represents most of the population that can be considered relevant to the study. Therefore, most of the results can be considered valid and reliable for company X. However, since the study only focuses on data gathered from a single company, it cannot be considered generalizable for all companies that conduct KAM practices. But, the results give a strong indication of how multinational professional service organizations select the customers that they entitle for KAM practices.

Also, as the earlier literature suggests, no criterion should be used singly. The results of the study actually indicate that the KA selection is done based on several criteria, due to fact that none of the models fully explained the KA selection. The various main sample models correctly classified between 80-85% of the KAs and approximately 98% of the OAs. In other words, none of the predictor variables, even used together, correctly classified all the KAs in question. Therefore, there is a risk that some other variables would actually explain a lot better the KA selection that the ones used in the study. There might even be a single measurement that is used when KAs are selected. These issues affect both the reliability and validity of the study. However, the empirical study is built upon models that are tested with several data analysis methods to get as reliable results as possible. Thus, the conclusions and interpretations are backed by a combination of tests.

Furthermore, the results of the empirical study are based on the KA selection of a single fiscal year, i.e. FY16. However, the predictive variables and control variables are assembled from historical data from FY14 and FY15 according to the data timeframe.
illustrated in figure 4 and 5. The fact that the empirical study is based on a single fiscal years KA selection weakens the reliability of the results. But, since KAM is considered as a long-time investment, it is unlikely that the KA selection criteria would vary drastically between years. It can even be argued that it is more important that the results are based on the newest data possible. The customer data in this empirical study is based on the latest KA selection (FY16) at hand. Therefore, the results can be considered at least up to date.

Lastly, measuring customer profitability by using gross profit and gross margin as a percentage could in some cases seem inappropriate since indirect costs, such as sales and marketing related costs, are not included into the calculations. Also, these profitability measurements in question are only measuring the current profitability. Thus, no estimates of the future profitability of KAs can be made based on this study. However, in company X the gross margin and gross profit acts as an accurate measurement of current customer profitability due to the fact that everything from administration to the actual service delivery is billed to the customer based on an hourly fee. This means that the amount of indirect costs that can be associated with and specific account can be considered extremely small. Gross margin and gross profit could be considered more problematic for instance to business-to-business manufacturing companies that have a much bigger portion of the customer related costs as indirect costs. Therefore, the metrics used to measure customer account profitability can be considered valid in this study.
7 CONCLUSIONS

In this chapter the conclusions of the discussion are summarized. In addition to the summary, the theoretical contributions and the managerial implications of the study are discussed. Furthermore, suggestions for further research are presented.

7.1 Concluding remarks

As discussed in the earlier chapter, the relationship between KA selection and customer account profitability in company X is complex. The relationships between the variables in question vary depending on what type of profitability measure is used. Also, other possible KAs had to be taken into consideration in order to get reliable results. The conclusions of this study are made based on the results of several tests and various models that have been compared to each other with adequate comparison techniques.

It can be concluded that the selected KAs are more profitable than OAs when profitability was measured in monetary terms. But, when profitability was measured as an actual margin (percentage), no significant differences between KAs and OAs could be found. Further tests proved that account revenue is actually a better predictor than profitability in monetary terms for a customer to be selected as a KA. Moreover, the correlation matrix showed a nearly full positive correlation between account revenue and profitability in monetary terms. Together, these results strongly indicate that the higher profitability in monetary terms is only a byproduct of the fact that the same customers have higher account revenues. Therefore, the results strongly indicate that profitability, even in monetary terms, has not been used as a KA selection criterion by company X.

Furthermore, the total assets of a customer and the number of identified sales opportunities proved to be the best predictors for being selected as a KA. Hence, the size of the customer and the amount of future sales possibilities may have been contributing factors when the KAs have been selected. In contrast, the tests conducted proved also that the length of the customer relationships does not have a significant role in the KA selection process.

Consequently, it seems that customers with a lot of purchasing power are preferred as KAs. This claim can be supported by the fact that increased customer size, higher
account revenue and a higher number of sales opportunities add the odds of being selected as a KA.

7.2 Theoretical contribution and managerial implications

The results from the study have both theoretical and managerial implications. From a theoretical perspective it can be argued that the KA selection literature have clearly lacked studies were the relationship between KA selection and customer profitability has been researched in detail. The earlier literature such as Pels (1992) and Wengler et al. (2006) have discussed KA selection from a very general perspective. On the other hand, Sharma (1997) did highlight the role of profitability within KAM and introduced guidelines for KA selection, but still focused mainly on describing what types of customers prefer KAM. Nevertheless, it can be concluded from the Guesalgas and Johnston (2010) literature review that KA selection as a research topic has not been a broadly studied within KAM. Therefore, the KA selection literature can be considered quite narrow.

Furthermore, the results of this study are also unique due to the fact that nearly all of the KA selection literature has focused on manufacturing companies. For example, Sharma (1997) and Pels (1992) discussed KA selection from a supplier and buyer perspective, whereas this study has solely focused on the KA selection of a professional service provider. However, since the empirical part of this study has only focused on a single company’s KA selection, the results cannot be generalized for all professional services originations. Nevertheless, professional service organizations are known to have similar organizational structures, which is the reason why this study still can be considered to give reliable indications of how a typical professional services organization prioritize KAs. Also, most of the studies that have discussed KA selection, such as Pels (1992), Sharma (1997) and Wengler et al. (2006) have been qualitative or based on surveys. In contrast, this study has quantitatively analyzed internal and external company data.

Moreover, the data timeframe illustration presented as figure 4 can be utilized as a framework in further studies that aim to investigate the KA selection process of a company. The KA selection criteria can be changed according to the aim of the study. Also, the timeframe illustration in question can be considered adaptable for most of the business-to-business companies.
Lastly, company X itself has showed a strong interest towards the study. The study may help company X to identify weaknesses and strengths of their KA selection. The company might even find reasons to reconsider the criteria by which it prioritizes customer accounts. As mentioned in 7.1. “Concluding remarks” subsection, it seems that company X prefers to prioritize KAs based on criteria that indicate if the customers have a lot of purchasing power, while not taking to consideration current customer profitability related criteria. This type of approach works as long as the customers that have a high level of purchasing power are in monetary terms more profitable than other types of customer. However, if these types of customers would become less profitable in monetary terms due to increased costs of service delivery, it would not be noticed in the KA selection. Therefore, it is crucial for company X and other similar actors to take profitability related criteria to consideration when selecting new KAs.

7.3 Suggestions for further research

There are several topics within KA selection that could be addressed due to the fact that KA selection have not got as much attention in the academic literature in comparison with other KAM related topics. However, since profitability is one of the most important goals of KAM, it would be beneficial to study the relationship between KAM and profitability further. It would be interesting to conduct an event study where customer profitability would be measured before the customer is being selected as a KA and after customer has been enrolled to a KAM program for a number of years. This type of study would measure quite well if KAM activities actually increase the customer profitability of the customer account. Another interesting topic of research, which is related to profitability, would be to measure if companies that utilize KAM are generally more profitable in comparison with companies that do not utilize KAM. With a big enough sample and reliable data this type of study could prove to be a valuable addition to the KAM literature. However, the problem with this type of study is that many companies give special treatment to the most important customers without admitting it. This is what Wengler et al. (2006) call “hidden key account management”.

Furthermore, the KA selection literature lacks studies that focus the buying side, i.e. the customers that are prioritized. For instance, it would be interesting to study if the customers that are enrolled in KAM programs benefits from the KAM actions financially or my other means. A qualitative explorative study would probably be
necessary to conduct, where after it would be easier to gather the relevant data for a more generalizable quantitative study. Also, cultural differences in KAM and KA selection could be an interesting topic to study. There might be clear differences on how customers are prioritized between countries, such as the USA and Russia, or regions, such as South America and Asia.
SVENSK SAMMANFATTNING

Lönsamhet som ett kundprioriteringskriterium – Bevis från ett professionellt tjänsteföretag

Introduktion

Handeln mellan företag har förändrats drastiskt under de senaste årtiondena p.g.a. globaliseringen och den snabba teknologiutvecklingen. Denna förändring har ökat på kundkraven som har ställts på försäljningsorganisationer samtidigt som kostnadstrycket i företagen har stigit (Jones et al. 2005). Kundkrav, som t.ex. ökad teknisk kompetens, tydligare kommunikation, hög nivå av industriförståelse samt snabba reaktionsförmåga, har gjort kundhantering (account management) och nyckelkundhantering (key account management) till en mycket viktig del av affärsprocessen (Jones et al. 2005).

Starkt konkurrensutsatta företag som t.ex. professionella tjänsteföretag måste ofta sälja sina tjänster till ett orimligt lågt pris för att vinna de mest ansedda och mäktiga företagen som sina kunder (Nätti & Palo 2012; Piercy & Lane 2006). Detta fenomen ökar på risken att de ansedda och mäktiga kunderna förblir olönsamma för de säljande företagen (Piercy & Lane 2006). Olönsamma affärsrelationer med kunder orsakar i många fall dålig tjänste品质 som kan betydligt påverka de säljande företagens rykte (Piercy & Lane 2006). Därför kan inte onlösamma affärsrelationer med kunder tolereras under en längre tidperiod.

För att undvika olönsamma affärsrelationer är det mycket viktigt för företag som bedriver handel mellan företag att förstå vilka kunder som bör prioriteras, d.v.s. vilka som klassificeras som nyckelkunder. Dessa företag bör inse att inte enbart prioritera kunder som förväntar sig att bli prioriterade utan istället se till att prioritera de kunder som är lönsamma (Sharma 1997).

I forskningslitteraturen klassificeras kundprioritering (key account selection) som en del av nyckelkundhanteringsprocessen. Nyckelkundhanteringsprocessen har fått mycket uppmärksamhet i såväl den akademiska världen som i företagsvärdens. Detta framgår av Guesalga och Johnstons (2010) litteraturöversikt vars resultat presenteras i tabell 1. Av litteraturöversikten framgår det att ämnen som t.ex. organisering av
nyckelkundhanteringen, implementering av nyckelkundhanteringsprocessen och framgångsfaktorer i den har behandlats omfattande. Det som också framgår av litteraturöversikten är att själva kundprioriteringsprocessen har hamnat i skymundan. Därutöver har det lilla som skrivits om kundprioritering fokuserat på bolag inom tillverkningssektorn. Därför finns det ett klart behov av att forska i kundprioriteringsprocessen i företag som säljer tjänster åt andra företag.

**Syfte**

Syftet med avhandlingen är att mäta relationen mellan kundprioritering och kundlönsamhet i ett professionellt tjänsteföretag när andra kundprioriteringskriterier tas i beaktande.

Följande mer specifika forskningsfrågor har ställts upp:

FF1: Finns det en signifikant skillnad i kundlönsamhet mellan en nyckelkund och andra typer av kunder i ett professionellt tjänsteföretag?

FF2: Kan kundlönsamhet signifikant förutspå ifall en kund prioriteras som en nyckelkund när andra möjliga kundprioriteringskriterier tas i beaktande?

**Angreppsätt och begränsningar**

Den empiriska studien baserar sig på intern kundinformation som har samlats från ett professionellt tjänsteföretag. Företaget ifråga går under namnet företag X i denna avhandling. Kundinformationen av företag X har analyserats med hjälp av kvantitativa analysmetoder. Variablerna som baserar sig på den interna kundinformationen har uppställts utifrån kundlönsambetesiffror och kundprioriteringskriterier som introducerats och behandlats i tidigare forskningslitteratur.

Studien baserar sig på antagandet av Homburg et al. (2002) som förutsätter att nyckelkundhantering innefattar alla aktiviteter som har att göra med att hantering av de viktigaste kunderna. Följaktligen fokuserar den empiriska studien enbart på kundprioritering och inte på andra faktorer i nyckelkundhanteringsprocessen.
Lönsamhetsmätten som används i studien beskriver endast den nuvarande lönsamheten och används i studien som ett kundprioriteringskriterium. Företag X är ett multionationellt professionellt tjänsteföretag som har olika kundprioriteringar i olika geografiska områden. Denna empiriska studie fokuserar därför enbart på nordiska kundprioriteringar av företag X.

**Presentation av tidigare forskning**

Den teoretiska referensramen består av fyra delar, vilka är: introduktion till nyckelkundhantering, nyckelkundhantering i professionella tjänsterföretag, kundprioritering och kundlönsamhet.


Det bör även nämnas att nyckelkundhanteringen kan beskrivas genom olika dimensioner som aktiviteter, aktörer, resurser och nivå av formalitet (Homburg et al. 2002). Nyckelkundhanteringsaktiviteter kan bestå av anpassad prissättning, skräddarsydda tjänster och produkter, skräddarsydd kundservice, informationsutbyte, gemensam samordning av arbete och övertagande av funktioner utlagda av kunden (Homburg et al. 2002). Aktörer som är inblandade i nyckelkundhantering kan vara allt från högsta företagsledningen till de nyaste arbetstagarna. Trots det är forskningslitteraturen ense om att företagsledningen måste involveras i nyckelkundhanteringsprocessen. Från ett resursperspektiv kan det konstateras att istället för att enbart använda sig av personal inom försäljning och marknadsföring i nycklundhanteringsarbetet så borde även avdelningar som IT, logistik, tillverkning, finans och redovisning involveras (Homburg et al. 2002). Informationssystem är också
viktiga i de ifrågavarande processerna (Homburg et al. 2002). Nivån av formalitet varierar också i olika nyckelkundhanteringsprogram.


Därmed är kundprioriteringsprocessen under fokus i denna studie. Kundprioritering, som en del av nyckelkundhanteringsprocessen, bygger på den kända Pareto-principen som utgår från att 80 % av en specifik effekt orsakas endast av 20 % av effekten (Brynjolfsson et al. 2011). Det kan t.ex. antas att 80 % av försäljningen kommer från 20 % av kunderna (Brynjolfsson et al. 2011).

Kundprioriteringsprocessen i ett företag handlar alltså om att bygga upp en process som systematiskt ser till att de företag som borde prioriteras verkligen prioriteras. För att nå detta mål ska finansiella och icke-finansiella kriterium ställas som beskriver hur kunderna bör bli prefererade. (Pels 1992; Piercy & Lane 2006; Tzemeplikos & Gounaris 2013). Med hjälp av att kombinera olika kundprioriteringskriterier kan företag bygga upp modeller som de kan utnyttja i sin kundprioriteringsprocess. Dessa kriterier bör
kombineras på ett sätt som är i linje med det säljande företagets strategi (Sharma 1997; Ojasalo 2002).


**Data, metod och genomförandet av studien**

Datasamleit består huvudsakligen av interna kunddata av företag X. Detta företag har medvilligt överlåtit kundinformationen på villkoret att de kan bevara sin anonymitet. Dessutom får ingen känslig kundrelaterad information, som t.ex. kundernas namn, nämnas i studien. I studien används också extern kundinformation som har samlats från databaserna Odin och Orbis.

Variablerna som används i studien är nyckelkund kontra annan kund (KPS), kundintäkter (AR), bruttovinst (GP), bruttovinstmarginal (GMP), längd av affärsrelation (RL), identifierade försäljningsmöjligheter (SOI), totala tillgångar (TA) och ifall de är börsnoterade eller inte (PT). Nyckelkund kontra annan kund (KPS) och ifall kunden är börsnoterad eller inte (PT) är dummyvariabler. Variablerna bruttovinst (GP) och bruttovinstmarginal (GMP) fungerar som nuvarande kundlönsamhetsmått. Alla variabler förutom nyckelkund kontra annan kund (KPS) representerar möjliga kundprioriteringskriterier. Datasamleit som används i studien består av 798 kunder varav 89 är nyckelkunder och det har även kontrollerats för industri (CI) och land (HQ).


För att svara på den första forskningsfrågan har tre stycken envägs-variansanalyser (ANOVA) använts. I dessa analyser användes de finansiella måtten kundintäkter (AR), bruttovinsten (GP) och bruttovinstmarginalen (GMP) som beroende variabler (DV) medan nyckelkund kontra annan kund (KPS) användes som oberoende variabel (IV).
För att svara på den andra forskningsfrågan så användes det en mängd olika binära logitregressioner. Dessa regressioner har som beroende variabel (DV) nyckelkund kontra annan kund (KPS) och resten av variablerna är en kombination av oberoende variabler (IV). Alltsomallt utfördes 12 olika typer av regressionsmodeller som jämfördes med varandra med hjälp av Akaike (AIC) och Bayesian (BIC) informationskriterierna samt likelihood-kvotstest (LRT). Nagelkerke $R^2$ har också använts för se ifall resultaten av AIC och BIC måtten är i linje med pseudo $R^2$ måttet.

För att se till att datasamplet är användbart har det testats för multikollinearitet och heteroskedasticitet i enlighet med de krav som ANOVA-testen och de binära logitregressionerna ställer på datasamplet. Åtgärder har gjorts så att både ANOVA-testen och de binära logitregressionerna kan anses vara trovärdiga.

**Resultat redovisning**


Även de binära logitregressionerna påvisade att lönsamhet som en marginal inte har använts som ett kundprioriteringskriterium. Men de indikerar ytterligare att lönsamhet inte över huvudtaget har använts som ett kundprioriteringskriterium. Detta påstående stöds av att korrelationstestet visade en nästan full korrelation mellan variablerna kundintäkter (AR) och bruttovinst (GRU), samtidigt som AIC- och BIC-värdena visar att modellerna där kundintäkter har tagits i beaktande är mera sanna än motsvarande modeller som tar i beaktande bruttointäkter. Detta tyder på att den högre lönsamheten i monetära termer hos nyckelkunderna orsakas av högre kundintäkter.

Genom att kombinera olika varianter av binära logitregressionsmodeller och jämföra deras AIC- och BIC-tal samt därefter utföra LRT kan det dras slutsäten som säger vilka av de oberoende variablerna bäst förklarar valet av nyckelkunder. Dessa jämförelser
bevisar att en högre mängd totala tillgångar hos en kund förklarar bäst ifall en kund blir vald som nyckelkund hos företag X. Även en större mängd av identifierade försäljningsmöjligheter och högre kundintäkter förutspår signifikant ifall en kund blir vald som nyckelkund. Trots det visar det sig att längden av en affärsrelation med en kund inte signifikant förutspår om en kund blir vald som nyckelkund.

**Konklusioner**


Resultatet indikerar klart att kunder med stor köpkraft prioriteras utan att lönsamheten i större grad tas i beaktande. Denna typ av förfarande fungerar så länge som kunder med stor köpkraft är lönsammare än andra kunder. Dock kan detta förfarande bli problematiskt ifall en stor andel av de kunder som anses ha stor köpkraft blir olönsamma p.g.a. ökade kostnader som kan relateras till utförandet av tjänsterna. Därför borde även lönsamheten tas i beaktande då kundprioriteringen görs.

Slutligen måste det även konstateras att studien baserar sig på nuvarande lönsamhet. Därför kan inga slutsatser om den framtida lönsamheten dras. Resultaten kan inte generaliseras för alla bolag p.g.a. att studien använder sig av interna data från ett enda bolag. Trots det ger studien en bra inblick i hur kundprioriteringen görs i professionella tjänsteföretag.
REFERENCES


Gujarati, D.N. 2011, Econometrics by example, Palgrave Macmillan, Houndmills, Basingstoke, Hampshire ; New York.

Homburg, C., Totzek, D. & Droll, M. 2010, "All customers are equal, but some are more equal SHOULD FIRMS PRIORITIZE THEIR CUSTOMERS?", GfK-Marketing Intelligence Review, vol. 2, no. 1, pp. 16-25.


Storbacka, K. 2012, "Strategic account management programs: alignment of design elements and management practicesnull", *Jnl of Bus & Indus Marketing*, vol. 27, no. 4, pp. 259-274.


### APPENDIX 1

**Model LM**

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<tr>
<th>Variables</th>
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<th>S.E.</th>
<th>Wald</th>
<th>P (Sig.)</th>
<th>Exp (B)</th>
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<th>More details</th>
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<td>AIC</td>
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<tr>
<td>BIC</td>
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<td>Correct predictions % (KA)</td>
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<td>Correct predictions % (OA)</td>
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<td>Correct predictions % (total)</td>
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Note: Controlled for CI customer Idustry (18+1) and HQ - customer headquarter country (3+1). Significant when $P<0.5$. The nested model refers to the reduced model.
### Model LM1

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More details

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Note: Controlled for CI customer Industry (18+1) and HQ - customer headquarter country (3+1). Significant when $P \leq 0.5$. The nested model refers to the reduced model.
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More details

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Note: Controlled for CI customer Industry (18+1) and HQ - customer headquarter country (3+1). Significant when P<0.5. The nested model refers to the reduced model.
### Model LM3

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More details

| n          | 610            | 0.822 | 110,733 | 166,733 | 188,722 | 82.9 | 98.5 | 96.6 |

Note: Controlled for CI customer Industry (18+1) and HQ - customer headquarter country (3+1). Significant when P<0.5. The nested model refers to the reduced model.
# APPENDIX 2

## Model summary LS, LS1, LS2, LS3

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<tr>
<th>Variables</th>
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<th>LS2 (+ GMU)</th>
<th>LS3 (+ GMP)</th>
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<td>Exp (B) P (Sig.)</td>
<td>Exp (B) P (Sig.)</td>
<td>Exp (B) P (Sig.)</td>
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<td>n</td>
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<td>610</td>
<td>610</td>
<td>610</td>
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<td>0.266</td>
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<td>99.3</td>
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<td>(total)</td>
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Note: Controlled for CI: customer Industry (18+1) and HQ: customer headquarter country (3+1). Significant when P<0.5. The nested model refers to the reduced model.
## Model summary LS4, LS5, LS6, LS7

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<th>LS6 (+ TA)</th>
<th>LS7 (+PT)</th>
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<td>Exp (B)</td>
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Note: Controlled for CI: customer Industry (18+1) and HQ: customer headquarter country (3+1). Significant when P<0.5. The nested model refers to the reduced model.