

Measuring marketing productivity A comparative study between fuzzy-set and regression analysis

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Department of Marketing Aalto University School of Business

Author Kalle Korhonen					
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Thesis advisors Henrikki Tikkanen, Sami Kajalo					
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Abstract

Measuring marketing productivity and linking it to the bottom-line of the firm has gained a lot of attention among marketing researchers. However, most of marketing literature consists of models examining only the direct linear effects and neglecting the combinatorial effect of inputs.

This thesis uses a novel approach called Fuzzy-Set Qualitative Comparative Analysis (FS/QCA) that overcomes the weaknesses of traditional methods by examining the marketing activities as configurations that lead to certain outcome. Additionally, the results are compared against traditional regression based models.

The thesis focuses on measuring the effectiveness of airline ticket promotions for specific routes. The case company is Finnair - the largest airline of Finland and the fifth oldest airline in the world. The case data consists of all promotions for one European point of sale carried over the full year of 2015.

The most important contribution of this thesis is to describe the relationship between the performance outcomes and the different marketing configurations - the selected marketing promotion variables. It is shown that FS/QCA methodology results in more managerially meaningful explanation of promotion performance and that the configurations can be only partially explained by the traditional regression methods. Theoretically the study contributes to the validation of the rather new methodology FS/QCA in the field of marketing.

Keywords marketing performance measurement, fuzzy-set qualitative comparative analysis, regression analysis

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Tiivistelmä

Markkinoinnin suorituskyvyn mittaaminen ja sen yhdistäminen rahalliseen lopputulokseen on saanut paljon huomiota markkinoinnin tutkijoiden keskuudessa. Kuitenkin pääosa markkinoinnin kirjallisuudesta on keskittynyt suorien lineaaristen vaikutusten havainnointiin ja siten sivuuttanut kombinatoristen vaikutusten tutkimisen.

Tämä tutkielma käyttää tuoretta lähestymistapaa nimeltä Fuzzy-Set Qualitative Comparative Analysis (FS/QCA), joka sivuuttaa perinteisten menetelmien heikkoudet tarkastelemalla markkonointiaktiviteettejä konfiguraatioina jotka johtavat tiettyihin lopputuloksiin. Lisäksi tämä tutkimus vertaa tällä menetelmällä saatuja tuloksia perinteisen regressioanalyysin tuloksiin.

Tutkielman tutkimuskohteena on lentolipputarjousten suorituskyvyn mittaaminen tietyillä reiteillä. Tutkittavana yrityksenä on Finnair - Suomen suurin lentoyhtiö. Tutkimusaineisto koostuu kaikista vuoden 2015 aikana toteutetuista tarjouskampanjoista yhdessä eurooppalaisessa myyntiyksikössä.

Tutkimuksen tärkein tulos on selittää markkinoinnin konfiguraatioiden eli tarjousten eri piirteiden ja myynnin suorituskyvyn välinen suhde. Tutkimus osoittaa, että FS/QCA metodologia johtaa käytännönläheisempiin ja ymmärrettävämpiin selityksiin markkinoinnin suorituskyvystä ja että saadut konfiguraatiot voidaan vain osittain selittää perinteisen regressioanalyysin avulla. Teoreettisesti tutkimus osallistuu uuden FS/QCA menetelmän validointiin markkinointitutkimuksessa.

Avainsanat markkinoinnin suorituskyvyn mittaaminen, fuzzy-set qualitative comparative analysis, regressioanalyysi

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1 Introduction

Measuring marketing productivity and linking it to the bottom-line of the firm has been one of hottest topics in marketing lately. Literature has been full of different models of linking marketing performance to firm performance (e.g. O'Sullivan and Abela, 2007; Rust et al., 2004) and Marketing Science Institute has listed marketing analytics and measuring the value of marketing activities and investments as one of its research priorities (Marketing Science Institute, 2014).

However, most of the marketing literature has been consisting of models that examine direct effects. That is, considering the effect of individual input variables to the outcome as one entity and therefore neglecting the combinational effect of inputs. This can be seen for example in regression, which assumes linearity in the variables and that their contribution is independent of each other (Kent, 2005).

In reality, many marketing problems consist of different configurations that result into an outcome. In other words, the marketing outcome can be accomplished using different means that are independent of each other and therefore examining the problem involves classification using several characteristics (Frank and Green, 1968). Thus the problem falls under configurational theory where elements of configuration are causally connected to specific outcome (Fiss, 2008).

Traditionally, examining such problems has been done in two ways. First approach is to identify natural groupings in the data and after that define a formal model describing the output using the groups (Frank and Green, 1968). The second approach is to assume moderating effects – that is, making a hypothesis that the inputs affect some moderating variable, which then affect the output (Sharma et al., 1981).

Both approaches have their limitations. The limitation of the first approach is that the groupings are independent of the output. The grouping considers only the similarity of the observations – by grouping them as units of analysis neglecting the configurational view. Usual method for this approach is to use clustering or factor analysis to the data to find the groupings and then applying regression to examine their causal relationship to the output (Kent and Argouslidis, 2005; Fiss, 2008; Vorhies and Morgan, 2003; Punj and Stewart, 1983). As Kent and Argouslidis (2005) argue, this illustrates the limitation of the approach

as the groupings are done using based on statistical measures of similarity, not by explaining them in terms of outcome.

The limitation of the second approach is that the existence of moderator must be known before the analysis. That is, the method does not find the possible moderators itself, but needs the guiding hand of the researcher. Methods that use the second approach include step-wise regression (Hair et al., 2012: 176) and structural equation modeling (Hair et al., 2012: 541).

One way of overcoming these limitations is to use set-theoretic methods that do not disaggregate the observations into independent and analytically separate aspects, but treat their configurations as different types of cases (Kent, 2005). Thus, in this study I assume that marketing productivity is explained using different combinations of variables. In literature this causality of combinations has been referred as equifinality, typologies, or taxonomies. According to Bertalanffy (1950), equifinality occurs when the final state may be reached from different initial conditions and in different ways. Thus, the marketing activity can be classified using different typologies (Kotler, 1972) or taxonomies (Frank and Green, 1968). It is important to note that the latter can be used to offer meaningful interpretation of the data, thus provide linguistic summarizations from the data that are associated with the cases (Mendel and Korjani, 2012: 1). That is, the aim is to offer a full description of a rather complex phenomenon (Frank and Green, 1968).

One of recent studies that have targeted this shortcoming has been the configurational explanation of marketing outcomes research process (Vassinen, 2012). It provides clear guidelines for the research using methodological quantitative tool Fuzzy Set Qualitative Comparative Analysis (FS/QCA) developed by Charles Ragin (1987, 1992, 2000, 2008). The approach is interesting especially considering its usability in contexts with limited amount of data, which makes it suitable for applications such as marketing management or decision support systems (MMSS: Wierenga et al, 1999; MDSS: Lilien, 2011).

Within that background, I am going to use the FS/QCA methodology to replicate a similar empirical study of airline ticket promotions for boosting the revenue of the specific routes (see Vassinen, 2012: 117-154). The aim is to show the methods usability and also address the lack of triangulation in Vassinen's research by comparing the results to traditional regression based models. Additionally, the objective of course is to explain what configura-

tions of promotion properties explain the revenue outcomes and how the results differ between different methods.

1.1 Research questions and objectives

This thesis investigates the performance of promotions through looking at configuration of their properties. Additionally, it examines the relationships of these configurations not only to the positive revenue outcome, but also the negative. Because the aim of the thesis is both validating and comparing the rather new research process, the research question can be formulated as:

How does FS/QCA explain the marketing actions relation to outcomes and how the outcomes compare to results from regression analysis?

In order to simplify the research question, the question can be divided into following questions:

Which permutations of promotion properties, found using FS/QCA, are relevant considering effective outcome?

Can these configurations be validated using triangulation with regression analysis?

Which advantages or disadvantages does FS/QCA have compared to other methods?

1.2 Methodology

As the study is methodological (validation) by nature, the justification of the quantitative method is self-explanatory. Note that FS/QCA is described as attempt to bridge quantitative and qualitative approaches (see Ragin, 1987 or Chapter 3 in Vassinen, 2012), so that it would yield managerially relevant information otherwise difficult to assess and interpret. As Morgan, Clark, and Gooner (2002) argue, new methodologies should be contextually relevant in order to be managerially meaningful and practical. Therefore opening the infamous 'black box' of marketing by explaining the promotion outcomes as configuration of its properties.

In the context of marketing research I see the approach more quantitative than qualitative. Although the data gathering can be of qualitatively inquiry, it is a logical – not statistical – technique and the fuzzy set treatment requires at least some mathematical quantitative understanding. It is also similarly heuristic method than clustering, which is considered as quantitative method. The empirical data is obtained by observing the promotion details from announcements from the business manager initiating the promotion and collecting the data from the case company's electronic sources. The case company is Finnair – the largest airline of Finland and the fifth oldest airline in the world owned by majority stake by the government of Finland.

1.3 Research contribution

The contribution of this thesis is to describe how different marketing configurations (i.e. the selected marketing promotion variables) and their outcomes (e.g. performance measures such as profit, Ambler et al., 2004) can explained using specific models (i.e. FS/QCA and regression). It is shown that using the FS/QCA methodology the researcher can acquire more managerially meaningful way of explaining the promotion performance. This thesis identifies the promotion configurations which have the largest revenue impact and shows that the configurations can be only partially explained by the traditional regression methods. Theoretically, the study contributes to the validation of the rather new methodology (FS/QCA) in the field of marketing.

1.4 Structure of the thesis

This thesis is organized as follows. In the Chapter 2, literature reviews is made and the theoretical framework of the thesis is formulated. Then in the next Chapter 3, the different analysis tools used in this thesis are introduced – namely Qualitative Comparative Analysis, Fuzzy-set Qualitative Comparative Analysis, and regression analysis. In Chapter4 I will present the case company, conduct the analysis, and present the results. Finally in Chapter 5, I will present the conclusions of this thesis, discuss its managerial implications, and present its limitations.

2 Literature review

The purpose of this chapter is to review the theoretical antecedents of this thesis in marketing literature. The context of this research is in the study of strategic marketing and marketing performance measurement. The chapter is structured as follows. First, I will discuss strategic marketing and its historical development and definition. Then, I will move to discuss marketing performance measurement – different frameworks, valuation measures and the difference between them. And last, I will combine the topics discussed into the theoretical framework used in this thesis.

2.1 Strategic marketing and the resource based view of the firm

The strategic role of marketing can be defined as "a link between the delivery of value to customers and levels of customer satisfaction leading to potential market share and profitability gains" (Fahy and Smithee, 1999). One of the most common concepts defining this link is the resource-based view of the firm (RBV), which sees market-based assets as resources explaining performance and competitive advantage (Wernerfelt, 1984; Peteraf, 1993; Srivastava, Shervani, and Fahey, 1998; Fahy and Smithee, 1999). These assets are generated through marketing activities and have characteristics such as value, rarity, barriers to duplication, and non-substitutability (Srivastava, Shervani, and Fahey, 1998; Fahy and Smithee, 1999). Thus the attributes are explaining why using the resources result in sustainable competitive advantage.

2.1.1 The development of the resource-based view

As a rather complex theory of firm heterogeneity, the meaning of resource-based view has developed over time (Fahy and Smithee, 1999). Originally hailing from strategic management, RBV was characterized as a process of industrial development. The discussion addressed the potential importance of firm-specific resources. Instead of concentrating on market structures, the researchers argued that "exceptional advantages for its trade" were important factors in achieving surplus profit (Robinson, 1933 as cited in Shove, 1933). Some authors even argue that the early research identified the same key assets – such as brand awareness – that are fundamental in strategic marketing literature (Fahy and Smithee, 1999).

Similarities can be also found from the literature of strategic management. For example, in the seminal work by Ansoff (1970) that considered the fit of internal capabilities to the outside opportunities when making decision to expand or diversify. Or in the work by An-

drews et al. (1982) that included the key attributes of the implementers to the company's strength and weaknesses. Or the well-known five forces model of Porter (1979), which showed how firms could benefit by positioning themselves along various stakeholders.

The term resource-based view of the firm was finally introduced in 1984 by Wernerfelt (1984) and it changed the focus from production to how firms use their resources. Wernerfelt (ibid: 172) gives such examples of resources as: "brand names, in-house knowledge of technology, employment of skilled personnel, trade contacts, machinery, efficient procedures, and capital" and describes his paper as "a first cut at a huge can of worms" (ibid: 180). But it was only until late 1980s when the academics became interested in firmspecific variables instead of industry specific attributes or external market forces. Thus a wide variety of papers emerged to discuss cases of companies having certain skills or capabilities that explained their outperformance compared to others (see e.g. Barney, 1986; Ghemawat, 1986; Grant, 1991). For example, Barney (1986) explains the above normal returns of companies using their different expectations about the future value of strategic resource. In 1994, Wernerfelt's original resource based view article was awarded Strategic Management Journal best paper price for being truly seminal (Wernerfelt 1995).

2.1.2 The definition and characteristics of resources

A number of different definitions and classification of these resources have been made. Originally Wernerfelt (1984) defined them loosely as anything that can be strength or a weakness for the firm. Few years later, Grant (1991) defined them as resource inputs to the production process. And Barney (1991) defined them as all assets, capabilities, organizational processes, firm attributes, information, knowledge controlled by the firm, which can be used to implement strategies to improve effectiveness and efficiency. In other words, a resource can be almost anything controlled and contained by the firm internally.

The common factor in most of the literature is that the usage of the resources leads into competitive advantage or sustainable competitive advantage. According to Barney (1991) competitive advantage can be defined as a value creating strategy not simultaneously being used by competitors, and sustainable competitive advantage as a strategy that is not reproducible by competitors. Thus having competitive advantage means exceeding performance vis-a-vis firms that are operating in the same industry.

The key in resources creating competitive advantage is that they have so called VRIN characteristics (Barney 1991). The most used definition is that of Barney's (ibid) and it

consists of valuable, rare, imperfectly imitable, and non-substitutable resources. I will discuss them separately in the following paragraphs.

Resources are valuable when they are enablers of strategies that improve efficiency and effectiveness. Barney (ibid.) even argues that valuability is antecedent of an attribute to be considered as a resource, by which he means something that can be used to exploit opportunities or neutralize threats in market environment.

On the other hand, resources are rare when they are not accessible to competitors. That is, a common and available resource cannot be a source of competitive advantage due to is prevalence. It is worth noting that rare resource can consists of a bundle of resources – a particular mix of physical capital, human and organizational capital (ibid.).

How valuable and rare the resource is, an additional constraint is that is has to be imperfectly imitable. Company accruing a valuable and rare resource can give first mover advantage, but in order it to be sustainable other firms should not be able to reproduce it. Non-imitability of a resource can be explained using three reasons: unique historical conditions, causal ambiguity, and social complexity. Unique historical conditions mean that the source of the resource cannot be understood independent of its history. Meaning that there is a path which firm follows through history obtaining valuable and rare resources that cannot be replicated (Arthur et al., 1987). On the other hand, causal ambiguity means that the link between resources and competitive advantage is not completely understood (Dierickx and Cool, 1989). And finally, social complexity means organizational attributes like social relations, culture, traditions that are usually very difficult to imitate (Barney, 1986a).

The last attribute of the resources is substitutability. The resource cannot be a source of competitive advantage if there exists other equivalently valuable resources. Two valuable resources are equivalent if they can be used to implement the same strategies (Barney, 1991). As a result, numerous companies can achieve similar results with different means. Substitutability has at least two forms (ibid.). First, the resource can be substituted by similar resource. For example, a high performing team cannot be exactly copied, but it is possible to develop similar team. Second, substitution can be done using different resource. For example, the same strategy can be achieved using strategic vision or a formal strategy planning process.

As with definition of resources, the VRIN characteristics differ depending on the author. Grant (1991) defines them as durability, transparency, transferability, and replicability and leans towards imitability and substitutability side of Barney's (1991) attributes. Collis and Montgomery (1995) define them as durability, inimitability, appropriability, substitutability and competitive superiority. And finally, Amit and Schoemaker (1993) list a total of eight attributes: complementarity, scarcity, low tradability, inimitability, limited substitutability, appropriability, durability and overlap with strategic industry factors. All in all, the common characteristics of these attributes is that they bring value to the company and competitors are unable to duplicate them.

2.1.3 Resource-based view and marketing

RBV's influence in marketing can be found in the studies of Hunt and Morgan (1995) on competitive advantage and Day's (1994) study marketing capabilities. First, I discuss the latter and then link the capabilities to the former competitive advantage.

In RBV resources have been typically divided into assets and capabilities (Day, 1994; Fahy and Smithee, 1999). Assets are usually the resources the business has accumulated and they can be divided into tangible and intangible. A tangible asset is for example a physical facility and intangible asset nonphysical brand equity, but their similarity lies in that their value can be measured. On the other hand, capabilities differ in their in-measurability and that they are, for example, routines and practices that cannot be imitated (Dierickx and Cool, 1989). Capabilities are complex bundles of skills and accumulated knowledge that enable firms to make use of their assets through different business processes (Day, 1994). The problem is, of course, that capabilities are not easily observed, which makes them hard to identity. Sometimes the capability is really tacit and dispersed in the organization.

Day (ibid.) divides marketing capabilities into market sensing, customer linking, and channel bonding capabilities. Market sensing consists of the ability of learning about customers, competitors, and channel stakeholders. Strictly speaking market sensing is enabled by the firm's systematic process of gathering, interpreting, and using market information in capturing customer needs, wants, and preferences. It enables the firm to determine events and trends in their market ahead of competitors and make more accurate responsive actions. On the contrary, customer linking means creating and managing close customer relationships. Thus, instead of working at arm's length the aim is to collaborate with the customer in communication, and problem solving. Finally, channel bonding is similar to customer linking, but involves relationships with channel members such as wholesalers and retailers (Song et al., 2005).

Day (1994) argues that these capabilities result into organization with market orientation, which can be described as the ability of the organization to use information about customers and competitors (Kohli and Jaworski, 1990) or the application of resources in creation of superior customer value (Narver and Slater, 1990). Therefore the capabilities result into superior performance and competitive advantage.

The capabilities of Day (1994) match the needs of Hunt and Morgan's (1995) comparative advantage theory of competition. Hunt and Morgan (ibid.) argue that we should expand the meaning of resources from tangible to include intangible resources such as organizational culture, knowledge and competences. And also, that these resources should not be only used efficiently, but new ones should be created. They argue that these kind of resources bring comparative advantage, which leads to competitive advantage in marketplace and finally to superior financial performance.

This theory also explains why firms continuously create new resources in the marketplace. Hunt and Morgan (ibid.) explain that the industry demand is always changing – for example, customer's preferences change – and customer have always imperfect knowledge of products matching their tastes as obtaining such information is costly. The firm's resources enable to produce a matching market offering, but as competition is a constant struggle for these resources and superior financial performance occurs only when a firm's comparative advantage in resources continues to yield competitive advantage, there is a constant need for renewal (ibid.). Interestingly, superior financial performance is defined only compared to competitors – not maximum possible performance – due to bounded rationality and impossibility to have and use perfect information (Simon, 1979).

2.1.4 Critique within RBV and marketing

Resource-based view and its derivatives have not been dignified without criticism. First, Srivastava, Fahey, and Christensen (2001) argue that RBV researchers (such as Barney, 1991; Grant, 1991; Wernerfelt, 1984) have underestimated the fundamental processes by which resources are transformed to something valuable to customers. They also claim that similar marketing theorists (such as Day, 1994) have not fully articulated the processes, which are used in transforming resources into competitive advantage.

Second, Dickson (1996) claims that the comparative advantage theory is not dynamic and does not take external and internal change into account. That is, there is not enough importance put on path dependency and higher order learning processes. However, Hunt and Morgan (1996) responded to this criticism by adding feedback loops from competitive advantage and performance back to resources. They also noted that they not only incorporate high order learning processes, but also show how firms learn from the process of competition itself, and that their theory accommodates path dependencies as the theory contains evolutionary elements.

Third, because of its focus on capabilities of internal resources Hooley, Möller and Broderick (1998) criticize RBV for ignoring the external market changes and orientation. That is, "runs the risks of myopia in rapidly changing turbulent environments" (Hooley, Möller and Broderick 1998: 98). However, their discussion is based on the premise that resource-based view and market orientation are two separate themes in marketing strategy literature. Thus, although acknowledging that the themes are somewhat contradictory, they admit that these two approaches can be reconciled – therefore affirming the relationship between resources and marketing assets and capabilities.

2.2 Marketing performance measurement

The idea and need for measuring marketing performance is certainly not new as demonstrated by the still taught quote from John Wanamaker, US department store merchant: "Half the money I spend on advertising is wasted; the trouble is I don't know which half." According to O'Sullivan and Abela (2007) the ability of measuring marketing performance has significant impact on performance and profitability. It shifts the attention away from budgets and programs towards measurements efforts. O'Sullivan and Abela (ibid.) divide the marketing performance measurement into three categories: measurement of marketing productivity (Morgan, Clark, and Gooner, 2002; Rust, Lemon, and Zeithaml, 2004), identification of metrics (Ambler, 2000), and measurement of brand equity (Aaker and Jacobson, 2001; Ailawadi, Lehmann, and Neslin, 2002). The interest of this study leans to the side of measurement of marketing productivity. In the following section I discuss two different frameworks for measuring marketing productivity: the chain of marketing productivity and the framework for marketing accountability.

2.2.1 Chain of marketing productivity

The final goal of marketing performance measurement is to measure marketing productivity. Marketing productivity can be defined as how the marketing investments influence marketplace performance (Clark and Ambler, 2001; Rust et al., 2004). According to O'Sullivan and Abela (2007) this should not focus on products, pricing, or customer relationships, but on the marketing activities, which they define as marketing communication, promotion and other activities. This influence can be evaluated by using a framework called chain of marketing productivity developed by Rust et al. (2004). The framework, seen in Figure 1, conceptualizes a chain-of-effects model where the marketing actions of the company propagate to the financial standing point. Marketing performance measurement examines how marketers can measure the results along the chain of marketing productivity – which metrics and factors can be used (O'Sullivan and Abela, 2007). In the following, the elements of the chain are described.

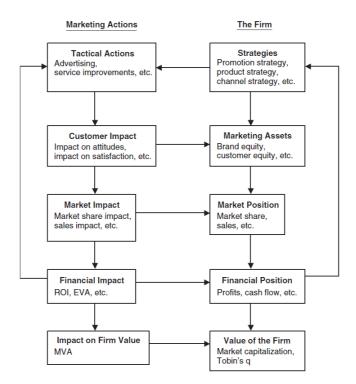


Figure 1. The chain of marketing productivity (Rust et al. 2004)

Strategies and tactical marketing actions. This includes the market strategy of the company and its contribution to the used tactical marketing actions that cause marketing expenditure. Marketing actions can be measured, for example, using share of voice: the share of media exposure compared to the industry total in the product category (Jones, 1990). This can be calculated as a share of marketing expenditures (Tellis and Weiss, 1995) or as sales volume that is easily observed and measured isolating the action from other decisions or competition (Webster, 2005). However, as Webster (2005) notes, strategy should always guide tactical actions.

Customer impact. Customer impact considers how marketing actions affect customers' knowledge. These can be measured using five dimensions of customer mindset: awareness, associations, attitudes, attachment and experience (Ambler et al., 2002; Rust et al., 2004).

Marketing assets. Marketing assets are customer-focused measures of the value of the company. Two common measures of marketing assets are brand equity and customer equity. The former is the intangible value of the company that surpasses the physical assets (Duncan, 2008: 93). The latter is the sum of all current and future customers' lifetime values, where the lifetime value is the discounted profit stream from the customer (Rust et al., 2004).

Market impact and position. Market impact and position consider the company's market share and sales, and the related competitive market position. Thus the benefits arising from the improvements in the marketing assets (Rust et al., 2004). For example, a company having a superior position and strong brand leads to higher perceived value of the offering.

Financial impact and position. Financial impact relates the market impact to the marketing expenditures. The most commonly known approach is to calculate return-of-investment, which is the discounted return expressed as percentage of discounted expenditure (Rust et al., 2004). Other common measures are the internal rate of return, the discount rate that would make the return equal to the expense; the net present value, return minus the expense; and the economic value added, the net operating profit minus the cost of capital. According to Rust et al. (2004) many managers consider financial impact as the most crucial measure. In other words, the effect on sales is important considering any marketing effort. However, the problem with accounting based measures is that they are retrospective and examine only the historical performance. The financial impact, on the other hand, affects the financial position of the firm that can be measured as profits or cash flow.

Impact on the value of the company. This final element connects the marketing actions to the changes in the company's market value and the market value added. Several measures can be used that rely on the company's stock performance, such as market capitalization and the total value of the outstanding shares of the company. In marketing perspective, the most interesting measure is how the market value of the company relates to the tangible

assets of the company. Thus marketing is expected to effect to the intangible value of the company.

2.2.2 Framework for marketing accountability

The problem with the chain of marketing productivity is that the links from actions to assets, and finally to value of the firm, is extremely complex to measure as simple inputoutput ratios do not capture the cumulative impact of marketing processes and activities (Grewal, 2009). Marketing academics spend most of their time analyzing marketing assets like brand equity while higher management emphasize financial impact like revenue or return on investment (Stewart, 2009). Additionally, there is only little common agreement how to measure the long-term effects of marketing (Dekimpe and Hanssens, 1995). Therefore a common simplification is to analyze the link between actions and cash flows, which are seen as antecedents of shareholder value (Srivastava, Shervani, and Fahey, 1999). According to Srivastava, Shervani, and Fahey (1999) shareholder value drivers are strongly linked to cash flow and its properties: acceleration of cash flows, enhancing cash flows, and reducing the risk and volatility of cash flows.

One such simplification of the chain of marketing productivity is Stewart's (2009) framework for marketing accountability. Stewart calls cash flow as the "ultimate marketing metric" and argues that marketing activities outcomes should be examined respect to their cash flow. Thus it is not sufficient to stop the measurement of marketing outcomes to the intermediate outcomes, such as increase in brand equity, but further need exist to link the intermediate outcome to financial outcome as seen in Figure 2.

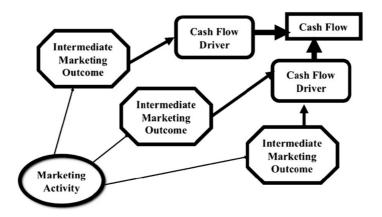


Figure 2. A framework for marketing accountability (Stewart 2009).

Stewart takes also in account that marketing activities can produce many different types of outcomes ranging from short-term to long-lasting effects. Figure 3 illustrates these three

options: short-term effects, long-term effects, and real options. Short-term effects are currently the most successfully identified, for example, in the increase of sales associated with price promotion. On the other hand, long-term effects occur in the present, but simultaneously alter the market over long term giving persistent gains (Dekimpe and Hanssens, 1995). An example of such activity is building of brand equity. Finally, the third type is real options – the opportunities that marketing create to the firm that may or may not be pursued in the future (Stewart, 2009). For example, a strong brand that can be extended in the future, an opportunity that can be either used or not, but still has a value (Luehrman, 1998).

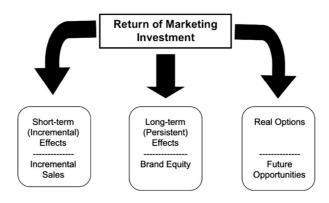


Figure 3. Types of return on marketing activities (Stewart 2009).

The framework of marketing accountability can be used as a formal audit process to assess the return on marketing activities (Stewart 2009). The first step is to identify the cash flows of the company. Then in the second step, the firm must identify the intermediate marketing outcomes that clearly link to the observed cash flows. In the third step, the marketing metrics need to be conceptually and causally linked to the cash flow drivers, and every marketing action should have at least one identifiable outcome metric. Finally in the fourth step, the assumptions between the linkages need to be identified and tested.

2.3 Theoretical framework

Both the chain of marketing productivity and the framework for marketing accountability have similar view of marketing actions as a driver of financial results. In this thesis, marketing actions play a central role when examining the effectiveness of promotions. Rather said, the marketing actions are thought to consist of different properties that as an entity result into intermediate marketing outcome and can been finally seen in cash flow. The knowledge of using these properties efficiently can also be discussed in terms of the resource based view of the firm, in which value creating assets are divided into tangible –

such as money and physical resources – and intangible – such as knowledge (Srivastava, Shervani, and Fahey, 1998). The intangible market-based assets are further divided by Srivastava, Fahey, and Christensen (2001) into relational and intellectual. Relational assets are external assets not under control of the organizations such as customer perceptions. Intellectual assets are internal to the organization and cover, for example, the know-how of promotion properties that this thesis discusses.

According to Srivastava, Fahey, and Christensen (2001: 5) "Business strategy involves identifying and selecting market segments, developing appropriate offerings and assembling the resources required to produce and deliver offerings." In this context, I use marketing performance measurement in identifying and selecting appropriate offerings. In other words, promotion planning is an organizational process which converts intellectual market-based assets into offerings that customer's desire – generating economic value for the firm (Srivastava, Fahey, and Christensen, 2001). This is well in line with the resource-based view, which emphasizes strategic choice: identifying, developing and deploying key resources to maximize returns (Srivastava, Shervani, and Fahey, 1998; Wernerfelt, 1984). Finally, the resource-based theory underscores that capabilities originate from the activities undertaken by people within firms – such as the business manager planning the promotion (Amit and Schoemaker, 1993; Barney, 1986a; Dierickx and Cool, 1989; Leonard-Barton, 1995; Nonaka, 1994).

Following the work of Stewart (2009), Figure 4 depicts the framework of this thesis. Marketing activities consists of different configurations of properties. These properties are then used in executing the marketing action, which result into marketing outcomes. Finally these marketing outcomes result into financial results. Therefore the aim is to implement an audit of marketing accountability by identifying different configurations, marketing outcomes and cash flows, and then identifying linkages between configurations and marketing outcomes, and outcomes and cash flows.

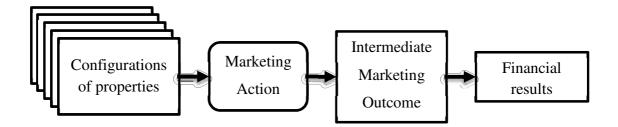


Figure 4. Linking configuration of marketing actions to financial outcomes.

I argue that systemically examining the different marketing configurations and their outcomes, the firm creates new knowledge and this can enable increases in cash flows. As Vorhies and Morgan (2005) argue, market-based organizational learning is an important source of competitive advantage. Thus, the generated knowledge in this thesis can be seen as an intangible resource (Hunt and Morgan, 1995; Wernerfelt, 1984) for the firm and the manager using this resource through promotion process can be seen as a capability (Day, 1994) or market-based asset (Srivastava, Fahey, and Christensen, 2001) that can be used to leverage more responsive advertising and promotions (Keller, 1993).

In this thesis the different marketing configurations are examined using two different methodologies. First, a rather new approach in marketing – FS/QCA – is used, which has already generated promising results in discovering configurational explanations for marketing outcomes in suitable research contexts (Vassinen, 2012; Vassinen and Tikkanen, 2011). Second, a more traditional regression method is used to validate the results from FS/QCA. Finally, the results and their differences are discussed along with their managerial implications.

3 Methods

The difficulty of finding right combination of variables or elements of marketing activities and business strategy is well documented in marketing literature (Vorhies and Morgan, 2003). For example, how to measure whether marketing activities are organized so that particular business strategy can be implemented or how this affects performance (ibid.). Marketing activities of a firm can be described by different configurations – e.g. characteristics and feature properties of promotion – that lead to different outcomes and these outcomes are finally linked into financial performance. When measuring marketing performance, it is important to determine which configurations lead to certain outcome and which of them lead into superior financial performance.

The objective of this thesis is to examine how various marketing promotion characteristics effect on marketing performance. In this study a configurational method Fuzzy-Set Qualitative Comparative Analysis (FS/QCA) is used as an approach and methodology in examining how different configurations of promotion characteristics affect marketing performance. This approach has its root in comparative research: forming a law by singling out the circumstances which result into an outcome by two methods (Mill, 1884). This is done in two steps: first by comparing together different instances where the outcome occurs, and then by comparing instances where the outcome occurs with instances in other respects similar which it does not.

FS/QCA is rather novel approach for studying marketing configurations. Similar to classification methods such as support vector machines (James et al., 2013: 337) and tree classification methods (Moore and Carpenter, 2010) it overcomes the weaknesses of traditional methods used in marketing such as regression (Fiss, 2007; Short, Payne, and Ketchen, 2008). The advantage of FS/QCA is that it is able to determine how individual elements contribute to the configuration and how combination of elements can cause a certain outcome (Miller, 1996; Fiss, 2007). Similarly to other classification methods, it can be used in determining equifinality – a situation where different initial conditions and different paths can result in a system to reach the same final state (Doty, Glick and Huber, 1993; Katz and Kahn, 1978).

The validity of FS/QCA in examining configurational explanations for marketing outcomes has been already demonstrated by Vassinen (2012). Additionally more traditional

regression analysis is used to triangulate the results and a comparison between the methods is made.

The chapter is structured as follows. First, I will describe the basic method of Qualitative Comparative Analysis (QCA) for dichotomous variables. Then I will move to the enhanced version of QCA, Fuzzy-Set Qualitative Comparative Analysis (FS/QCA), which uses continuous fuzzy variables. Finally, I will go through the basics of regression analysis.

3.1 Qualitative Comparative Analysis

Although new to marketing, QCA is rather old analysis method used mainly in social sciences and it has just turned 25 years old (Ragin, 1987; Marx, Rihoux and Ragin, 2014). QCA is a comparative case-based research approach and methodology. In other words, the phenomenon is examined in analytical units of cases while also controlling contextual conditions (Rihoux and Ragin, 2009: xviii). This is comparable to case study research in marketing, where the aim is to reason from observations of cases towards generalizable inductive principles (Bonoma ,1985). QCA is a collection of techniques based on Boolean algebra and set theory, and it tries to combine both qualitative and quantitative research methods – to gain insight into different cases in order to capture their complexity while attempting to form some sort of generalization (Ragin, 1987).

QCA can be used at least for five different research purposes (Marx, Rihoux and Ragin, 2014). First, it can be used to summarize data. Similar to clustering, it can describe different cases as a truth table that can be further used in topology building. Second, it can be used to check the coherence of cases with respect to specified model by finding logically problematic configurations called contradictions. Therefore it allows the researcher to identify anomalies in the proposed model. Third, it can be used to evaluate existing theories. Fourth, it can be used to assess new hypothesis formulated by the researcher – i.e. to be used for data exploration. Fifth and last, it can be used in elaboration of new theories or uses. Thus the formulas derived using QCA can be used in in-depth examination of the cases in the study. This thesis concentrates on the last purpose.

3.1.1 Background

The aim of the QCA method was to develop an approach in which the researcher could combine case-oriented (qualitative) and variable-oriented (quantitative) approaches. The method had originally five main components (Marx, Rihoux and Ragin, 2014):

- The approach emphasizes case based nature of comparative research. Each case could be considered as an entity and the integrity of the cases should be maintained through the analysis. The cases would be represented as configurations of variables with the aim of linking the configurations of causally relevant conditions to outcomes.
- 2) The approach is comparative so that it allows the researcher to determine similarities and differences across comparable cases by comparing configurations and pooling similar cases together. The output of the approach is a truth table, which shows all the configurations of conditions in a matrix of all logically possible configurations of causal conditions. Therefore it makes possible to examine the cases which differ on one or more conditions, and which cases result into identical causal conditions.
- 3) The approach offers method for a dialogue between theory and evidence. This can be seen in contradictions, which occurs when an identical configuration is linked to both possible outcomes (Rihoux and De Meur, 2009). Contradictions should be resolved, primarily by identifying omitted causal conditions. In other words, resolving contradictions guides the development of explanatory model.
- 4) The approach allows evaluation of multiple conjunctural causation, which consists of three properties. First, usually a combination of conditions causes the outcome. Second, several different combinations can result into same outcome. And third, a condition may have different impact on outcome based on context. Thus, QCA does not specify only a single model as usual in statistical techniques, but a number of different causal models a property called equifinality that assumes that multiple paths to a desired outcome may coexist (Fiss, 2007).
- 5) The approach allows the researcher to determine the degree which he wants to reduce the empirical complexity of the cases by using Boolean logic. Boolean algebra allows one to identify causal regularities that are parsimonious: which combines the fewest possible conditions in a set of conditions considered in analysis. In other words reducing the description of cases to shortest possible expression.

All in all, QCA introduced a method for comparing a set of cases, exploring their causal outcomes, and reducing this explanation to parsimonious solution: the simplest explanation that can explain the outcome in particular context.

3.1.2 Configurational causality

The subjects of examination in QCA are called configurations. A configuration is a specific combination of conditions – i.e. values of variables – that produce an outcome (Rihoux and Ragin, 2009: xviii). This configurational approach, the cases and their conditions are examined based on set theory (Ragin, 1987; Rihoux and Ragin, 2009). The cases are viewed as being members of one or more sets defined by the researcher. These sets and their memberships are manipulated and logically reasoned using mathematical operations, which enables systematic analysis of the data. The operations of this technique rely on Boolean algebra, which requires that each case to be reduced to a series of variables – conditions and an outcome – thus allowing the results to be replicable (Rihoux, 2006). The aim is to find conditions that allow the researcher to identify relevant conditions resulting into an outcome.

A key difference to statistical methods compared to QCA is that the set relations are fundamentally asymmetrical (Ragin 2008: 7). Membership in one set does not guarantee membership or non-membership in another set. In other words, set theoretic approach does not focus on general patterns of association, but uniformities or near uniformities (Ragin, 2006: 19). This also leaves the possibility that not all causally relevant characteristics are understood. Therefore the conventional frame of analysis is broadened by relaxation of assumptions, which is against the assumptions of conventional statistical techniques (Berg-Schlosser, De Meur, Rihoux and Ragin, 2009: 8). Causality in QCA is not assumed to be permanent, but being linked into specific context, conjecture, and contingency. Also, as discussed, the causality is not assumed to be symmetrical.

3.1.3 Necessary and sufficient conditions

The validity of causality in QCA is developed using two causal conditions. Necessary, which means that a condition must be always present for an outcome to happen. And sufficiency, which means that a condition can by itself produce a certain outcome (Ragin, 1987: 99-101).

A necessary condition X is a condition that must be satisfied to outcome Y to be true – that is $Y \subseteq X$. Thus if X is necessary condition and we do not have X, we won't have Y. Note that with necessary condition, the presence of X does not guarantee Y. Necessity is measured based on coverage that indicates the degree which the configuration is necessary to an outcome to occur (Ragin, 2008). Using analogy to statistical methods, it is comparable to the statistical significance of the configuration.

A sufficient condition X is a condition that if satisfied, assures the outcome Y – that is, X $\subseteq Y$. Thus, if X is present and is a sufficient condition we must have Y. Presence of X does guarantee Y. Sufficiency is based on consistency – a measure that states that the configuration leads to the outcome systemically. It states if the combination of explanatory variables is sufficient to cause the outcome similar to the explanatory power of a regression model.

3.1.4 Configurational analysis with crisp sets

Although this thesis concentrates on fuzzy set QCA, a short description of crisp set QCA eases the further discussion. First in the QCA method, truth table is constructed, which is a tabular display that shows all configurations of conditions that produce an outcome in a given data set. A frequency threshold can be applied to determine how many observations warrant the inclusion of configuration. If a case is determined to be reliable enough, then even a single case can defined to be sufficient evidence for causality.

After that the satisfaction of conditions are observed. Conditions still present in the data are necessary conditions as part of some configuration. Sufficient configurations are those that are sufficient to determine outcome, although the presence of only single sufficient observation is rare. It should be noted that in contrary to statistical analysis, counterfactual cases, outliers, and influential observations (see e.g. Hair et al., 2012: 190-192) are valuable part when investigating configurational causality. After all, "a well-executed QCA should go beyond plain description and consider modest generalizations." (Berg-Schlosser, De Meur, Rihoux, and Ragin, 2009: 12).

3.2 Fuzzy-Set Qualitative Comparative Analysis

After the introduction of QCA, which used only crisp-sets – i.e. binary logic – Ragin continued to develop the framework further towards fuzzy-sets – i.e. towards continuous variables (Marx, Rihoux and Ragin, 2014). This led to the introduction of Fuzzy-Set Qualitative Comparative Analysis in the book Fuzzy-Set Social Science (Ragin, 2000). The approach has two main features. First is the use of fuzzy logic, which is especially useful in examining degrees of difference. Second is the possibility of membership calibration, which means determination of the degree of membership in a configuration (Ragin, 2009: 89). These properties make the fuzzy sets simultaneously quantitative and qualitative approach (Ragin, 2009: 88).

3.2.1 Fuzzy sets and memberships

In fuzzy sets, the variables are not handled as dichotomies, but as degrees of membership varying from zero to full membership. Traditional crisp sets have only categorical distinctions that are fully qualitative – either the condition is present or not (Ragin, 2009: 89). Thus, the membership of the condition is usually associated with Boolean value of true (1) and non-membership with value of false (0).

Broadening this logic to allow partial membership scores between (0) and (1) extends the expression to fuzzy sets. In FS/QCA this means that each case has a distinct position in a property space determined by its fuzzy set. For example, in three property space dimensions the values can be (0), (0.5), and (1). In other words, a case with fuzzy membership score of 0 would be associated with non-membership and lies in extreme end of the property space (ibid.: 90). Similarly a membership score of (1) would be associated with full membership. Fuzzy membership score of (0.5) would lie on the crossover point and represent maximum ambiguity (ibid.: 90).

It is up to the researcher to decide the different number of levels in fuzzy sets and there is even no need to use equal intervals between the levels. The main idea when developing fuzzy sets it that "the researcher must calibrate the membership scores using substantive and theoretical knowledge" (ibid.: 92). In other words, the fuzzy values do not measure how observations differ from each other, but denote qualitative state of belonging to a configuration. These states are called qualitative anchors and they distinguish between relevant and irrelevant variation (ibid.: 92). Usually the states are also described with linguistic qualifiers (Ragin 2000: 156). This means fuzzy membership value does not have meaning beyond multi-dichotomy. Table 1 illustrates different fuzzy sets and their verbal descriptions.

1 = fully in			set
I = Iully III	1 = fully in	1 = fully in	1 = fully in
0.5 = neither fully in or fully out	0.67 = more in than out	0.9 = mostly but not fully in	0.5 < x < 1 Degree of more in than out
0 = fully out	0.67 = more out than in	0.6 = more or less in	0.5 = crossover: neither in or out
	0 = fully out	0.4 = more or less out	0 < x < 0.5 Degree of more out than in
		0.1= mostly but not fully out	0 = fully out
	0.5 = neither fully in or fully out	0.5 = neither fully in or fully out $0.67 =$ more in than out $0 =$ fully out $0.67 =$ more out than in	0.5 = neither fullyin or fully out $0.67 = more in thanout0.9 = mostly butnot fully in0 = fully out0.67 = more outthan in0.6 = more or lessin0 = fully out0.67 = more outthan in0.4 = more or lessout0 = fully out0.4 = more or lessout0.1 = mostly but not$

Table 1. Crisp set compared to different fuzzy sets (Ragin 2009: 91).

3.2.2 Triangular covariance

One aim of FS/QCA is to interpret triangular patterns of covariance (Kent, 2005). Traditional regression methods assume that values of independent input variable *X* are linearly associated with values of output dependent variable *Y*. The covariance pattern or scatterplot of distribution following this assumption is seen in Figure 5.

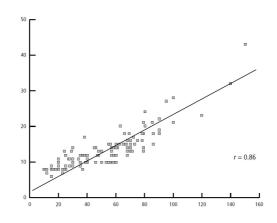


Figure 5. Typical covariation pattern (Kent 2005).

But in some cases the covariance pattern is triangular as seen in Figure 6 where only high values of Y are associated with high values of X, but low values of Y can be associated of whole range of values for X. As can be seen, the value of Y acts as a ceiling for values of X and this cannot be explained using traditional regression analysis (Kent, 2005). With fuzzy sets, set Y is subset of X if the membership scores of Y are less than or equal to the membership scores of X. Thus instances of outcome Y are a subset of instances of cause X indicating necessary, but sufficient condition.

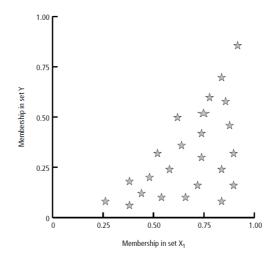


Figure 6. Fuzzy-set necessary but not sufficient condition (Kent, 2005).

On the contrary, a fuzzy subset relationship where the cause X is found to be sufficient, but not necessary, to the outcome Y is shown in Figure 7. In this case the high membership of the cause X acts as a floor for values of outcome Y (Kent, 2005).

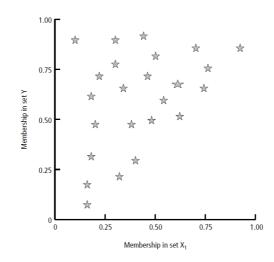


Figure 7. Fuzzy-set sufficient but not necessary condition (Kent, 2005).

3.2.3 Calibration of fuzzy sets

As the calibration of fuzzy sets influence the outcome significantly, it is one of the most important stages in the analysis and requires thorough qualitative consideration (Ragin, 2009: 93). It is a key determinant for both the reliability and the validity of the model. In other words, the calibration of fuzzy sets demands theoretical and practical justifications and without them the resulting model is invalid. Also if the calibration process is not documented well enough, the replicability of the study diminishes

The aim of calibration is to produce measures that match to known scales so that measurements are directly interpretable (Ragin, 2008: 72). In natural sciences, researchers calibrate measures by adjusting them to match to known standards. This means that the calibrated scales are anchored to qualitatively understandable or interpretable values (Byrne, 2002) – e.g. points where the changes happen like the freezing and boiling point. These points can be accrued through managerial practice or from previous academic research. This approach is contradictory to the usual statistical techniques such as regression, where only linearity and equal variance is expected – i.e. the variation is considered equally relevant through the scales.

There are two methods for calibrating interval-scales to fuzzy sets using external criteria: the direct method and the indirect method (Ragin, 2008: 85). In the direct method, the researcher decides the values at three fundamental breakpoints – full membership at 1.0, full non-membership at 0.0, and the crossover point at 0.5 (Ragin, 2008: 90). As discussed, the membership score at 0.5 represents maximum ambiguity – point of indifference where we do not know whether a case should be considered a member or a non-member of the set (Ragin 2009: 90). Therefore assigning a 0.5 fuzzy membership score for a case should be avoided (Schneider and Wagemann, 2012).

The direct method uses estimates of the logarithm odds of full membership as an intermediate step (Ragin, 2008: 87). This procedure is illustrated in Table 2. The first column shows the verbal labels that are attached to different degrees of membership. The second column shows the degree of set membership linked to each verbal label. And the third column shows the odds of full membership using the following formula:

odds of membership =
$$\frac{degree \ of \ membership}{1 - degree \ of \ membership}$$

The fourth column shows the natural logarithm of the odds shown in third column. The usefulness of log odds metric is that it is completely symmetric around zero an does not suffer from floor or ceiling effects – very large values that are undistinguishable from each other (Ragin, 2008: 88). It is important to understand that the resulting membership scores are not probabilities, but simply transformations of interval scales instead.

Verbal Label	Degree of membership	Associated odds	Log odds of full membership
Full membership	0.993	148.41	5.0
Threshold of full membership	0.953	20.09	3.0
Mostly in	0.881	7.39	2.0
More in than out	0.622	1.65	0.5
Cross-over point	0.500	1.00	0.0
More out than in	0.378	0.61	-0.5
Mostly out	0.119	0.14	-2.0
Threshold of full non-membership	0.047	0.05	-3.0
Full non-membership	0.007	0.01	-5.0

Table 2. Mathematical Translations of Verbal Labels (Ragin 2008: 88)

The direct method of calibration uses the discussed three qualitative anchors to structure the calibration: the thresholds for full membership, full non-membership, and the cross-over point. Once these three values have been selected, the calibration of membership is done in two parts: for the values above the cross-over point and for the values below. First, log odd metrics are calculated using the following formula:

$$\hat{p}_{observation} = (p_{observation} - p_{crossover}) \frac{p_{treshold}}{p_{treshold} - p_{crossover}},$$

Where $p_{observation}$ is the value of the observation, $p_{crossover}$ is the value for the cross over point, and $p_{treshold}$ is the value of the high and low thresholds. Then this log odds metric is scaled to interval of [0, 1] to represent calibrated fuzzy membership score using:

$$\mu = \frac{e^{\hat{p}}}{1+e^{\hat{p}}},$$

Where \hat{p} is the log odds of the observation.

In contrary to the direct method, which relies on the specification of the three qualitative anchors, the indirect method uses external qualitative assessment to divide case memberships to a number of broad groupings according to their degree of membership in the target set (Ragin, 2008: 84). The intention is to perform initial sorting into different levels of membership described by a linguistic qualifier and to assign a preliminary fuzzy score. These qualitative interpretations of cases must be grounded in substantive knowledge: the stronger the empirical basis for qualitative assessments, the more precise the calibration of the values. Finally, a continuous transformation function is used to refine the membership scores. For example, Ragin (2008: 85) uses fractional logit model that uses information

from both the variable values and corresponding initial membership scores. The aim of the indirect method is to re-scale the indicators to reflect the knowledge based qualitative groupings.

3.2.4 Configurational analysis with fuzzy sets

Similarly to QCA, a truth table is the key tool for systematic analysis of possible causal configurations in FS/QCA (Ragin, 2000). It lists all logically possible combinations of causal combinations along with the outcomes of the cases belonging into each combination (Ragin, 2008: 124; Ragin, 2009: 104). The number of causal combination – seen as truth table rows – is exponential function of the number of causal conditions 2^k , where *k* is the number of different conditions (Ragin, 2008: 124; Ragin, 2008: 124; Ragin, 2008: 124; Ragin, 2008: 124; Ragin, 2009: 104). Thus the causal conditions construct a property space, a vector space of *k* dimensions, with 2^k corners corresponding to crisply defined causal conditions.

The truth table summarizes the statements of each causal combination represented by the corners (Ragin, 2008: 129; Ragin, 2009: 104). Two properties of these corners are especially important: 1) the number of cases with so called strong membership in each causal combination and 2) the information on the consistency of the data for each causal combination as a subset of focal outcome (Ragin, 2009: 105). In other worlds, the analysis process translates the fuzzy set into crisp truth tables and the key relation studied is the subset relation.

The fuzzy set membership scores determine the position of a case in the property space. Each case has varying degrees of membership in the different corners of the vector space and therefore varying degree of membership in each truth table row as illustrated in Figure 8 (Ragin, 2009: 104). The calculation of membership score with respect to a corner in the property space is based on fuzzy set intersection: The membership scores are joined together using logical AND function so that the degree of membership of a case in a given corner of a fuzzy set vector space is calculated using the minimum membership score in the conditions combined (Ragin, 2008: 129). Simply put, a case is considered to have strong membership in a corner when its membership score exceeds 0.5. Therefore it is only possible for a case to be a strong member in only one corner of the property space (Ragin, 2008: 131; Ragin, 2009: 106).

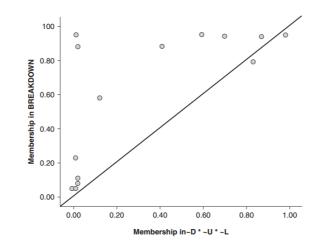


Figure 8. Plot of the degree of membership (Ragin, 2009:103)

Although each case will be always closest to one corner, cases will still usually be partial members to many corners in the property space. Using this property increases the potential for finding sufficient conditions to explain causality. The proximity of fuzzy cases to crisp location defined by their membership scores determine whether cases are considered to be the same kind (Ragin, 2008: 188). However, if all cases have low membership in a location, then it is pointless to conduct assessment to that combinations link to the outcome (Ragin, 2009: 106).

Similar to QCA, the frequency threshold is applied to determine how many observations warrant the inclusion of configuration. That is, the researcher needs to formulate threshold for determining which combinations of conditions are relevant, based on the number of cases with strong membership (Ragin 2009: 107). If combination has enough cases with strong membership, called instances, it is reasonable to assess the fuzzy subset relation. The threshold should be set to a level where empirical diversity is maximized with reliable level of trust to the correctness of the data. Important considerations are the total number of cases in the study, the degree of precision in the calibration of fuzzy sets, and the extend of measurement and assignment error (ibid.).

Especially when the number of cases exceeds hundreds, using a frequency threshold becomes important part of the analysis (Ragin, 2008: 133; Ragin, 2009: 107). It is not enough for cases to have instances, but to assess which combination have enough instances to be included. For example, the researcher could rule that there needs to be at least 5 instances in a causal combination in order to continue the assessment of fuzzy subset relation.

3.2.5 Consistency and coverage

Once the relevant causal combinations have been identified, QCA has two measures that enable the researcher to evaluate the degree which a model explains the outcomes observed and the relative weight of each combination. These are called consistency and coverage (Ragin, 2008: 44).

Set-theoretic consistency evaluates the degree to which a combination of conditions constitutes a subset of an outcome (Ragin, 2009: 108). In other words it measures the degree to which one set is contained within another. If the consistency of configuration is low, then the configuration is not supported by the data. The degree of consistency is calculated with the following formula:

Consistency
$$(X_i \leq Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum X_i},$$

Where X_i is the membership scores in a combination of conditions and Y_i is the membership score in the outcome. It should be noted that consistency weight large inconsistencies substantially more than near misses (Ragin, 2009: 108). Compared to statistical methods, consistency values are analogous to correlation estimates (Woodside, Hsu, and Marshall, 2011).

On the other hand, set-theoretic coverage determines the proportion of the sum of the membership scores in the outcome it covers (Ragin, 2008: 44). Thus it evaluates a consistent combination's empirical importance. If there are many configurations leading to the same outcome, the coverage of a single configuration may be low. Again comparing it to statistical methods, coverage is analogous to effect size estimates – i.e. power (Woodside, Hsu, and Marshall, 2011).

Similar measures exist for evaluation of necessary conditions. The consistency of a necessary condition is the degree which the condition is a superset of the outcome. The coverage of a necessary condition is the degree which the outcome covers the necessary condition. According to Ragin (2009: 110), it is useful to check necessary conditions before conducting the truth table analysis. If the necessary condition makes sense being necessary, it can be dropped from the truth table analysis. However, the condition identified by this procedure should be considered relevant to sufficient conditions and included in the discussion. If the necessary condition is included in the truth table analysis, it is often removed from solutions including logical remainders, which are the non-observed cases (Ragin, 2009: 110; Rihoux and De Meur, 2009: 59). As these are unknown cases that can be evaluated using researcher's theoretical and substantive knowledge, Ragin and Sonnett (2004) have developed procedures that limit their usage. From this analysis three solutions are formed: 1) complex solution where no logical remainders are used, 2) parsimonious solution where all logical remainders can be used, and 3) intermediate solution where the logical remainders developed by the researcher are incorporated to the solution.

3.2.6 Constructing and analyzing the truth table

After truth table has been generated and pruned using the frequency threshold of cases, a suitable consistency threshold must be selected and the remaining truth table minimized. Consistency threshold determines the minimum requirement that cases in a configuration must meet to be considered a consistent fuzzy subset of outcome (Ragin, 2009: 109). Configurations with consistency above the cutoff value are designated subsets of the outcome and are coded with binary (1). Those below the cutoff are not fuzzy subsets and are coded with binary (0).

Selecting the consistency threshold should be done with care. The configurations that are fuzzy subsets of the outcome determine the kinds of cases where the outcome is consistently found. A similar method to scree plot in factor analysis can be used, thus to determine a substantive gap – breaking point – in consistency scores of configurations (Hair et al., 2012: 108). According to Ragin (2009: 118) consistency thresholds below 0.75 should be avoided in practice.

It should be noted that some cases indicating the outcome may be found among configurations with low consistency. These contradictory configurations are perfectly normal in the analysis process and they should be either resolved or their amount minimized (Rihoux and De Meur, 2009: 48). The strategies for resolving them include adding or removing variables, adjusting the calibration, reconsidering the scope of the output variable, reconsidering the sample population used, re-examining the cases qualitatively, and recoding the contradictory configurations outcome as zero or the most common value (Rihoux and De Meur, 2009: 49). However, the researcher must remember that usage of these strategies must be justified on empirical or theoretical grounds – not the result of opportunistic manipulation. After that, the truth table is minimized by simplifying the causal combinations into a shorter and more parsimonious form (Rihoux and De Meur, 2009: 33). The outcome of minimization is a logical expression of the factor configurations. A plethora of algorithms exists for logical minimization and the most commonly used with FS/QCA is the Quine-McCluskey algorithm (Quine, 1952; Quine, 1955; McCluskey, 1956), which is implemented in most of the FS/QCA software packages (Dusa, 2007; Ragin, Drass, and Davey, 2006; Thiem and Dusa, 2013). As discussed, the minimization procedure is recommended to be run for four different configuration sets: for both with and without logical remainders, and for both output conditions (Rihoux and De Meur, 2009: 64).

Finally, the logical expression of factor configurations is analyzed. Each configuration has three different types of coverage (Rihoux and De Meur, 2009: 64). First is the unique coverage, which means the proportion of cases leading to the outcome explained by that combination only. Second is the raw coverage, which means the proportion of the outcome explained by combination and all the related combinations. And third is solution coverage, which is the proportion of outcome explained by all the configurations.

In the end, the researcher must interpret the minimal formula that represents the causal configurations with logical operators. The goal of interpreting the minimal formula is to link the results of analysis to the previous knowledge of the studied phenomenon, which can be either theory or case driven (Rihoux and De Meur, 2009: 65). This requires concentration to the most relevant cases. Rihoux and De Meur (2009: 65-66) recommend to ask more focused causal questions of the mechanism producing the combinations in order to construct a narrative of the data – and focus on big picture instead of interpreting relations between single conditions and the outcome.

3.3 Regression analysis

Regression analysis is definitely the most used dependency technique used in business research and marketing (Hair et al., 2012). Regression analysis is a statistical technique that is used to analyze the relationship between a single dependent variable and one or several independent variables. The aim of the regression analysis is to estimate weights for the independent predictor variables so that the dependent variable is predicts the outcome as good as possible by the selected criterion. The resulting formula is called regression model and the weights themselves denote the relative contribution of the variables to the outcome. The regression model can be formulated as equation as

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 $Y = X_1 + X_2 \dots + X_n + \varepsilon,$

where *Y* is the metric dependent variable and *X* are the metric independent variables. When the solution involves only one simple independent variable the technique is called simple regression and similarly with multiple variables multiple regression. It is also possible to use non-metric data as the independent variable by coding them as binary dummy variables. The independent variables can also have interaction effects, which can be presented using moderator coefficients – e.g. X_1X_2 .

The most usual criteria for the goodness of the model is the sum of squared errors, which can be minimized using the least squares procedure (ibid.: 159). Thus compared to QCA, regression analysis focuses on causal conditions that are both necessary and sufficient (Schneider and Eggert 2014). It should be noted, that regression is a linear combination of variables – thus it cannot directly be used in examining non-linear phenomena.

Traditionally in marketing research, causality is recognized when one variable is found to affect the output. In regression analysis this means isolating the effect of each causal variable and keeping the other variables static (Kent 2005). Therefore the effects are measured assuming independence among the variables, the outcome of analysis being statistically significant correlation and the variance explained by each independent variable (Ragin 2000). In this approach, the dependence of variables is even seen as a problem referred as multicollinearity. As Kent (2005) argues, the statistical significance in regression analysis offers no proof of causal connection, although commonly stated as evidence of it, and proves that the result merely cannot be explained as a product of sampling error.

4 Case Finnair – promotion of airline tickets

For the empirical part of this thesis I present the analysis of ticket airline promotions for one European point of sale carried over the full year of 2015. The aim is to discover what configurations of promotion properties can explain the increase in tickets sold and revenue. This analysis is done using two methods, with Fuzzy-set Qualitative Comparative Analysis and with regression analysis, and the results from the methods are compared against each other.

This chapter is organized as follows. First, the background of the case and the company is presented in the first section. Then in the second section, the data collection procedure is described. In the third section, I will discuss how the initial data is translated into the data used both in FS/QCA and regression analysis. The fourth and the fifth sections undergo the analysis using FS/QCA and regression, discuss the results – their implications, reliability and validity. Finally, in the sixth section comparison between the two different analysis methods is made.

4.1 Background

Finnair is the Finland's flagship carrier that is by majority owned by the government of Finland (Finnair 2016). Established in 1923 it is one of the world's oldest still operating carriers. In 2015 it had turnover of 2.3 billion and transported over 10 million passengers to 15 domestic, over 60 European, 13 Asian and 4 North-American destinations. It is part of the Oneworld alliance and has several joint businesses with flights covering Europe and North America, and Europe and Japan.

Revenue management and pricing is one of the main functions of Finnair's operations. It involves ensuring competitive ticket pricing in the markets and allocating availability of those ticket prices. Ticket pricing works on the point of sale level while revenue management allocates the availability of those tickets on the network level. This dual split in the responsibilities ensures that the revenue is maximized on aggregate level – not locally.

This same principle is used to determine whether there is capacity that is not expected to be sold. In order to fill the capacity that has no demand, pricing usually launches promotions to those destinations. This usually is a continuous process, so new promotions are launched almost constantly. As the flights are sold one year ahead until departure, there is always some weaker periods or flights to be promoted.

The main characteristic of the ticket promotion is of course the discount from the regular price. However, in the airline context this is not as trivial as it sounds. The discount price can be decided by the pricing analyst – called business manager in Finnair context – or it can be determined by benchmarking the prices with other carriers. But the pricing decision has also effect on the availability of the ticket. Airlines typically use so called bid-prices to set a threshold price whether the ticket is available to sale (Talluri and Van Ryzin, 2004: 32-33). The bid-prices are calculated for every seat of the plane and their values are essentially approximations of the displacement cost of the passenger in the network. Thus, when determining the availability of a promotion ticket, a dynamic process is made where the price is compared to the revenue which the passenger is expected to displacement cost, the ticket is available for purchase.

The revenue management and pricing department at Finnair determines the characteristics of the promotion including

- Destinations to be promoted
- The promotional prices
- Sales dates when the offer is valid
- The travel dates when the offer is valid.

After that the revenue manager reviews the destinations, prices, and travel periods, and informs the respective business manager about the availability of the tickets with those characteristics. In reality, these tasks are usually done collaboratively and simultaneously in order to ensure effectiveness. Before the promotion is launched, marketing communications makes sure that promotion prices are promoted in newsletters and website banners.

Although the revenue obtained from promotions is not that drastic, its contribution to the bottom line is needed due to air traffic being rather low margin business. International Air Transport Association (IATA 2015) expects airline profit margins for European carriers to be 4.3% on average, which means a nifty \$8.8 profit per passenger.

4.2 Data collection

For the data of this thesis, I collected all the quantitative data on all promotions undertaken during 2015 for a certain point-of-sale. This included all the promotion data – announcements and follow-ups – sent by the business manager to sales unit and the revenue manag-

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er. Although the data already contained the detailed passenger and revenue numbers of the promotion to each destination, I additionally gathered route-specific information about the total passenger numbers and revenue data. The data did not have any missing values and there should not be significant measurement errors as it was gathered from financial reporting.

4.3 Selection of the property space

The initial data for the analysis contains a wide variety of qualitatively diverse data and its description can be seen in Table 3. It contains several outcomes, several conditions of the promotion, and even several reference values. It contains 183 cases in total, which in statistical analysis sense is quite small compared to the approximately twenty variables available (Hair et al. 2014:171). It also involves qualitative and categorical variation that makes any statistical analysis difficult.

Condition	Description
Origin market	Origin market of the promotion (e.g. Germany).
Destination airport	Destination airport of the ticket.
Origin airport	Origin airport of the ticket.
Promotion fare	The fare from the origin to the destination.
Regular fare	The lowest published available fare.
Discount	The discount percentage compared to regular fare.
Sales start date	The first date the tickets are available for sale.
Sales end date	The last date the tickets are available for sale.
Travel period start date	The first possible travel start date.
Travel period end date	The last possible travel start date.
Travel completion date	The last possible travel completion date.
Advance purchase	How many days in advance before departure the ticket has to be pur-
	chased.
Minimum stay	How many days one has to stay in the destination.
Maximum stay	How many days can one stay in the destination.
Day specific travel rules	Special day of week specific rules (e.g. No Sunday return).
Stopover rules	Can one stay over in intermediate destination before final.
Cancellation rules	Can the ticket be cancelled and with what fee.
Change rules	Can the ticket be modified and with what fee.
Promotion tickets sold	The number of tickets sold during the promotion period.
Promotion revenue	The revenue accrued for promotion tickets sold.
Regular tickets sold	The number of lowest published fare tickets sold during the promotion
	period.
Regular ticket revenue	The revenue accrued for lowest published fare tickets sold during the
	promotion period.
Total tickets sold	The number of all tickets sold during the promotion period.
Total ticket revenue	The revenue accrued for all tickets sold during the promotion period.

Table 3. The initial	property space	for conditions a	nd outcomes.
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This rudimentary property space was constructed from the data available and the aim is to narrow it to a significantly smaller subset. This aim can be reasoned in multiple ways. First, the data contains many conditions which do not change significantly. For example, maximum stay is usually defined until the travel period end and therefore does give any additional information to the analysis. Secondly, from managerial perspective it is important to focus on most relevant conditions and to form conditions relevant for this study. For example, the data is challenging as it does not have data of the relative performance of the promotion – i.e. the performance is quite self-explanatory for most demanded and farthest destinations – but does not answer which promotions increase the sales relative to the normal sales. Finally, the resulting data set and property space size should be suitable for both the FS/QCA method and regression analysis.

4.3.1 Unit of analysis

The unit of analysis was selected to be an individual route promoted within a promotion. Another alternative would have been to examine the promotions as a whole, but as done in Vassinen (2012), separating the routes allows the route level outcomes and different qualitative conditions (e.g. type of the destination) to be examine more thoroughly.

4.3.2 Final Property space

As discussed, the initial – and maximum – property space was defined by the available data. Selecting the final property space dependents heavily on the case described. In this process the property space needs to be pruned not only for it being applicable in regression analysis, but also in managerial relevance in mind. Having tens of different properties to explain revenue outcome can be academically interesting, but handling them in daily work is a whole different story. Each additional property will also increase the rows of the FS/QCA truth table exponentially and the table can become too sparse having too many logical remainders. Also, the process of selecting variables should be done iteratively so that optimal properties are found for the research and the company.

But in order for the initial property space to be useful for examination, additional qualitative generalization conditions and composite conditions of property space are needed. Following compositions and transformations for the property space were made:

• The relative revenue outcome was selected as the output value as specified in the theoretical framework. The revenue outcome is calculated as relative value: as the proportion of result relative to the value of regular and promotion tickets sold. Cal-

culating the relative value against all tickets sold was also investigated, but it showed serious skewness against the destination. This was due to all ticket revenue containing also the business customers – i.e. in business destinations their relative share was high and the output would have been described solely by that fact. How-ever, promotions are targeted to leisure customers to whom the regular tickets are also sold. Additionally, calculating the outcome as relative figure diminishes the variation caused by other parameters such as sales period length. Although it must be noted that the effect of sales period length has also non-linear components – i.e. we cannot expect sales flow to be constant over the promotion.

- Following Vassinen (2012), the destinations are characterized by three conditions: whether it is a seasonal destination (the demand having peaks and lows during the year), a city destination (a capital or similar big city), or a Nordic destination.
- The sales period was transformed into length of the period instead of start and end dates. Also, the travel periods were transformed relative to the sales start date.

Additionally, several conditions were discarded before calibration. The usual reasoning behind was that there were no variations in them between the cases or they were strongly correlated with other variables. The full list of discarded conditions is:

- Origin market was discarded as there is no variation.
- Only one origin airport was selected as the other airports were so small that their contribution to the sales was only 3-4% from the total. That is, their results were small enough to be regarded as outliers. This reduced the sample into 108 cases.
- Highpriced was discarded as it correlated almost completely (-0.97) with Nordic destination.
- Regular fare was discarded and only discount percentage was left to the data. As with highpriced, regular fare correlated higly with Nordic destination.
- Sales completion date was discarded as travel period end date contained the same information.
- Fare rules advance purchase, minimum and maximum stay, day specific rules, stopover, change, and cancellation rules were discarded as there was only little variation in them. Most promotions had exactly the same rules applied.

The final property space covering 9 conditions containing the changes described is shown in Table 4 with the respective data types.

Condition	Туре	Description
Revgain	metric	Proportion of promotional revenue to reference revenue of regular and
		promotion tickets.
Discount	metric	The discount percentage compared to regular fare.
Saleslenght	metric	Sales period length in days.
Travelsoon	metric	Days to first travel date.
Travellate	metric	Days to last travel date.
Nordic	non-metric	Nordic destination
City	non-metric	City destination
Seasonal	non-metric	Destination with seasonal demand.

Table 4. Final property space and the data types.

4.4 Fuzzy-set qualitative comparative analysis

As discussed, fuzzy-set qualitative comparative analysis is the base method used in this thesis. In this section, I will go through the steps discussed in Section 3.2: first I will calibrate the data and explain the reasoning behind, then I will construct the truth tables using several criteria, and finally I will conduct the configurational analysis of the resulting minimal formula and interpret the results verbally.

For the analysis, I used QCA: Qualitative Comparative Analysis package version 2.1 for R (Duşa and Thiem, 2016) with the help of reference manuals (Duşa, 2007; Thiem and Duşa, 2012: 51-81; Thomann and Wittwer, 2016).

4.4.1 Calibration of the data

After the cases and their configurations have been selected to the final property space, all five metric conditions need to be calibrated from their original values to fuzzy-set membership scores and the three non-metric conditions to be assigned. From statistical analysis perspective, the metrics do not show significant correlation except for city and seasonality, see Table 5, which makes the data a good candidate for comparative analysis. The calibration of the conditions is done using the direct method also known as assignment by transformation (Ragin, 2008: 85-90; Thiem and Duşa, 2012: 55-62). I used the piecewise log-odds method described earlier in thesis (Ragin, 2008: 89-94; Thiem and Duşa, 2012: 51-81), which uses the three threshold values for non-membership, crossover point and full membership.

Revenue gain. The outcome of revenue gain from promotion is calculated as the proportion of promotional ticket revenues to regular and promotional revenues. The reason not to cal-

culate it as a share of regular tickets only was due to the fact that for some destinations during the promotion only promotional tickets were sold – i.e. simply calculating gain compared to regular or even all tickets would have resulted into infinite gain. However, the decision was based on the fact that infinite values cannot be used with regression analysis – using fuzzy set scores infinite values would just have saturated to full membership score.

	revgain	discount	saleslength	travelsoon	travellate	nordic	city	seasonal
revgain	1.000	0.148	0.123	-0.284	0.114	-0.162	0.188	-0.259
discount	0.148	1.000	0.039	0.182	0.037	-0.405	-0.207	0.210
saleslength	0.123	0.039	1.000	-0.071	-0.027	-0.177	-0.022	0.008
travelsoon	-0.284	0.182	-0.071	1.000	0.362	-0.297	-0.136	0.109
travellate	0.114	0.037	-0.027	0.362	1.000	-0.464	0.276	-0.244
nordic	-0.162	-0.405	-0.177	-0.297	-0.464	1.000	-0.181	0.149
city	0.188	-0.207	-0.022	-0.136	0.276	-0.181	1.000	-0.906
seasonal	-0.259	0.210	0.008	0.109	-0.244	0.149	-0.906	1.000

Table 5. Pearson correlation of the properties

The value of revenue gain varies between 0 and 1 with median and mean of 0.43, and standard deviation of 0.26. The frequency distribution seen in Figure 9 is quite equally distributed, but with clear peak around 0.6. The membership thresholds were chosen by using the statistical values with 1^{st} quartile being 0.22 and 3^{rd} quartile being 0.60, and by qualitatively deciding that revenue gain of 60% would be considered as success as the tipping point indicates. Therefore the non-membership score was set to 0.2, the cross-over point to 0.4, and the full membership score to 0.6. The calibration is illustrated in Figure 10 and the distribution of membership scores in Figure 11.

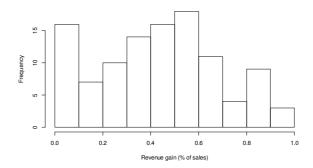


Figure 9. Frequency distribution of Revgain.

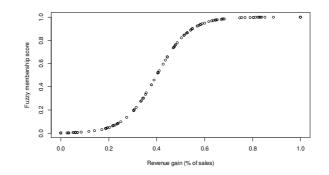


Figure 10. Calibration of Revgain.

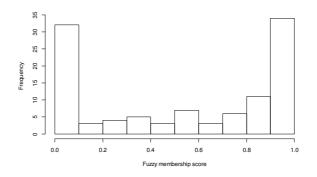


Figure 11. Frequency distribution of calibrated Revgain.

Discount. The discount of the ticket is a discrete percentage, which is interpreted by a customer to either small or large. The calibration of discount must take into account the perception that moderate the purchase behavior of the customer. Therefore this property was found to be the hardest to calibrate.

The values of discount varied between 5% and 40%. Using the statistics only as approximate thresholds – the 1st quartile being 16.7%, median 19.6%, mean 21.3% and 3rd quartile 24.4% – quite large amount of the values would have belonged near the point of unambiguity that should be avoided (Schneider and Wagemann, 2012). This can be easily observed from the frequency distribution seen in Figure 12. Therefore the membership point was decided by qualitatively anchoring based on discussion with the business manager. It was decided that 20% discount is enough, which is a considerable sum in tickets costing several hundred euros. This perceptual impact in mind, I needed also to make the change in membership scores steep enough to ensure that values in the first quartile would be considered as non-members. Thus the non-membership score was chosen to be 12% with the cross-over point in between on 16%. The calibration is illustrated in Figure 13. This selection of thresholds also ensure that only small amount of discounts belong near the cross-

over point as seen in Figure 14. However, with this selection one can criticize the small amount of cases belonging to the non-discount category.

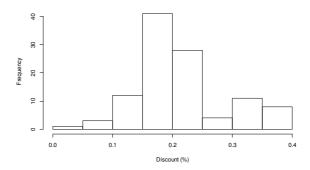


Figure 12. Frequency distribution of Discount.

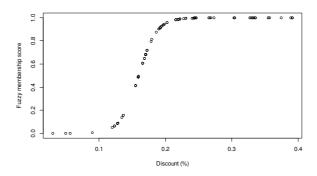


Figure 13. Calibration of Discount.

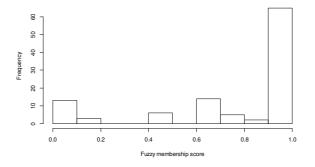


Figure 14. Frequency distribution of calibrated Discount.

Saleslenght. Generally the length of the sales period varied between 2 to 4 weeks. The longer sales period among cases was preferred as its mean is at 24 and median is at 25 days, which can be seen from the frequency distribution in Figure 15. This skewed distribution posed a challenge to the calibration as the 1^{st} quartile is at 23 and the 3^{rd} quartile at 27 – with rather small standard deviation of 3.2 days. Based on the statistics, the full membership was chosen to be at 27 days and the cross-over point at 24 days. The full-non mem-

bership point was put to 21 days, a bit below the 1st quartile in order to have some variation. The calibration is illustrated in Figure 16 and the corresponding histogram in Figure 17.

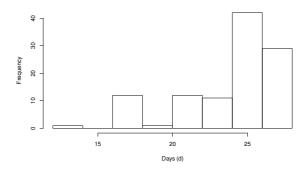


Figure 15. Frequency distribution of Saleslenght.

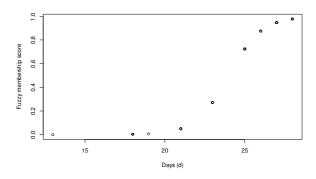


Figure 16. Calibration of Saleslenght.

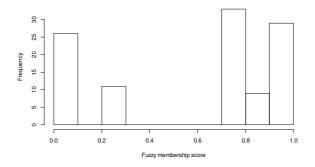


Figure 17. Frequency distribution of calibrated Saleslenght.

Travelsoon. The number of days to travel varied between 4 and 160 days. The reason for such a large variation is that the destinations are usually promoted for low demand periods. Therefore in some cases the travel period can be indeed half a year from the present. The frequency distribution can be seen in Figure 18. The mean and median are around 43 days with standard deviation of 37 days. 1st quartile is at 8 days and 3rd quartile is at 60 day. The perception of days to travel is relative. For example, Zauberman et al. (2009) have found

that the subjective the length of time follows a logarithmic function. Simply put, the difference between one and two weeks is quite same than one and two months. Therefore the thresholds were chosen qualitatively near the quartile points: 14 days indicating full membership, 30 days being the cross-over point, and 60 days indicating full non-membership. The calibration of values is illustrated in Figure 19. Also the distribution of the calibrated values seen in Figure 20 fall nicely to two distinct categories.

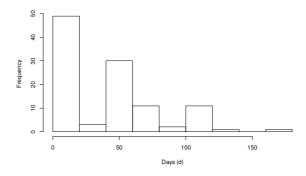


Figure 18. Frequency distribution of Travelsoon.

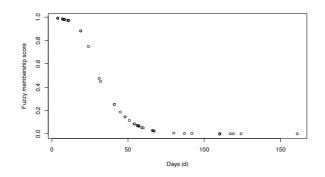


Figure 19. Calibration of Travelsoon.

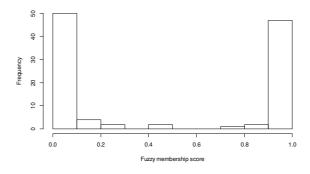


Figure 20. Frequency distribution of calibrated Travelsoon.

Travellate. Similarly to the first travel date, the last travel date varies considerably between 42 and 330 days. The 1st quartile being at 117 days, median at 163 days, mean at 180 days,

and 3rd quartile at 253 days. These points were again thought to be good starting point for the threshold selection and inspecting the frequency distribution in Figure 21 the quartiles are quite nicely at the peaks of the distribution. Therefore the non-membership point was chosen to be at 120 days, the cross-over point in between at 180 days, and the full membership set at 240 days. The resulting calibration is illustrated in Figure 22 and the corresponding frequency distribution in Figure 23.

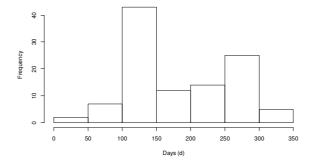


Figure 21. Frequency distribution of Travellate.

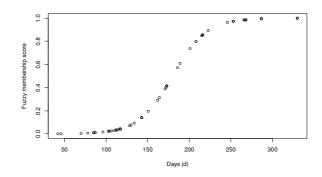


Figure 22. Calibration of Travellate.

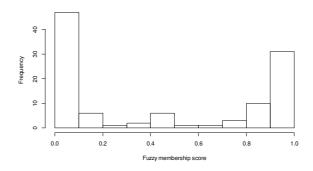


Figure 23. Frequency distribution of calibrated Travellate.

Nordic. Finally, the membership of non-metric variables is assigned and Nordic destinations were the easiest one in this crisp-set category. Naturally if the destination is in the Nordic countries, it will be assigned full membership. Other cases were assigned as nonmembers. There are 25 member cases and 83 non-members.

City. If the destination is characterized as a capital or a city type of a destination, opposed to a smaller town or resort like destination, it will be assigned full membership. Note that some relative evaluation needed to be made. Helsinki is clearly a city destination compared to Rovaniemi. But on the other hand, is there same relation between Beijing and Xian as the latter is quite similar municipality, but still holds almost as much people as the whole population of Finland? In this case it was defined not to be a city and assigned with non-membership. There are 65 member cases and 43 nonmembers

Seasonal. If the destination can be characterized as a seasonal destination, it will be assigned a full membership. This includes ski destinations as well as beach destinations despite their other characteristics. The validity of the condition was also examined using the seasonal demand pattern of the destination and they matched with the qualitatively reasoned assignments. There are 46 member cases and 62 nonmembers.

The calibration process, the distributions and methods used, are summarized in Table 6.

Condition	Distribution	Calibration method
Revgain	Continuous	Direct log-odds with statistical distribution based thresholds
Discount	Continuous	Direct log-odds with qualitative anchoring
Saleslenght	Discrete	Direct log-odds with statistical distribution based thresholds
Travelsoon	Discrete	Direct log-odds with qualitative anchoring
Travellate	Discrete	Direct log-odds with statistical distribution based thresholds
Nordic	Categorical	Boolean
City	Categorical	Boolean with qualitative assignment
Seasonal	Categorical	Boolean

Table 6. Final property space and calibration method

4.4.2 Constructing the truth tables

After calibrating the properties, the truth table can be constructed. As discussed, the truth table is constructed by assigning the fuzzy cases to binary configurations using strong memberships and then the relation to outcome is validated using minimal consistency threshold (Ragin, 2008: 131; Ragin, 2009: 105-106). It is worth noting, that even with

quite small property space of 8 conditions, the final truth table is quite large containing 2^8 =256 rows. That is, there is one row for each possible combination and one case can be assigned to one and only one row.

For validating the outcome, Ragin (2008: 118) recommends a consistency over .75 to be an adequate sufficiency. Some authors propose even larger thresholds (Thomann and Wittwer, 2016). In this thesis, the threshold is selected based on the point where consistencies start to decrease – i.e. the breaking point method that is used for example with scree plot in factor analysis (Hair et al., 2012: 108). Because of the large number of cases in this examination, 108 in total, I defined that at least two cases need to be in a causal combination to be used in the assessment of fuzzy subset relation. This reduced the number of used cases only by 9, which left 99 cases to be used in the analysis. The sorted consistency values for positive and negative outcome cases can be seen in Figure 24, and based on that the consistency threshold of .85 was chosen. The truth tables for both the positive and negative outcomes can be found in the Appendix.

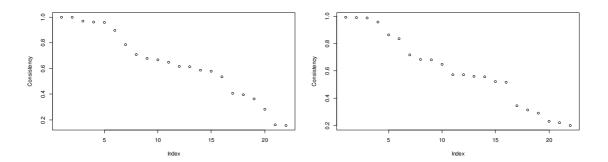


Figure 24. Consistency values for positive (left) and negative outcome (right).

4.4.3 Configurational analysis

Finally the truth table is minimized in order to explain the outcomes in a functional form. The enhanced Quine-McCluskey algorithm found in QCA package was used in minimization (Duşa and Thiem, 2016). The minimization yield two different solutions: The complex solution that does not use any logical remainders and the parsimonious solution in which all logical remainders may be used (Ragin, 2009: 111). Both of these solutions are formed for both positive and negative outcome – i.e. for positive revenue gain and negative revenue gain – and the results are analyzed and interpreted. Altough Ragin (2009: 110) recommends to check necessary conditions before the analysis, QCA package is designed so that it is not necessary to check them (Duşa, 2007).

4.4.3.1 Analysis of positive revenue gain.

I will start the analysis by interpreting the complex solution of positive revenue gain. The result of the minimization comes in function form usually consisting of several configurations that explain the outcome. These solutions are the reduced expression also known as prime implicants (Rihoux and De Meur, 2009: 35). The observed complex solution was found to be the following:

```
SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*~SEASONAL +
DISCOUNT*~SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL +
DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*~CITY*SEASONAL +
DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*~SEASONAL +
DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*SEASONAL +
DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*SEASONAL +
```

Where multiplication indicates logical AND, addition logical OR, and tilde sign negation. The solution has rather good consistency of 0.97 and coverage of 0.41 - i.e. 41% of the outcome is explained by the combinations. As seen, the solution has examples of causal complexity, which configurational analysis tries to explain: the same condition affects the outcome differently when it is part of another configuration. For example, long sales length has a positive effect in all but the second configuration. Also, note that travelsoon is a necessary condition present in all configurations.

The complex solution is the most rigorous and strict explanation for the outcome. On the other hand the parsimonious solution is the loosest explanation, and in this case is explained using three formulas:

```
TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC +
(~SALESLENGTH*TRAVELSOON*~NORDIC)
=> REVGAIN
TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC +
(~SALESLENGTH*~TRAVELLATE*~NORDIC*~SEASONAL)
=> REVGAIN
TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC +
(~SALESLENGTH*~TRAVELLATE + OISCOUNT*SALESLENGTH*NORDIC +
(~SALESLENGTH*~TRAVELLATE*~NORDIC*CITY)
=> REVGAIN
```

The solution has consistencies of 0.87, 0.90, and 0.90, and coverages of 0.47, 0.48, and 0.49. Although the parsimonious solution offers simpler causalities, the validity of the solution needs to be reasoned. Noting that the truth table contains 22 rows means that there

are 106 logical remainders, which are not observed in the data. Therefore using them as configurations without identified outcome makes the solution highly questionable. This can be seen in the last prime implicants of all three configurations. While the first prime implicant is explained with a common sense – e.g. long travel period – the last ones seem more of random remainders – e.g. short sales length with short time to the last travel date to non-Nordic cities. Hence, the logical remainders should be reviewed individually and only the ones clearly belonging to the "don't care" category included in an intermediate solution. But as the complex solution seem to prescribe the causal relationship of the promotion variables rather well and the consistency and coverage do not improve drastically in the parsimonious solution, I decided to use the complex solution in the further analysis. Let's discuss the five configurations from the complex solution, which are summarized in Table 7.

The first configuration has long sales period and long travel period to a city destination. The interesting part of this configuration is that it does not include the amount of discount which is then irrelevant regarding the outcome. The configuration can be verbally summarized as all year city destinations with good travel and sales period. The configurations positive revenue contribution did not come as a surprise as promotions to such destinations are continuous and mostly dictated by competitive actions against other airlines promotional fares. Also, when examining all the 13 cases they showed a wide variety of destinations. Therefore this configuration was the most consistent among similar kinds of destinations and also had the largest coverage of them all.

The second configuration is characterized by having short sales period compared to other configurations. Similar to the first configuration it contains non-seasonal, non-Nordic city destinations, but the difference is that it includes a short travel period and a discount. This configuration can be verbally described as last minute travel deal – again very qualitatively understandable promotional action. The cases were individually checked and the destinations and sales seasons varied between the observations – i.e. this configuration was again quite consistent within the selected property space.

The third configuration is characterized being seasonal and Nordic non-city destination – i.e. Lapland seasonal destinations. Similar to previous configuration this includes near departures, a short travel period, and a hefty discount. But the difference is that the sales period is long. A verbal description of this configuration can be summarized as seasonal

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promotion to Nordic leisure destinations. Again the causality is easy to interpret as the customers usually like to book their tickets to this kind of destination more near departure than compared to e.g. Asian destinations. On the other hand, the cases in configuration need further examination when the promotion was made as the demand for seasonal destinations vary drastically between seasons. Further examination of these two cases only in this configuration revealed that both cases were end of season promotions.

The fourth configuration is pretty much the same as the third with the difference that it is to Nordic, non-seasonal cities. In other words, to the destinations where passengers book usually within month before departure, therefore making the explanatory narrative rather easy. Verbally this could be summarized as near departure promotion to Nordic cities. When examining the case there was only one destination with varying sales season.

The fifth and final configuration is similar to the third one, but this time the seasonal destination is not in Nordics. As can be guessed, such destinations include for example beach holidays and are generally booked well in advance. Therefore the long sales and travel period is intuitive to understand. Verbal description of this configuration is promotions to southern seasonal destinations. When checking through the cases the destinations were indeed beach destinations.

	Configuration	Cases	Consistency	Raw	Unique
				coverage	coverage
1	SALESLENGTH*TRAVELSOON*	13	0.963	0.199	0.168
	TRAVELLATE*~NORDIC*CITY*~SEASONAL				
2	DISCOUNT*~SALESLENGTH*TRAVELSOON*	5	0.998	0.084	0.053
	~TRAVELLATE*~NORDIC*CITY*~SEASONAL				
3	DISCOUNT*SALESLENGTH*TRAVELSOON*	2	0.897	0.029	0.029
	~TRAVELLATE*NORDIC*~CITY*SEASONAL				
4	DISCOUNT*SALESLENGTH*TRAVELSOON*	5	1.000	0.063	0.063
	~TRAVELLATE*NORDIC*CITY*~SEASONAL				
5	DISCOUNT*SALESLENGTH*TRAVELSOON*	3	0.960	0.066	0.066
	TRAVELLATE*~NORDIC*~CITY*SEASONAL				

Table 7. Causal configurations for high revenue gain.

4.4.3.2 Analysis of negative revenue gain

Then I move to the analysis of negative revenue gain, which is done similarly as the positive revenue case. The complex solution was found to be the following:

```
~DISCOUNT*~TRAVELSOON*~TRAVELLATE*~CITY*SEASONAL +
~DISCOUNT*SALESLENGTH*~TRAVELLATE*NORDIC*~CITY*SEASONAL +
SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~NORDIC*~CITY*SEASONAL
=> ~REVGAIN
```

The solution has little lower consistency than the positive revenue gain of 0.90 and also the raw coverage is lower being at 0.31. Note that in this solution ~city, ~travellate and seasonal are necessary conditions. Similarly to the positive revenue outcome, the parsimonious solution contains several formulas:

```
~DISCOUNT*~TRAVELLATE + (SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~CITY)
=> ~REVGAIN
```

```
~DISCOUNT*~TRAVELLATE + (SALESLENGTH*~TRAVELSOON*~TRAVELLATE*SEASONAL)
=> ~REVGAIN
```

The solutions have consistencies of 0.83 and coverages of 0.39. The same reasoning what solutions to further investigate can also be used in this outcome case and therefore the following description of causal explanations is based on the complex solution summarized in Table 8.

	Configuration	Cases	Consistency	Raw	Unique
				coverage	coverage
1	~DISCOUNT*~TRAVELSOON*	12	0.968	0.175	0.078
	~TRAVELLATE*~CITY*SEASONAL				
2	~DISCOUNT*SALESLENGTH*	7	0.912	0.123	0.060
	~TRAVELLATE*NORDIC*~CITY*SEASONAL				
3	SALESLENGTH*~TRAVELSOON*	7	0.851	0.112	0.078
	~TRAVELLATE*~NORDIC*~CITY*SEASONAL				

Table 8. Causal configurations for low revenue gain.

The first configuration is characterized as non-discount, short travel period promotion to seasonal, non-city destinations. It can be verbally summarized as non-discounted, short travel period promotion to leisure destinations. Thereby, the explanation is that from customer perspective such promotions do not make sense and thus pinpointed leisure promotions without discount do not work. Interestingly, when going through the individual cases, the destinations were varied indeed from beach to snow destinations – with no specific sales season.

The second configuration has similar characteristics, but this time the leisure destination is Nordic and has long sales period. The addition of long sales period regarding to negative revenue outcome is difficult to understand without considering that Nordic is included in the first configuration. So the second configuration is addition to the first considering only the Nordic destinations and verbally emphasizing that even long sales periods do not work in that case. Investigating the individual cases, this was found to be true for several Nordic destinations. However, the investigation also revealed that there is no similar non-Nordic case in the data. Thus, such a case is a logical remainder. If that logical remainder would be used in forming an intermediate solution the second configuration would be included in the first configuration completely. But as there is no evidence of such case and the outcome cannot be reliably determined, the configuration was left as is in the analysis.

The third and last configuration is characterized as non-Nordic, non-city, seasonal promotion with short travel period and long sales period. Again, one has to consider that this configuration is extension to the first one and the main difference is that in southern leisure destinations even the discount does not make a difference when the travel period is short. Looking though the cases this was true for many seasonal destinations without any pattern in sales season. Interestingly, the configuration considers only long sales period which is hard to explain intuitively. By examining the truth table one can notice, that a configuration with short sales period exists with consistency of 0.71. Therefore one could consider not including the sales period in this configuration at all.

All the solutions and output permutations are consolidated in the Appendix.

4.4.3.3 Validity and reliability

Assessing the validity and reliability of the FS/QCA method is no easy task. Being methodology that involves participation by both the researched and preferably by the case company, its successfulness depends largely on the informedness of the researcher.

In this thesis, the selection of cases was done by collecting all the promotion data for the whole year. Therefore the cases are consistent and do not involve any pre-selection by the researcher. As discussed, the study focused only on one origin and its selection was justified explicitly and in detail (Schneider and Wagemann, 2012). As Schneider and Wagemann (2012) suggest, the selection of the suitably small amount of conditions and the outcome was based on adequate theoretical and empirical prior knowledge – especially taking

into account that similar case with similar conditions is already found in the literature by Vassinen (2012).

In this study, the used consistency thresholds were set higher than recommended by Ragin (2008: 118) and the threshold captured adequate number of cases from the data. Although the coverages of the solution are quite small, they were not that different from the examples given in the literature (see e.g. Thiem and Duşa, 2012: 72).

As method involves iterations between theory and the case, the knowledge evolves during the process as illustrated in Figure 25. In this sense, the validity of the method is hard to indemnify. Anchoring the fuzzy sets is always partially based on qualitative inquiry as there are no general rules how they should be exactly calculated. Additionally, the causal configurations should be explained using narratives – a method that always involves interpretation.

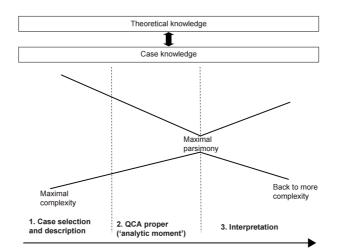


Figure 25. Knowledge generation in QCA method (Rihoux and Lobe, 2009: 229)

The reliability of the analysis is attempted to be guaranteed by pedantically reporting the analysis process: the software used, the selection of variables, their calibration with reasoning, and the algorithms used. This includes detailed explanation how to execute the analysis and also all the outputs like truth tables, minimization outputs, coverage and consistency statistics shown in Appendix. In other words, the recommended rules which guarantee replicability were used (Duşa, 2007; Thiem and Duşa, 2012: 51-81; Ragin, 2009: 87-121; Rihoux and De Meur, 2009: 22-68; Rihoux and Lobe, 2009: 222-242).

4.5 Multiple regression analysis

Many of the previous studies using FS/QCA have lacked triangulation of the findings using other methods. Although such studies have emerged (Seawright, 2005; Grofman and Schneider, 2009; Cooper and Glaesser, 2011; Vis, 2012), one of the aims of this thesis was to assess the validity of results of the FS/QCA and also compare the differences of the methods.

As configurational analysis tries to explain causal complexity, for example in the form of triangular scatterplot pattern simply implying heteroscedasticity, the comparison to traditional statistical techniques is rather difficult. A bit like similar technique would be multiple regression analysis with moderator effects, which I will use in this thesis. This is not an easy task as Ragin (2008: 175) reminds, the joint effects of the conditions in FS/QCA are difficult to examine with conventional techniques such as regression. Especially remembering that some causally complex paths to same result possible in FS/QCA method are impossible to accommodate with regression. For example, moderator effects with exclusive-or like characteristics (i.e. $A \cdot B \rightarrow C$).

In this section, I will first perform traditional least squares based multiple regression analysis, and then add moderator variables using stepwise approach. The analysis is done in R with the help of reference manuals (James et al., 2013; Kabacoff, 2015).

4.5.1 Data and model assumptions in regression analysis

The regression analysis uses the same data as earlier consisting of 108 observations. With all the properties used as variables, this means 15.4 observations per independent variable – a little over than recommended 15-20, but still sufficiently over the minimum of 5 (Hair et al. 2014:171). With sample of 108 with 7 independent variables and significance level of .05, the analysis will identify relationships explaining about 13% of the variance at power of .80 (Hair et al. 2014:170). The data is used in the form collected without any transformations as in FS/QCA method except for first days to travel (travelsoon), which was negated due to be comparable with the fuzzy-set transformation. That is, it is expected that longer the days to travel less the revenue gain. Next I must consider the assumptions in multiple regression analysis, which are linearity, constant variance of error terms, independence of error terms, and normality of the error distribution (ibid :178).

The linearity between the dependent variable and independent variables can be explored using scatterplots illustrated in Figure 26. The scatterplots reveal that there is no obvious linearity, which will cause problems in the analysis. In some cases the relationship even shows non-linear U shaped pattern. However, there is no clear non-linearity that could be easily corrected with transformations. Also, note the familiar triangular pattern for example between revenue gain and sales length, which is a key feature used in FS/QCA analysis.

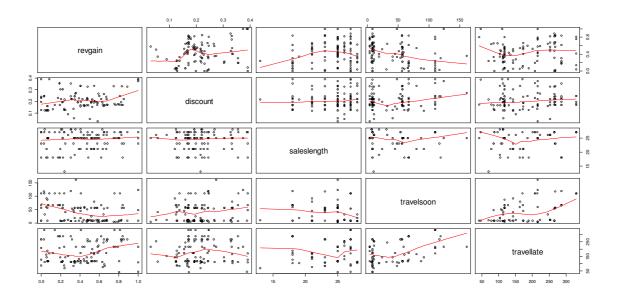


Figure 26. Scatterplot of the dataset.

Before I investigate the other assumptions, I must actually estimate the regression models, which is done in the following sections.

4.5.2 Estimating the models

In this thesis, two different regression models are used in comparison to the FS/QCA method. First, I will present the basic regression model without moderator coefficients and then move to more complex regression model with moderator coefficients, which is formulated using stepwise approach.

4.5.2.1 Multiple regression model without moderator coefficients

The general regression model without moderator coefficient can be defined as

$$Y = b_0 + b_1 X_1 + \dots + b_n X_n + \varepsilon,$$

where *Y* is the estimated dependent variable, *X* are the independent variables, and *b* are the estimated coefficients. The model was estimated with revenue gain as the dependent variable and the other properties used in FS/QCA analysis as the independent variable using the least squares method (James et al., 2013). The result of the estimation can be seen in Table 9. The model is statistically significant with p-value of 0.00006, but the coefficient of determination R^2 is rather small and explains only 26% of the variance.

Examining the model coefficients, two of them are significant at .01 level, one at 0.05 level, and two at 0.10 level. The relative importance of the model variables can be done by investigating the standardized coefficients, which are the coefficients if the data would have been standardized before the estimation (Hair et al. 2014:195). Their advantage is that they eliminate the problem with different units of measurement and indicate the relative impact on the dependent variable of a change in one standard deviation in either variable. Based on the standardized coefficients the most important coefficients are in order of importance: seasonality, days to travel, city destination, discount, and days to last date of travel. However, one must remember that the coefficients can vary largely when there is multicolline-arity present.

Variable	Estimated	Standardized	Standard	t	р		VIF
	coefficient	coefficient	Error				
Intercept	0.402	0.000	0.253	1.589	0.115		
Discount	0.729	0.214	0.341	2.139	0.035	**	1.35
Saleslength	0.006	0.071	0.007	0.804	0.423		1.07
Travelsoon	0.003	0.404	0.001	4.121	0.000	***	1.30
Travellate	0.001	0.188	0.000	1.769	0.080	*	1.54
Nordic	-0.051	-0.084	0.070	-0.733	0.465		1.76
City	-0.211	-0.400	0.110	-1.908	0.059	*	5.94
Seasonal	-0.294	-0.565	0.106	-2.771	0.007	***	5.63

Table 9. Regression result for the model without moderator effects

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

Then I must evaluate the models and validate the assumptions of multiple regression analysis.

First, I have to evaluate the model by assessing multicollinearity and identifying influential observations. In order to regression analysis to be useful, the independent variables should correlate with the dependent variable, but should have low collinearity and multicollinearity – i.e. correlation between independent variables (Hair et al. 2014: 161-162). As already shown in Table 5, there is not significant correlation with revenue gain and other variables, which unlike with comparative analysis makes the data bad candidate for regression analysis. However, there is high correlation between city and seasonality. This collinearity can be also observed by calculating the Variance Inflation Factors (VIF). The square root of VIF is the degree which the standard error has been increased due to multicollinearity (ibid.: 197). These values are found in Table 9, which shows both city and seasonality hav-

ing VIF around 6. Although this is less than generally accepted level of 10 (ibid.: 201), the value can be said to indicate problems in the model.

Influential observations can be visualized with added variable plots, which can be seen in Figure 27. I reviewed the influential observations and concluded them as relevant cases for the study – e.g. one city destination that always showed exceptional performance – and therefore they could not be labelled as outliers.

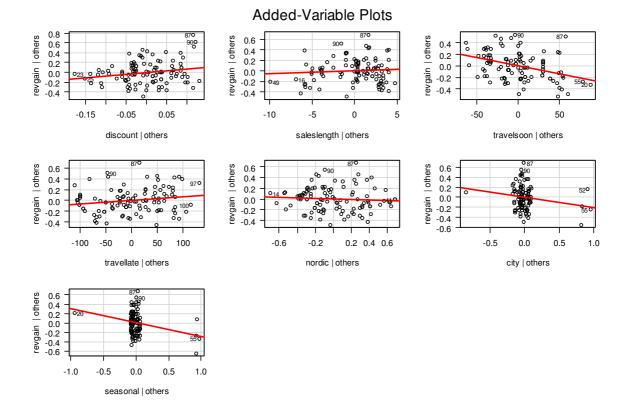


Figure 27. Added variable plots for the model without moderator effects.

Next, I move to the assumptions of multiple regression analysis and investigate the presence of unequal variances. The simplest diagnostics for investigating heteroscedasticity is to use residual plots against the predicted dependent values and check that the scatter resembles a null plot (Hair et al. 2012: 181). These plots are illustrated in Figure 28 and they clearly contain non-linearity and heteroscedasticity. This can be confirmed using studentized Breusch-Pagan's (1979) test for heteroscedasticity, which gives p value of 0.016 (<0.05) indicating heteroscedasticity. Unfortunately based on the residual plots, there is no easy transformation for stabilizing the variance of errors. This means that with this data the confidence intervals and p-values calculated are generally invalid.

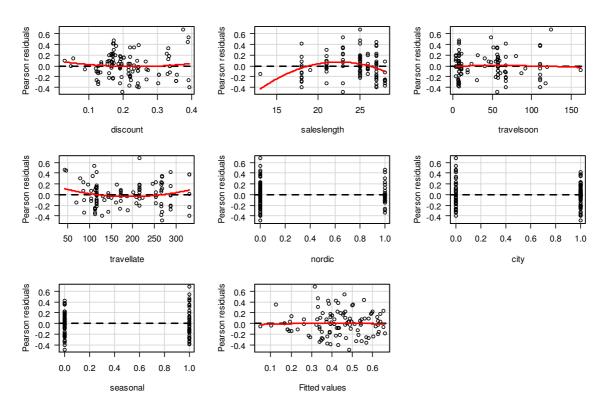


Figure 28. Residual plots of the fitted data for the model without moderator effects.

On the other hand, based on the data I would expect that the error terms are independent of each other, which can be tested using Durbin-Watson statistic (Durbin and Watson 1950). The statistic returned value of 1.034 indicating that predictions are not related to each other. And finally, I examine the normality of the error term distribution, which is illustrated using QQ-plot and histogram of residuals in Figure 29. The figures do not indicate non-normality and also the Shapiro-Wilk normality test for the residuals has a p-value of 0.36 (>0.05) indicating normality (Royston 1982).

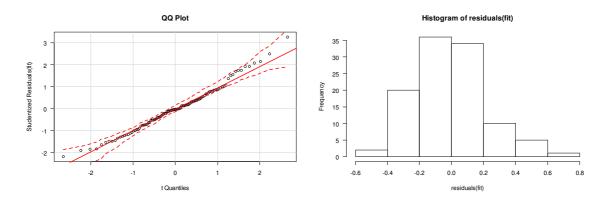


Figure 29. QQ-plot and histogram of residuals for the model without moderator effects.

4.5.2.2 Regression model with moderator coefficients

The general regression model with moderator coefficient can be defined as

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_1 X_2 + \dots + \varepsilon$$

where Y is the estimated dependent variable, X are the independent variables, and b are the estimated coefficients. Note that in FS/QCA the moderator effect can vary from two-way interactions (X_1X_2) to maximum of seven way interaction $(X_1X_2X_3X_4X_5X_6X_7)$ with all the properties included. From technical point of view some authors describe inclusion of such terms as a headache (Kent 2005).

Because it would not be sensible to add all the possible moderator variables – although such model would fit the data the best possible way, the generalizability and interpretability of such model is pointless – a better way of selecting the variables is needed. One approach for selecting the variables is to identify and analyze them one by one so that the researcher understands their operation and relationship with the output (Sharma et al., 1981). However, with multiple moderator variables this approach is impractical. Other widely used, but controversial (see e.g. Irwin and McClelland, 2001), method is the stepwise estimation (Hair et al., 2014: 184). In stepwise estimation, the researcher starts with the simplest model possible. Then each possible variable is considered for inclusion to the model and the variable with the greatest contribution is added first. The process is repeated until a statistically significant addition to the current equation is achieved (McIntyre, 1983). There are several different criteria for addition and most of them have a penalty for each additional variable in order to guarantee the generalizability of the model. The process described is called the forward selection method. Naturally, one could start from the most complex model and use backward selection to remove the variables.

In this thesis, I will use the forward stepwise regression method with Akaike Information Criteria (AIC), which is an entropy maximization principle (Akaike 1981; James et al., 2013: 210-213). The criterion aims to give a good trade-off between the goodness of the model fit and the complexity of the model. The aim is to find the model with the smallest AIC iteratively by adding or removing one variable at time. Note that this method is not based on statistically significant p-values. I used the default penalty factor of 2 for additional variables, which leads to likelihood-ratio tests with p-values < 0.1573 (Man and Chen, 2009).

The resulting model can be seen in Table 10. The model is statistically significant with pvalue of 0.000007 and the coefficient of determination R^2 has improved only slightly to 31%. Examining the model coefficients, three of them are significant at .01 level, three at 0.05 level, and two at 0.10 level. Based on the standardized coefficients the most important coefficients are: seasonality, seasonality with discount, Nordic destination with days to last date of travel, Nordic destination, City destination, days to travel, and days to last date of travel. It is worth noting that only two-way interaction terms were added by the step-wise process, but their relative importance is quite high.

Variable	Estimated coefficient	Standardized coefficient	Standard Error	t	р		VIF
Intercept	0.765	0.000	0.196	3.903	0.000	***	
travelsoon	0.003	0.374	0.001	3.874	0.000	***	1.3
nordic	0.322	0.527	0.188	1.712	0.090	*	13.6
seasonal	-0.601	-1.152	0.199	-3.026	0.003	***	20.9
discount	-0.458	-0.135	0.701	-0.654	0.515		6.1
city	-0.234	-0.444	0.107	-2.190	0.031	**	5.9
travellate	0.001	0.224	0.000	2.121	0.036	**	1.6
seasonal: discount	1.423	0.732	0.787	1.807	0.074	*	23.7
nordic: travellate	-0.003	-0.605	0.002	-2.045	0.044	**	12.6

Table 10. Regression result for the model with moderator effects.

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

As can be seen, the VIF values are considerably higher than in the model without moderators. Three of the variables have VIF values over 10 indicating problems with multicollinearity. This is not a surprise as moderator variables are naturally correlated with the original variables themselves. Although mean-centering has been proposed as a solution to reduce collinearity between linear and moderated terms – and thus increase the results validity – Echambadi and Hess (2007) have proven that it neither changes the computational precision of the parameters nor the sampling accuracy of the main and interaction effects. Therefore the only suitable method for coping with multicollinearity would be to drop one or more of the collinear variables (Mason and Perreault, 1991). The influential observations can be similarly determined using added-variable plots seen in Figure 30. Again, the observations were relevant and must be left to the data.

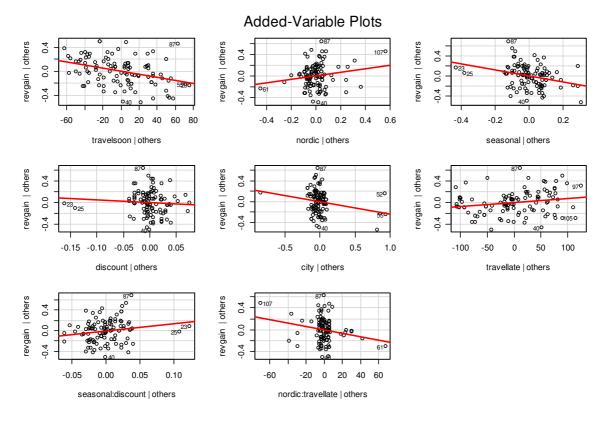


Figure 30. Added variable plots for the model with moderator effects.

Then the heteroscedastity can be investigated using Breusch-Pagan's (1979) test, which gives p value of 0.001 (<0.05) indicating again heteroscedasticity. Similarly the Durbin-Watson (1950) statistic returned value of 1.358 indicating that predictions are not related to each other. Finally, the normality of the error term distribution is illustrated using QQ-plot and histogram of residuals in Figure 31. The figures do not indicate non-normality and also the Shapiro-Wilk normality test for the residuals has a p-value of 0.51 (>0.05) indicating normality.

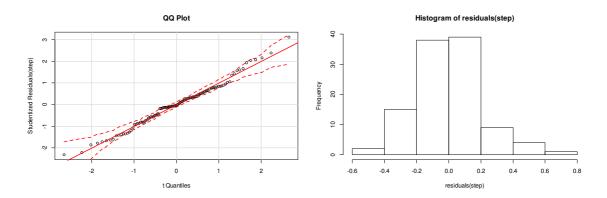


Figure 31. QQ-plot and histogram of residuals for the model with moderator effects.

4.5.2.3 Interpreting the regression models

Next we must examine and interpret the models, and make comparison between them. When comparing the adjusted R^2 between the models, the model with moderation effects has adjusted R^2 higher of (0.04). Thus, the increase is not that large to compensate the additional complexity. But as their performance is similar, it is interesting to study the similarities and differences between them. I will discuss and explain the coefficients in the order of importance indicated by the analysis.

When examining the coefficients from the models, both indicate that that seasonality has the most important and negative effect to the revenue gain. This is interesting finding and cannot be reasoned as seasonal destinations are promoted regularly. Short time to first travel date has positive relation as could be expected, since passengers are usually late than advance booking even for leisure segment and search for last minute travel deals. City destinations have negative relation, which would indicate that promotions work better on leisure type destinations, but combined with the negative effect of seasonality there is only one rather peculiar destination.

Discount has positive relation in the model without moderator, but is moderated with seasonality in the moderated model. This is one of the main differences between the models, especially considering that it is the second important coefficient in the latter model. Thus, based on the difference one could say that the discount affects more on seasonal destinations and such effect is actually positive to the revenue gain.

Days to last date of travel have positive contribution in both models. But it is also moderated with Nordic destinations in the second model, and the effect is negative. Therefore indicating that near term, shorter travel periods would have positive effect considering the revenue. It is also worth noting, that Nordic coefficient has negative value in the first model and positive in the second.

However, one must remember that the relative effect of the moderator coefficients and the dummy variables related to them must be questioned due to their collinearity. Therefore even the signs of their effects cannot be verified, which hampers their usability in describing the causalities. Additionally, as Irwin and McClelland (2001) demonstrate, the coding of the dummy variables using dummy codes (0 and 1) or contrast codes (-1 and 1) can change the results and the interpretation considerably.

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4.5.2.4 Validity and reliability

The resulting model from regression can be validated in several ways: assessing the adjusted R^2 , splitting the sample into two subsamples, evaluating alternative regression models, confirmatory approach using independent variable, and adding nonmetric independent variables (Hair et al., 2014: 202-203). Because the aim of the analysis was only to make comparison to FS/QCA method, I will only examine the R^2 values: the adjusted R^2 show only little loss (~0.05) compared to the R^2 value for both the regression models, which indicates a lack of overfitting. It should be noted though that the R^2 values obtained are rather low and explain less than half of the variation. Meaning that most of the variation is left to the residuals of the model.

4.6 Comparison of the FS/QCA and regression results

As expected based on the methods fundamental differences, the results acquired from FS/QCA method and regression analysis were quite different from each other. In this section, I will try to identify their similarities and differences and will address them starting from simple necessary conditions to more causally complex configurations.

In the positive FS/QCA outcome, short period to first travel date was found to be a necessary condition. Thus, it is present in all configurations and therefore should be also found in the regression analysis. As discussed, in regression analysis the observed conditions are both sufficient and necessary (Schneider and Eggert 2014). The coefficient for this variable was found to be positive and statistically significant in the both regression models. Therefore similar finding was made using both methods.

Discount is present in all but one configuration where its value does not matter. In comparison to FS/QCA, discount has relatively high negative effect on the regression model without moderators, but in the model with moderators the discount is moderated with seasonality with positive effect. In fact, the sole discount coefficient in the latter model is not statistically significant. This difference can be also observed in the FS/QCA configurations, where the discount is not present in one of the non-seasonal configurations, but is present with half of the seasonal configurations. Thus, by simply observing that non-seasonality is present in more than half of the configurations, one could assume that its effect is negative in regression without moderation effects. However, one cannot make a clear conclusion about its effect in the moderated case due its high multicollinearity. The length of sales period has positive effect in all but one configuration. But it is not statistically significant in the first regression model and not even added in the step-wise model. This makes sense, when remembering that the parameter was difficult to calibrate due to its low variance. In other words, variation in variables is needed for regression analysis.

Long period to last travel date has positive effect in two configurations and negative in three. Therefore it is interesting to notice that its effect is positive in both regression models. One possible explanation for this is that the positive configurations coverages combined are higher than the negative three. As discussed coverage determines the amount of outcome it covers thus indicating effect size (Ragin, 2008: 44; Woodside, Hsu, and Marshall, 2011). And the effect size then determines the sign of the regression coefficients.

Finally, we discuss the three crisp properties: Nordic, city, and seasonal destinations. Their effect varies between the configurations, and the results from regression analysis are rather confusing. In the model without moderator effects, all the coefficients are negative. Based on that the revenue gain should be high to non-Nordic, non-city, non-seasonal destinations – rather an odd destination. The results are a bit different in the model with moderator coefficients, but as discussed, we cannot explain those coefficients due to high multicolline-arity. All in all, we can conclude that especially these binary properties contain complex configurational causality that is hard to evaluate with traditional statistical methods.

Comparing to the negative FS/QCA outcome is done similarly. With regression analysis, the difference between positive and negative outcomes is just the change in the signs of the estimated coefficients. With this in mind, it is no surprise that the two necessary conditions – short period to last travel date and seasonal destination – were the two consistently negative coefficients in both models. Thus, although those properties differed in positive outcome configuration, their explanation in terms of regression relates to the consistency in negative outcome configurations. However, this is not always the case as seen in non-city destinations resulting into negative outcome, while the regression indicates the contrary. When comparing the configuration to different outcomes, one can notice why this contradiction exists: if the outcomes are not opposites in terms of properties, it cannot be guaranteed that necessary condition in only one output would lead into consistent similarity in regression model.

Similarly two configurations require long period to first travel date, which significant and negative in both regression models. But two configurations also require long sales period,

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which is practically obsolete in both models. Also, the negative relation to discount is present only in one regression model, and the presence of Nordic and non-Nordic destinations in the configurations cannot be explained with the regression model.

5 Discussion

The aim of this thesis was to examine which properties of promotions explain their financial performance. The intention was to participate in the discussion of marketing performance measurement and link it the marketing capabilities – i.e. knowledge of which works and which not. Due to technological development and increasing amount of available data, this kind of measuring the value of marketing activities and investments is continuously selected as one of top priorities in marketing research (Marketing Science Institute, 2014).

This measurement process was executed with two different methodologies. First, a rather novel approach in marketing, Fuzzy-set Qualitative Comparative Analysis, was used in examining different causal configurations behind the financial performance. Then, the results were compared to more traditional statistical analysis technique: multiple regression analysis.

In this chapter, I will first conclude the results of this thesis. Then I will discuss the managerial implications. And finally I will conclude the thesis by reviewing the limitations of the study.

5.1 Conclusions

The contribution of this thesis is two-fold. First, it confirmed the results of previous study of Vassinen (2012) by using FS/QCA in explaining the outcomes of marketing activity. Furthermore, it used a rather large dataset of around 100 cases while usually smaller dataset is used (Kent 2005; Rihoux 2006). Second, it compared the configurations formulated in FS/QCA method to those obtained using traditional regression analysis modelling. Therefore it tried to answer to the common deficiency of FS/QCA, which is validating the result using an alternative methodology. As discussed, validation of FS/QCA is difficult, because the method involves large amount of qualitative consideration.

The main research question of this thesis was: Which promotion properties and permutations of properties, found using FS/QCA, are relevant considering effective outcome? The answer to this question is two-fold. First, the configurations resulting into positive revenue outcomes were extremely rational and corresponded to the know-how of the business and revenue managers. Some of them resulted even in linguistically common titles like 'last minute travel deal'. The common factor in the successfulness of promotion was that the period to the first travel date was short. This would indicate that customers are not, after all, very good in planning their trips well in advance. Although this by no means implies that early promotions would be useless, but they are not as effective in increasing revenues. This corresponds well with the most often asked question from airline employees: when you should buy the tickets? And when answering as early as possible – a no-brainer in many senses – the asker often just gives baffled looks.

Another common indicator for revenue gain was the amount of discount. This again was not a surprising result. However, the discount did not matter to city like destination types when the sales and travel periods were long. Such destinations have usually rather large amount of natural demand, but they are also the destination with the most competition. Thus these promotions were probably done only as a competitive action against other airlines promotional fares.

However, the successfulness of different travel periods depended on the destination type. That is also naturally explainable by known customer behavior patterns. Usually the customers prefer to book their tickets to short-haul destinations quite near departure. That is, to Nordic seasonal destinations and Nordic cities. On the contrary, non-Nordic seasonal destinations – i.e. in this case long-haul destinations – required longer period to last travel date.

Secondly, the configurations resulting into negative revenue gain were not that intuitive. For example, all the negative revenue gain configurations involved seasonal leisure destinations with short period to last travel date. It is obvious that such definition is rather strict requirement and there should be possible promotions to other kinds of destinations that are also destined to fail. One explanation behind this result is that the despite the rather large amount of cases, the amount of different configurations present in the truth table is still 22 out of 128 possible. In other words, the promotional configurations are selected based on the knowledge of the business manager and she definitely does not use combinations resulting into low revenue gain that she knows will fail for sure. Therefore the used configuration which might fail are mostly experimentations to new and unfamiliar destinations, which are usually seasonal leisure destinations.

However, there is still some insight in the negative outcome results: that long sales length and short time to departure to Nordic leisure destinations does not work without discount, and that even discount does not work in long-haul leisure destinations when the travel period is restricted.

This thesis has also two sub-questions. The first one is: Can these configurations be validated using triangulation with regression analysis? The answer is yes and no. Based on the coefficient of determination, it was clear that regression analysis did not explain the causality very well. In fact, the error terms were explaining most of the variation in the regression models. Therefore making clear, that using causally complex data in regression analysis does not result into well explainable outcomes. It is worth noting that similar coefficient of determination was found in other studies comparing FS/QCA to regression (Vis 2012).

When comparing the regression results to FS/QCA it was found that regression identifies conditions only if they are opposite in both positive and negative outcomes. Thus even necessary condition to only one outcome does not guarantee that similar effect can be found in regression analysis. I.e. indicating that conditions need to be necessary and sufficient to be identified. Consequently, the presence of different causally complex paths resulted into unexplainable and conflicting results. Especially for crisp properties the results between FS/QCA and regression were very different. While some of the causal complexity could be explained using moderator variables, their compliance to the homoscedasticy assumptions was severely violated meaning that their explanatory power was weak. Finally, the amount of moderator variables added by the step-wise method was small and considered only two-way interactions – compared to configurations which contained 7-way interactions. Such interactions could have been naturally added to the regression model, but such a model would naturally contain mostly statistically insignificant coefficients.

Then the next sub-question was: Which advantages or disadvantages does FS/QCA have compared to other methods? The obvious advantage of the FS/QCA method is that it can explain the behavior of rather complex configurations compared to traditional regression analysis. Therefore it offers more thick description to the phenomena examined in given business context. The researcher can even pinpoint the cases included in the configuration for further examination, which definitely regression lacks. It is also very versatile in that the thresholds can be determined by the researcher – for example, one could differentiate which configurations lead to exceptional financial performance by tightening the membership criteria and which configurations lead to acceptable performance by loosening the

criteria. Additionally, as Thiem and Duşa (2012) illustrate, the calibration can be done with non-linear U-shaped functions, which increase the possible use cases further.

The disadvantages of FS/QCA compared to regression relate to its rather thin burden of proof. It is not a statistical method and although some studies try to assess the lack of different validity measures the method has not gained traction in the top journals. For example, Eliason and Stryker (2009) have developed goodness-of-fit tests for fuzzy-set analysis, Skaaning (2011) has investigated the sensitivity of the calibration and developed robustness test for frequency and consistency thresholds, and Schneider and Wagemann (2012: 284) describe how to evaluate membership calibration, consistency levels, and case deletion and addition. For the most mathematically emphasized discussion, one should familiarize with the works of Korjani and Mendel, who offer step-by-step flowcharts for executing FS/QCA procedure (Mendel and Korjani, 2012), validate the FS/QCA for problems of initialization and function granulation (Korjani and Mendel, 2012), and evaluate the challenges and their solutions for using FS/QCA in engineering and computer science problems (Korjani and Mendel, 2012b).

Additionally, it became evident even in this thesis that the amount of different configurations from the total possible combinations and the amount of cases in a configuration might remain small even with relatively large dataset. Also, if there is not enough variation, just forcing the properties to be dichotomized does not work as was found when investigating the statistical significance of sales length variable in regression analysis.

5.2 Managerial implications

For managerial perspective, this thesis has three points. First, generally the effect of promotions were not thoroughly evaluated and no structured knowledge was generated. Although the passenger amounts and financial measures were collected and distributed, they are usually just acknowledged without detailed elaboration. Therefore no explicit and widely distributed knowledge which aspects of the promotions are important were available and the successfulness of promotions was grounded on the experience of the business manager – as Day (1994) argues, these marketing capabilities were indeed tacit and dispersed.

Second managerial implication is the results themselves. Although many of them were self-evident to the business manager – indicating the truth about academic studies in the saying "all sort of docents that tell what to do and not" – at least the ones leading to posi-

tive outcomes are now observed and labelled. Almost all of them – continuous promotions to city destinations, last minute travel deals, seasonal promotions to Nordics, et cetera – were already constantly used and belonged in the vocabulary of daily work. Indeed, managerial intuition has been proven to perform better than models in some situations (Wübben and Wangenheim 2008).

Third, the FS/QCA method itself proved some usefulness in managerial context. Compared to results from statistical methods, the method produced many empirical generalizations from the data. Although their real significance needs to be verified, at least the method makes possible to pinpoint the cases, which can be then examined individually. Additionally, the selection of calibration thresholds can be used to give different views to the same data – i.e. evolving the knowledge towards the analytic moment (Rihoux and Lobe, 2009: 229).

5.3 Limitations

Stewart (2009) indicates two problems in examining the effect of marketing. First, data limits the used models and researchers fail to measure what is important. Data is usually chosen from what is available, which does not guarantee that it is useful. Second, modeling is not substitute for good measures. Modeling with bad measures gives only unreliable outcomes. Additionally, models give only view to the history – and they do not necessarily work in the future without proper calibration.

Unfortunately these problems are present also in this thesis. First, as this study was not a controlled experiment, some of the property space variables had to be neglected as their values varied only a little. E.g. the promotions are usually done with the same fare rules: advance purchase time, minimum and maximum stay, et cetera. Their effect would be worth to study, but that would have meant more of a controlled experiment involving the business manager in executing different variations of the rules.

Second, the revenue gain metric used was a crude approximation of the reality. Differentiating increase in revenue due to promotion was found to be surprisingly hard to measure. One would have to take into account the target audience of the promotion: measure the effect for leisure passengers, not the business passengers. One would have also taken into account the possible down-sell, the possibility that the promotion caused revenue dilution. One would also need to investigate the temporal effects: not only to measure the effect on revenue during the promotion, but also before and afterwards. Third, can the causality be guaranteed in future? Or can the causality guaranteed at all? As noted, the calibration of properties in FS/QCA is always based on the knowledge and reasoning of the researcher. Even a small change in the calibration process can alter the output drastically. As the results from FS/QCA method are poorly triangulated with regression methods, then the validity of the results cannot be verified. In other words, the result can give insight to the data, but the results must be taken with a grain of salt. Additionally, the method is so much dependent on context so that any generalization to other settings cannot be done. To conclude, a lot is still to be done in order to validate the usability of FS/QCA in marketing research.

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7 Appendix

Truth table for positive outcome

		e value of cases in iency inclus [.]		ion							
$\begin{array}{c} 2 \\ 6 \\ 34 \\ 38 \\ 42 \\ 59 \\ 66 \\ 74 \\ 59 \\ 99 \\ 66 \\ 74 \\ 75 \\ 87 \\ 99 \\ 99 \\ 107 \\ 114 \\ 115 \\ 119 \\ 122 \\ 33 \\ 42 \\ 59 \\ 66 \\ 74 \\ 59 \\ 98 \\ 90 \\ 60 \\ 71 \\ 115 \\ 118 \\ 99 \\ 90 \\ 107 \\ 114 \\ 115 \\ 118 \\ 122 \\ 123 \end{array}$	0 0 0 0 0 0 0 0	0,36,40,73,70 71,79 ,47,49,50 ,101,102 27,37,38,69,3 58,75,77,85 74,86 ,48,51	0 0 0 1 1 0 0 0 1 1 1 0 0 0 0 1 1 1 1 1	TRAVELLATE 0 0 0 1 1 0 1 1 0 0 0 0 1 1 1 0 0 0 0	NORDIC 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	CITY 0 0 0 0 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0	SEASONAL 1 1 1 1 0 1 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0	OUT 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	3 3 2 4 3 3 2 3 2 10 5 6 5 10 2 7 3 5 2 5 3	$\begin{array}{c} 0.588\\ 0.283\\ 0.971\\ 0.616\\ 0.679\\ 0.578\\ 0.998\\ 0.650\\ 0.408\\ 0.787\\ 0.667\\ 0.613\\ 0.708\\ 0.536\\ 0.536\\ 0.897\\ 1.000 \end{array}$	0.010 0.009 0.011 0.436 0.959 0.425 0.521 0.997 0.462 0.997 0.462 0.138 0.641 0.563 0.521 0.521 0.546 0.347 0.347 0.949

The complex solution for positive outcome

n OUT = 1/0/C: 28/71/0 Total : 99

Number of multiple-covered cases: 0

<pre>M1: SALESLENCTH*TRAVELSOON*TRAVELLATE*_NORDIC*CTTY*-SEASONAL + DISCOUNT*SALESLENCTH*TRAVELSOON*ATRAVELLATE*NORDIC*CTTY*-SEASONAL + DISCOUNT*SALESLENGTH*TRAVELSOON*ATRAVELLATE*NORDIC*CTTY*-SEASONAL + DISCOUNT*SALESLENGTH*TRAVELSOON*ATRAVELLATE*NORDIC*CTTY*-SEASONAL => REVGAIN incl PRI cov.r cov.u incl PRI cov.r cov.u issalesLength*TRAVELSOON*TRAVELLATE* 0.963 0.955 0.199 0.168 -NORDIC*CTTY*-SEASONAL DISCOUNT*SALESLENGTH*TRAVELSOON*-TRAVELLATE* 0.998 0.997 0.084 0.053 -NORDIC*CTTY*-SEASONAL DISCOUNT*SALESLENGTH*TRAVELSOON*-TRAVELLATE* 0.897 0.882 0.029 0.029 NORDIC*CTTY*-SEASONAL DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.063 NORDIC*CTTY*-SEASONAL M1 0.968 0.960 0.409 M1 0.968 0.960 0.960 M1 0.968 0.960 0.409 M1 0.968 0.960 0.960</pre>
1 SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.963 0.955 0.199 0.168 2 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.998 0.997 0.084 0.053 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.998 0.997 0.084 0.053 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.897 0.882 0.029 0.029 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.960 0.949 0.066 0.063 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 6 M1 0.968 0.960 0.409 7 SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.409 7 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*_NORDIC*CITY*>SEASONAL 23,25; 1,7,8,22,31 7 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*_NORDIC*CITY*>SEASONAL 42,21,34,71,79 7 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*_NORDIC*CITY*>SEASONAL 41,42,45,48,51 9 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*>SEASONAL 41,42,45,48,51 9 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*>SEASONAL 41,42,45,4
-NORDIC*CITY*-SEASONAL 0.998 0.997 0.084 0.053 2 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.897 0.882 0.029 0.029 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.897 0.882 0.029 0.029 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.960 0.949 0.066 0.063 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 6 MI 0.968 0.960 0.409 0.066 0.066 6 MI 0.968 0.960 0.409 0.066 0.066 7 SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 7 MI 0.968 0.960 0.409 0.066 0.066 7 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 7 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* NORDIC*CITY*SEASONAL 23, 25; 1, 7, 8, 22, 31 32; 33, 67, 72; 80, 84 9 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 4, 21, 34, 71, 79
<pre>2 DISCOUNT*-SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.998 0.997 0.084 0.053 ~NORDIC*CITY*-SEASONAL 0 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.897 0.882 0.029 0.029 NORDIC*~CITY*SEASONAL 1 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 1.000 1.000 0.063 0.063 NORDIC*~CITY*SEASONAL 1 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 ~NORDIC*~CITY*SEASONAL 1 SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 ~NORDIC*~CITY*SEASONAL 1 SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.968 0.960 0.409 </pre>
<pre>3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 0.897 0.882 0.029 0.029 NORDIC*~CITY*SAASONAL 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE* 1.000 1.000 0.063 0.063 NORDIC*~CITY*SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* 0.960 0.949 0.066 0.066 ~NORDIC*~CITY*SEASONAL 6 O.968 0.960 0.409 6 Cases 7 Cases 7 SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*~SEASONAL 7 Cases 7 SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*~SEASONAL 7 Cases 7 SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 7 Cases 7 SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 7 Cases 7 SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 7 SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 7 SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 7 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 7 SDISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 7 SDISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 7 SDISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*SEASONAL 7 SDISCOUNT*SALESLENGTH*TRAVELSOON*CONTOR 7 SDISTON SOUTON FOR POSITIVE OUTCOME 7 SEVGAIN 7 STARVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*TRAVELSOON*~NORDIC 7 SEASONAL) 7 SRUGAIN 7 STRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC 7 CITY 7 SEASONAL 7 SRUGAIN 7 STRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC 7 CITY) 7 SRUGAIN 7 SRUGAIN 7 SRUGAIN 7 SRUGAIN</pre>
NORDIC*CITY*-SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE* NORDIC*-CITY*SEASONAL M1 0.968 0.960 0.409 Cases 1 SALESLENGTH*TRAVELSOON*TRAVELLATE*-NORDIC*CITY*-SEASONAL 23,25; 1,7,8,22,31 32,33,67,72,80,84 2 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*-NORDIC*CITY*-SEASONAL 4,21,34,71,79 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*-SEASONAL 4,21,34,71,79 3 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*-SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 6,97,100 The parsimonious solution for positive outcome n OUT = 1/0/C: 28/71/0 Total : 99 M1: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*TRAVELSOON*~NORDIC] => REVGAIN M2: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC *CITY) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC *CITY) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC *CITY) => REVGAIN
<pre>-NORDIC*~CITY*SEASONAL M1 0.968 0.960 0.409 </pre>
Cases 1 SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*~SEASONAL 23,25; 1,7,8,22,31 32,33,67,72,80,84 2015COUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 4,21,34,71,79 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 106,107 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 106,107 4 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*SEASONAL 41,42,45,48,51 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*SEASONAL 96,97,100 The parsimonious solution for positive outcome n OUT = 1/0/C: 28/71/0 0011 Total : 99 99 M1: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*TRAVELSOON*~NORDIC) :> REVGAIN *~SEASONAL) :=> REVGAIN **SEASONAL) :=> REVGAIN **SEASONAL) :=> REVGAIN **CITY) :=> REVGAIN **CITY*
<pre>1 SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*~SEASONAL 23,25; 1,7,8,22,31 32,33,67,72,80,84 2 DISCOUNT*~SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 4,21,34,71,79 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*SEASONAL 4,21,34,71,79 4 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 106,107 4 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 41,42,45,48,51 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*~NORDIC*CITY*SEASONAL 96,97,100</pre>
2 DISCOUNT*~SALESLENGTH*TRAVELSOON*~TRAVELLATE*~NORDIC*CITY*~SEASONAL 3 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*~SEASONAL 4 J.21,34,71,79 1 DISCOUNT*SALESLENGTH*TRAVELSOON*~TRAVELLATE*NORDIC*CITY*~SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*~SEASONAL 5 DISCOUNT*SALESLENGTH*TRAVELSOON*TRAVELLATE*NORDIC*CITY*SEASONAL 6 J.42,45,48,51 9 J.42,45,48,51 9 J.97,100 The parsimonious solution for positive outcome n OUT = 1/0/C: 28/71/0 Total : 99 M1: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*TRAVELSOON*~NORDIC) => REVGAIN M2: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN
The parsimonious solution for positive outcome n OUT = 1/0/C: 28/71/0 Total : 99 M1: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*TRAVELSOON*~NORDIC) => REVGAIN M2: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC) => REVGAIN
=> REVGAIN M2: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC *CITY) => REVGAIN
M2: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC => REVGAIN M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDIC *CITY) => REVGAIN
M3: TRAVELSOON*TRAVELLATE + DISCOUNT*SALESLENGTH*NORDIC + (~SALESLENGTH*~TRAVELLATE*~NORDI(*CITY) => REVGAIN
=> REVGAIN
incl PRI cov.r cov.u (M1) (M2) (M3)
1 TRAVELSOON*TRAVELLATE 0.869 0.836 0.332 0.216 0.262 0.262 2 DISCOUNT*SALESLENGTH*NORDIC 0.945 0.929 0.092 0.083 0.083 0.083
3 ~SALESLENGTH*TRAVELSOON*~NORDIC 0.880 0.825 0.163 0.029 0.056 4 ~SALESLENGTH*~TRAVELLATE*~NORDIC*~SEASONAL0.995 0.992 0.126 0.003 0.066 5 ~SALESLENGTH*~TRAVELLATE*~NORDIC*CITY 0.989 0.980 0.137 0.011 0.071

Truth table for negative outcome

OUT: outcome value n: number of cases in configuration incl: sufficiency inclusion score									
2 6 34 38 42 59 66 74 75 83 87 99 106 107 114 115 118 119 122 123	DISCOUNT 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1	SALESLENGTH 0 1 1 1 1 1 0 0 0 0 0 0 0 1 1 1 1 1 1	TRAVELSOON 0 0 0 1 1 0 0 0 0 1 1 0 0 0 0 1 1 1 0 0 0 1 1 1 1 1 1 1 1 1	TRAVELLATE 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0	NORDIC 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	CITY 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	SEASONAL 1 1 1 1 1 0 1 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0	OUT 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0	n incl PRI 3 0.958 0.932 3 0.991 0.990 2 0.994 0.991 4 0.988 0.986 3 0.681 0.564 3 0.865 0.842 2 0.314 0.020 3 0.716 0.575 2 0.648 0.473 10 0.560 0.475 5 0.345 0.003 6 0.573 0.344 5 0.836 0.762 10 0.557 0.253 2 0.571 0.437 7 0.516 0.400 3 0.521 0.257 5 0.683 0.553 2 0.230 0.118 5 0.290 0.000 3 0.220 0.013 11 0.199 0.009
2 6 34 38 42 54 59 66 74 75 83 87 99 106 107 114 115 118 119 122 123	$\begin{array}{llllllllllllllllllllllllllllllllllll$								

The complex solution for negative outcome

n OUT = 1/0/C: 20/79/0 Total : 99

Number of multiple-covered cases: 6

М1	: ~DISCOUNT*~TRAVELSOON*~TRAVELLATE*~CITY*SEASONAL + ~DISCOUNT*SALESLENGTH*~TRAVELLATE*NORDIC*~CITY*SEASONAL + SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~NORDIC*~CITY*SEASONAL							
		incl	PRI	cov.r	cov.u			
1 2 3	~DISCOUNT*~TRAVELSOON*~TRAVELLATE*~CITY*SEASONAL ~DISCOUNT*SALESLENGTH*~TRAVELLATE*NORDIC*~CITY*SEASONAL SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~NORDIC*~CITY*SEASONAL	0.912 0.903 0.123 0.			0.078 0.060 0.078			
	M1	0.896	0.874	0.314				
		cases						
1	~DISCOUNT*~TRAVELSOON*~TRAVELLATE*~CITY*SEASONAL	14,15,16; 58,62,65; 18,19; 57,63,64,66						
2 3 	~DISCOUNT*SALESLENGTH*~TRAVELLATE*NORDIC*~CITY*SEASONAL SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~NORDIC*~CITY*SEASONAL	57,63,64,66; 56,59,60 18,19; 91,92,94,101,102						

The parsimonious solution for negative outcome

n OUT = 1/0/C: 20/79/0 Total : 99

M1: ~DISCOUNT*~TRAVELLATE + (SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~CITY) => ~REVGAIN M2: ~DISCOUNT*~TRAVELLATE + (SALESLENGTH*~TRAVELSOON*~TRAVELLATE*SEASONAL) => ~REVGAIN

		incl	PRI	cov.r	cov.u	(M1)	(M2)
1	~DISCOUNT*~TRAVELLATE	0.834	0.777	0.305	0.208	0.208	0.208
_	SALESLENGTH*~TRAVELSOON*~TRAVELLATE*~CITY SALESLENGTH*~TRAVELSOON*~TRAVELLATE*SEASONAL					0.081	0.087
	 M1 M2		0.766 0.768				

The coefficients of the multiple regression model without moderator variables Residuals: Min 10 Median 30 Max -0.48648 -0.15214 -0.00818 0.12564 0.68257 Coefficients: Estimate Standardized Std. Error t value Pr(>|t|) (Intercept) 0.4022382 0.0000000 0.2532100 1.589 0.11532 discount 0.7289120 0.2142581 0.3407168 2.139 0.03484 * 0.0714632 0.4040295 0.804 0.42340 4.121 7.79e-05 saleslength 0.0058226 0.0072436 *** travelsoon 0.0028121 0.0006824 1.769 0.08001 travellate 0.0006478 0.1883281 0.0003663 -0.733 0.46528 -1.908 0.05925 . -2.771 0.00667 ** nordic -0.0511437 -0.2105538 -0.0836491 -0.3996818 0.0697739 0.1103481 citv -0.5646458 0.1062871 seasonal -0.2944699 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.2303 on 100 degrees of freedom Multiple R-squared: 0.2616, Adjusted R-squared: 0.21 F-statistic: 5.062 on 7 and 100 DF, p-value: 6.046e-05 The stepwise model path for the multiple regression model with moderator variables Stepwise Model Path Analysis of Deviance Table Initial Model: revgain ~ 1 Final Model: revgain ~ travelsoon + nordic + seasonal + discount + city + travellate + seasonal:discount + nordic:travellate Step Df Deviance Resid. Df Resid. Dev AIC 107 7.182167 -290.7372 1 2 6.602796 -297.8209 6.125046 -303.9325 5.881658 -306.3116 5.656626 -308.5248 5.472804 -310.0927 + travelsoon 1 0.5793716 106 1 0.4777495 1 0.2433883 1 0.2250315 1 0.1838226 + nordic 3 105 104 + seasonal 4 103 + discount 5 102 + discount:seasonal 6 1 0.1805433 5.292261 -311.7157 + city 101 8 + travellate 9 + travellate:nordic 1 0.1467476 1 0.2085237 100 5.145513 -312.7527 4.936989 -315.2206 99 The coefficients of the stepwise multiple regression model with moderator variables Residuals: Min 1Q Median 3Q Max -0.5004 -0.1393 -0.0072 0.1322 0.6313 Coefficients: Estimate Standardized Std. Error t value Pr(>|t|) 0.7649331 0.0000000 0.1959869 3.903 0.000173 *** 0.0026015 0.3737744 0.0006716 3.874 0.000193 *** 0.7649331 (Intercept) 0.3737744 0.5270223 3.874 0.000193 *** 1.712 0.089996 0.0026015 travelsoon nordic 0.3222252 0.1881970 -1.1520501 -0.1347431 -0.4444800 0.2237585 0.7323384 -3.026 0.003157 ** seasonal -0.6008088 0.1985385
 -0.1347431
 0.7010093
 -0.654
 0.514683

 -0.4444800
 0.1069228
 -2.190
 0.30877 *

 0.2237585
 0.0003629
 2.121
 0.036426 *

 0.7323384
 0.7871389
 1.807
 0.073770

 -0.6052268
 0.0015048
 -2.045
 0.043522 *
 discount -0.4583996 -0.2341537 citv travellate 0.0007697 seasonal:discount 1.4225074 nordic:travellate -0.0030770 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.2233 on 99 degrees of freedom Multiple R-squared: 0.3126, Adjusted R-squared: 0.2571 F-statistic: 5.628 on 8 and 99 DF, p-value: 6.944e-06