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How Non-Financial Customer Based Metrics are Associated with Company Performance? An Analysis of Customer Satisfaction, Customer Retention and Net Promoter Score in Telecommunications Industry

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Abstract
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HOW NON-FINANCIAL CUSTOMER BASED METRICS ARE ASSOCIATED WITH COMPANY PERFORMANCE? AN ANALYSIS OF CUSTOMER SATISFACTION, CUSTOMER RETENTION AND NET PROMOTER SCORE IN TELECOMMUNICATIONS INDUSTRY

PURPOSE OF THE STUDY

The purpose of this thesis is to examine, how a set of non-financial customer based metrics are associated with company performance. I study how three customer-driven metrics, namely customer satisfaction, customer retention and a customer loyalty measure of Net Promoter Score, are linked with value shares of telecommunication companies. A particular focus of this study is on discovering whether changes in these non-financial metrics are reflected in performance instantaneously or is there a time lag between the cause and effect.

DATA

The empirical analysis conducted in this study is based on two longitudinal datasets from the telecommunication industry covering a period of Q2/2007-Q1/2011. The first dataset is an extensive consumer survey conducted in 19 countries on a quarterly basis and it works as a source for the non-financial metrics. The second dataset is provided by GfK and it contains information on mobile handset prices and volumes on a country and brand level, and enables one to form performance proxies of value shares for different brands in different countries, respectively. In total, the final dataset, where the consumer survey and the GfK market tracking dataset have been combined, consists of 2032 quarterly observations for 19 countries and has records from 19 different mobile phone manufacturers.

RESULTS

My findings show that customer satisfaction and customer retention -metrics seem to be positively associated with company performance, here measured in value share development. Specifically, I find that changes in customer satisfaction are reflected in performance only after two quarters and changes hold explanatory power for up to five quarters, suggesting that customer satisfaction has a lagged effect on performance. Based on my results, current period customer retention rates are positively associated with value shares, and lagged variables of retention rate hold explanatory power for up to one year, or four quarters. Finally, my results indicate that the Net Promoter Score does not seem to be of relevance in explaining company performance.

KEYWORDS

Non-financial metrics, company performance, customer satisfaction, customer retention, Net Promoter Score, telecommunications industry

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Pro gradu -tutkielma
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Tiivistelmä
16 marraskuuta, 2011

KUINKA ASIAKASLÄHTÖISET EI-RAHAMÄÄRÄISET MITTARIT OVAT YHTEYDESSÄ YRITYSTEN MENESTYMISEEN? ANALYYSI ASIAKASTYYTYVÄISYYS, ASIAKAS-RETENTIO JA NET PROMOTER SCORE -MITTAREISTA TIETOLIIKENTEEN TOIMIALALLA

TUTKIELMAN TAVOITTEET

Tämän tutkielman tarkoituksena on selvittää, kuinka kolme erilaista asiakaslähtöistä mittaria ovat yhteydessä yritysten menestymiseen tietoliikenteen toimialalla. Työssä tutkitaan asiakastyytyväisyyden, asiakas-retentionin, sekä Net Promoter Score -mittarien yhteyttä matkapuhelinvalmistajien myyntimääräiseen markkinaosuuteen. Tutkielman erityisenä tavoitteena on tarkastella, heijastuvatko vaihtelut edellä mainituissa mittareissa yritysten menestymisessä välittömästi, vai onko näiden kahden asian välillä ajallista viivettä.

LÄHDEAINEISTO

Tutkielman empiirinen aineisto pohjautuu kahteen tietolähteeseen tietoliikenteen toimialalta ja tutkimusaineisto käsittää ajanjakson huhtikuusta 2007 maaliskuuhun 2011. Ensimmäinen osa tutkimusaineistosta koostuu laajasta asiakaskyselystä, joka on toteutettu 19 maassa vuosineljänneksittäin ja se toimii tutkimuksessa lähteenä asiakaslähtöisille, ei-rahamääräisille mittareille. Jälkimmäinen osa tutkimusaineistoa on GfK:n keräämää ja se sisältää informaatiota matkapuhelimien hinnoista ja myyntimääristä maittain, vuosineljänneksittäin sekä valmistajakohtaisesti ja mahdollistaa näin myyntimääräisen markkinaosuuden laskemisen kullekin valmistajalle neljännes- sekä maatasolla. Lopullinen analysoitava aineisto koostuu näin ollen 2032 neljännesvuosittaisesta havainnosta sisältäen havaintoja 19 maasta ja 19 eri matkapuhelinvalmistajalle.

TULOKSET

Tämän tutkimuksen tulokset osoittavat että asiakastyytyväisyys sekä asiakas-retentio mittarit ovat positiivisesti ja tilastollisesti merkitsevästi yhteydessä yritysten menestymiseen. Vaihtelut asiakastyytyväisyydessä näyttäisivät heijastuvan yritysten myyntimääräisessä markkinaosuudessa viiveellä ja viipeen tilastollinen merkitsevyys ulottuu kahdesta aina viiteen vuosineljännekseen saakka. Lisäksi tutkimustulokset osoittavat, että asiakas-retentio on positiivisesti yhteydessä yritysten menestymiseen tarkasteltaessa nykyistä ajanhetkeä. Asiakas-retentio-mittarin viivästetyt selittävät muuttujat ovat tilastollisesti merkitseviä aina neljään vuosineljännekseen saakka. Tämän tutkimusaineiston pohjalta voidaan todeta, että Net Promoter Score -mittari ei ole tilastollisesti merkitsevä selittäjä yritysten menestymisessä.

AVAINSANAT

Ei-rahamääräiset mittarit, yrityksen kannattavuus, asiakastyytyväisyys, asiakkaiden sitouttaminen, asiakas-retentio, Net Promoter Score, tietoliikenne

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I would like to thank my thesis supervisor, Professor Vesa Puttonen, and my thesis seminar peers for their valuable comments and suggestions. Additionally, I would like to thank my parents for their unconditional support throughout my studies. Lastly, I would like to thank my girlfriend, Annika. Thank you for being you.

Espoo, 16 November, 2011

Lasse Husgafvel

Table of contents

List of tables

List of appendices

1. Introduction

1.1. Academic and practical motivation

An appropriate selection of different performance measures is a critical task for companies. In order to compete efficiently, firms need to produce high-quality information that they are able to act upon. Development of technology during the last decades has given birth to various techniques that enable companies to measure their performance in all areas of business more efficiently, accurately, and cost-effectively than what have been previously possible. These developments, among others, have brought along a rising demand for transparency of corporate activities. Both internal and external stakeholders of companies are calling for an increasing transparency, and firms face a growing pressure to demonstrate the link between their activities and the financial performance.

As firms strive for to better understand the constantly changing business environment, they are utilizing a large set of measures, both financial and non-financial. A variety of financial metrics is well established, and authorities have strictly defined their usage and reporting practices. Non-financial metrics, on the other hand, are utilized in diverse ways, applied contextually, and their use is not regulated extensively. Nevertheless, companies worldwide are putting emphasis on non-financial information in an increasing manner and non-financial measures are now often regarded to be of equal importance with financial metrics. Especially customer based non-financial measures have become common nowadays.

According to a recent study (The NYSE Euronext CEO Report, 2008), companies are increasingly aligning their operations based on customers. A majority of surveyed chief executive officers worldwide expressed their intent to put customers at the top of a long list of things that must be addressed in order to develop growth. Both practitioners, as well as academic researches, are recognizing the importance of customers as the ultimate source for profits, but despite this, a large number of firms is still relying heavily on financial measures (e.g., Kumar and Shah, 2009; Ittner and Larcker, 1996).

A recent study by Deloitte and the Economist (2007) indicates that more than 90 % of the surveyed hundreds of top managers of large global companies considered that there are critical drivers of business, whose state cannot be measured in monetary terms. Such drivers included among others, customer satisfaction, product and service quality and employee commitment. The same survey also find that the top managers consider that their organizations are far more capable of producing financial than non-financial information, and they lack on high-quality, actionable non-financial information. Some researchers have proposed that non-financial measures might be regarded as being unclearly defined or firms might lack empirical knowledge on metrics' effect to performance and profitability (Gupta and Zeithaml, 2006). Therefore, it seems that albeit companies have a growing will to use non-financial metrics; there still exist barriers that hinder the adoption of them.

1.2. Research objective and contribution

The purpose of this thesis is to examine, how a set of non-financial customer based metrics are associated with company performance. I strive for to enhance the existing knowledge by examining how three customer-driven metrics, namely customer satisfaction, customer retention, and a loyalty measure of Net Promoter Score, are linked to company performance. In particular, I am interested whether changes in these non-financial metrics have a lagged effect on performance. In other words, are the changes reflected in performance instantaneously or should companies expect non-financial measures to have a lagged effect and thus could work as leading indicators for performance?

In this study, the relationship between the aforementioned non-financial metrics and company performance is examined in the context of telecommunications industry, which is an interesting field due to several reasons. First of all, information and communication technology (ICT) is today present everywhere, and the very basic structures of our economies are largely dependent on reliable and functional information networks. The tremendous success of wireless technologies and the liberalization of telecommunication markets during the past few decades have profoundly shaped the world we live in. From an economic perspective, this development has been associated, for instance, with higher productivity, lower costs, enhanced innovation, and increased world trade and exports (World Bank, 2010). Srivastava (2008) notes that the ICT technology is globally the fastest growing service sector and it has been a significant contributor to the growth of the world economy during the last fifteen years. Although the rapid development of ICT has naturally been a combination of variety of factors and technologies, the changes can be can be seen to culminate in one rather ordinary item in today's world - a mobile phone. Mobile phone has probably had a more profound effect on people's behavior than any other single invention during the last century. Therefore, performance of telecommunication companies, especially mobile handset manufacturers, and drivers of it, are an interesting research area.

In order to analyze, how customer satisfaction, customer retention, and the Net Promoter Score are linked to company performance and how these relations vary across time in the context of telecommunications industry, I examine two longitudinal datasets. The first dataset is an extensive consumer survey of mobile phone users, from which I extract the non-financial metrics, whereas the second dataset provides information about sales volumes and prices for mobile handset manufacturers on a country level, and enable me to calculate performance proxies for different mobile handset manufacturers, respectively. Specifically, I measure company performance with a proxy of value share, which will be further discussed in Section 4.2.1.

The existing studies broadly cover how non-financial, especially customer-driven metrics and performance of companies are associated. Conventionally, these studies examine how different non-financial measures are linked to accounting based financial measures or what is their linkage to changes in capital markets, often quantified as changes in stock returns. Generally, a variety of non-financial metrics have been suggested to be positively associated with (financial) performance. Although much evidence exists on this particular question, far less research has been conducted with time-series data.

Regarding the metrics of interest in this study, customer satisfaction is one of the most widely used and studied non-financial measures. It has raised considerable interest in the academic world, as well as among business practitioners, already for several decades. A large body of researchers is suggesting that customer satisfaction clearly has a positive effect on company success and improving satisfaction levels will lead to enhanced financial performance. Although the metric has been under extensive scrutiny, no consensus still exists on the strength and magnitude of the relation between customer satisfaction and performance. Therefore, this study provides more evidence about this relation based on a fresh and extensive dataset, and focuses especially on the possible lagged effect between these matters.

The second non-financial metric of interest in this study is customer retention. Compared to customer satisfaction, customer retention has emerged as a concept more lately, but it has been applied heavily in practice. This metric is of particular importance in the telecommunications industry, where manufacturers and network operators are keen on knowing how their customer bases are developing. The motivation to examine how customer retention and performance are associated is mainly based on the recent turmoil in the telecommunications markets, but also since the measure is extremely closely followed in the telecom markets, albeit has not been examined comparably well in the academic world. Additionally, a possible time lag effect of customer retention is interesting, because theoretically market share of a company can be derived based on customer retention and acquisition rates.

Finally, the Net Promoter Score is of special interest in this thesis. The metric was first introduced in a Harvard Business Review article in 2003, where the developer of the metric made a strong claim that the NPS can predict company growth significantly well and should be favored over other metrics. Since then, the NPS has been adopted by dozens of large companies worldwide and top managers are widely embracing it. Most interestingly, however, several researchers argue that the metric is not capable of predicting performance as originally suggested, nor is the foundation of the metric based on robust empirical research. My motivation to examine the NPS therefore stems from the rather uncommon controversy between the academic world and business practitioners and the fact that the metric has been widely adapted in practice provides an interesting starting point for the analysis. This study pursues to provide additional independent research, which is based on an extensive time-series cross-sectional dataset, on the relation between the NPS and company performance.

This study contributes to the existing knowledge on the link between non-financial measures and company performance by several ways. First of all, this study adds to existing research by providing fresh and up-to-date results between non-financial measures and performance on a general level. Secondly, this study features a unique dataset, which provides a comprehensive visibility to one industry, namely the telecommunications industry. Finally, probably the strongest contribution of the study is that it enriches the understanding of the time lag effects of non-financial metrics to performance.

1.3. Structure of the study

The rest of the study is organized as follows. First, in the next section, I will cover relevant prior literature related to non-financial metrics, and discuss individually about customer satisfaction, customer retention and the Net Promoter Score. Then, in the Section 3, I will present my research hypotheses, after which I discuss the data sources examined in this study. Section 5 introduces the different methodologies used to conduct the empirical analysis. Section 6 will review the research findings from the empirical analysis. Finally, in Section 7, the conclusions will be presented, and I will discuss the contribution and the limitations of the study, and propose suggestions for further research.

2. Literature review

The focus of this literature review is on customer-driven non-financial measures. Customers are the lifeblood of any commercial organization, and without customers, there are no profits or market value. Therefore, it is a critical task for companies to be able to measure and understand the value of their customers. However, traditional accounting based financial measures can be incapable of accurately reflecting the value of customer based assets, and it has been suggested that non-financial information may be a window through which light can be shed on key elements of corporate performance. In any case, non-financial measures are likely to hold value in providing supplementary information on corporate activities and enrich the understanding of various business dimensions. Specifically, as regards to this study, I will focus on three customer-driven non-financial metrics, which are customer satisfaction, customer retention, and a customer loyalty measure of Net Promoter Score.

The rest of this section is structured as follows. First, I will consider why companies use non-financial metrics, and discuss how they are linked to financial performance. Then, I will introduce the abovementioned three distinct metrics, and present evidence linking them to performance. Finally, I will shortly present evidence of customer metrics and financial performance in the context of telecommunications industry.

2.1. Reasons and ways companies use non-financial metrics

The ultimate goal of a firm is to make economic profit and create value for its owners. Traditionally, the created value is measured in monetary terms through prevailing accounting practices, and then quantified in financial reports. However, as firms strive for to better understand their business environment, they are utilizing a large variety of different performance measures. Although firms are in general still relying heavily on financial measures both in their internal activities as well as in their disclosure practices, many companies are starting to understand that a more holistic approach to performance measurement might provide them additional value. On the one hand, companies are interested how they can internally measure relevant drivers of their businesses efficiently and reliably. On the other hand, various stakeholders of companies are in need to better understand what the consequences of companies' actions are, and especially, to be able to quantify the value-relevance of each action. In an increasing manner, companies consider that by utilizing non-financial information, and metrics derived from it, might help them to better address these challenges.

Non-financial metrics include a variety of different constructs, and the only common denominator between them seems to be that they are not expressed in monetary terms. Interestingly, a principal rationale for companies to justify the use of non-financial measures is that they are believed to be leading indicators of financial performance. Companies consider that non-financial metrics are in some instances more capable, than traditional accounting based measures, of capturing meaningful elements and drivers of the business environment. From this perspective, non-financial measures can be considered as complementary tools, which help to analyze and understand the constantly changing business environment. According to Pangarkar and Kirkwood (2006), companies consider that financial metrics are short-term oriented, but the use of non-financial performance measures help them to focus on longer-term strategic objectives. Although companies seem to understand the possible benefits of non-financial metrics, there is evidence supporting a notion that managers are not utilizing them efficiently.

To shed light on how non-financial metrics are being used, Deloitte and the Economist interviewed 250 senior executives and board members of large companies around the world, asking them whether they feel that companies and investors are really monitoring the right indicators of long-term corporate health. The results were clear: the great majority of the interviewees said that they need incisive information about their companies' key non-financial drivers of success. However, such data is often non-available, and even when it is available, managers consider that they lack sophisticated methods to analyze it or there are doubts that the data is of poor value (Deloitte and the Economist Intelligence Unit, 2004).

To see whether things had changed in three years, Deloitte and the Economist (Deloitte and the Economist Intelligence Unit, 2007) carried the survey out again in 2007. Not so surprisingly, the results were remarkably similar to those of the previous study. Senior executives and board members still said that they lack on high-quality non-financial data that they can act upon. They considered their organizations are far more capable of producing and utilizing financial, than non-financial information. However, the results from the second survey indicate that a growing number of companies are starting to understand the value of non-financial metrics to company performance. Furthermore, the report suggests that firms continue to focus largely on traditional financial metrics, while, at the same time, paying closer attention to non-financial performance indicators.

The question, whether non-financial metrics are leading indicators of financial performance has attracted considerable attention in the academic world already for several decades. A large number of studies provide evidence to support claims that non-financial measures have predictive qualities towards future financial performance. For instance, Ittner and Larcker (1998) show that customer satisfaction might help in predicting future financial performance, whereas the results of Behn and Riley (1999) indicate that non-financial information appears to be useful in predicting revenues and expenses. Furthermore, Nagar and Rajan (2001) argue that non-financial quality measures are leading indicators for future sales and Morgan and Rego (2006) provide evidence, which suggests that several customer satisfaction and loyalty measures are helpful in predicting business performance.

Banker et al. (2000) claim that non-financial measures might be better predictors of long-term financial performance than traditional accounting measures, since the financial indicators may not capture long-term benefits of decisions made now. Moreover, Kaplan and Norton (1996) argue that improvements in certain non-financial metrics might contain information about future profits. They suggest that non-financial measures may be better predictors of future financial performance than historical, backward looking measures provided by current accounting systems and that these non-financial measures should supplement financial measures in internal performance measurement.

According to Ittner and Larcker (1998), the discussion about non-financial metrics as leading indicators of financial performance has resulted in a growing demand towards corporations to disclose relevant, non-financial information on the drivers of firm value. A report by American Institute of Certified Public Accountants (AICPA) noted already in 1994 that policymakers have expressed their concern on corporate disclosure practices. According to the U.S. policymakers, corporate accounting and disclosure practices have failed to keep in pace with the fast evolving business environment (AICPA, 1994). As a matter of fact, since the mid-1990s, legislators around the world have taken actions to promote the use of more comprehensive and opaque reporting practices. For instance, as of 2005, an amending act to the European Union Fourth Company Law requires companies to publish information, which is ‘to the extent necessary for an understanding about the company's development, performance or position… where appropriate, non-financial key performance indicators relevant to the particular business, including information relating to environmental and employee matters' (European Commission, 2003).

Petersen et al. (2009) suggest additional reasons for the growing popularity of non-financial metrics. First of all, they argue that the number of these metrics has increased as a result of several factors. Development of technology has opened new possibilities to collect and analyze information from various sources. Especially the Internet, among other new channels of distribution, has enhanced possibilities to measure various dimensions of the business environment. Additionally, Petersen et al. claim that that the recent academic research, which provides evidence on the positive relation between non-financial metrics and financial performance, has positively contributed to the adoption of these metrics.

2.2. Non-financial metrics and financial performance

Numerous different non-financial measures have been proposed of being able to predict financial performance, ranging from customer satisfaction to IQ of managers, but no single metric has been proven to be superior to others. It seems that the appropriateness of each applied metric should be considered on a case-by-case basis. However, there are some non-financial metrics that have been studied more extensively and also applied by practitioners, than others.

Managers need to understand the consequences of their actions and several different non-financial frameworks and metrics have been proposed to be helpful in this complicated task. For instance, the findings of Ittner and Larcker (2003) and Reichheld (2003), support intuition, and show that managers put high-value on non-financial metrics that are easy to measure, comprehend, and communicate to various stakeholders. Managers consider that non-financial measures should have simple and direct predictive relation with future business performance. However, it is hardly obvious to what non-financial metrics truly have predictive power towards future financial performance, if any. Previous studies examining this relation are showing somewhat mixed results, although there are non-financial metrics that have attracted more attention than others.

In the quest for finding non-financial, customer-driven metrics that are able to predict financial performance, a large body of researchers promotes various adaptations of customer satisfaction (Fornell et al., 1992, 2006; Anderson et al., 1994, 2004; Ittner and Larcker, 1998; Banker et al., 2000; Gruca and Rego, 2005), while some others advocate loyalty metrics (Reichheld 2003; Smith and Wright, 2004). According to Morgan and Rego (2006), one of the most widely used non-financial metrics is a 'top2box' satisfaction. The 'top2box' satisfaction is measured as a percentage of customers, who selected one of the top two boxes in a survey (normally measured on a scale from 1 to 5), indicating that they are extremely or very satisfied with a product or service in question. It is believed that increasing the portion of highly satisfied customers will eventually lead to better financial performance.

Regarding the existing research on the link between non-financial metrics and company performance, much of the evidence comes from the fields of marketing, accounting and management accounting. The topic of this research is interdisciplinary in nature as such, and I will pursue to keep the discussion practically oriented, and employ a holistic perspective, perhaps most widely applied in the field of management accounting.

The rest of the section is dedicated for a discussion about three non-financial metrics, which are of special interest in this study. I will first introduce these metrics, and then present earlier evidence on their link to company performance. In particular, I will start by introducing the concept of customer satisfaction, after which I will move on to discuss customer retention and Net Promoter Score. Finally, I will shortly consider non-financial metrics in the context of telecommunications industry.

2.3. Customer satisfaction

In order to understand customer satisfaction as a metric, it is first crucial to define the concept. Although several different definitions have been proposed for customer satisfaction, they do not seem to differ profoundly, but rather have slight differences in connotation. According to Tse and Wilton (1998), it is generally agreed that satisfaction can be defined as 'consumer's response to the evaluation of the perceived discrepancy between prior expectations… and the actual performance of the product as perceived after its consumption'. In other words, a consumer compares what is received to a pre-consumption expectation. If the consumption experience exceeds the expectation, the consumer considers herself satisfied.

Anderson et al. (1994) argue that customer satisfaction can be divided in two classes, which differ in terms of time dimension. These classes are transaction-specific and cumulative satisfaction. In the first case, satisfaction is viewed as a post-choice evaluative judgment of specific purchase occasion following a definition of Hunt (1977). By comparison, cumulative perspective views customer satisfaction as an overall evaluation based on the total consumption experience over time (Fornell, 1992). Gupta and Zeithaml (2006) point out that contemporary research tends to measure satisfaction on a cumulative level and focus on the overall experience customer has developed with a firm over time. As regards to this study, customer satisfaction is treated as a cumulative experience and satisfaction scores are considered on an aggregate level.

Intuitively, customer satisfaction might affect financial performance through several different ways. Anderson et al. (1994) summarize well these different mechanisms. In general, high customer satisfaction should lead to increased loyalty, decrease price elasticity, decrease customers' propensity towards competitive efforts, and lower costs of attracting new customers. Also, higher satisfaction means that companies can devote fewer resources to handling and managing complaints and defective items, which should have a positive effect on profitability by enabling a lower cost structure.

Customer satisfaction has attracted significant attention both among academics and top management of numerous companies already for several decades (See, for instance, Anderson et al. 1994; Ittner and Larcker, 1998; Gupta and Zeithaml 2006; Jacobson and Mizik, 2009). Already in 1989, Shoultz reports that out of 700 U.S. executives, who were interviewed in a survey, 64% of the respondents indicated that customers were their number one priority and the rest claimed it being one of their top priorities (Shoultz, 1989). Stressing the importance of customers has not shown signs of fading in twenty years. In line with the results of Shoultz, recent surveys find that a majority of chief executive officers worldwide expressed their intent to put customers at the top of a long list of things that must be addressed (The NYSE Euronext CEO Report, 2008).

According to Gupta and Zeithaml (2006), customer satisfaction is one the most commonly used perceptual metrics. They claim that it is a concept easy to understand by both consumers and managers, and it can be universally gauged for all the products and services. Additionally, Anderson et al. (1994) and more recently Anderson and Mittal (2000) argue that customer satisfaction levels and the various drivers of it have become important determinants of product's market success and in turn financial performance.

2.3.1. Customer satisfaction and financial performance

A growing body of literature suggests that customer satisfaction is positively associated with financial performance. Jones and Sasser (1995), and Kaplan and Norton (1996, 2001), for instance, provide evidence on this relation and argue that customer satisfaction is one of the most important factors in determining longer-term financial performance.

In their extensive article, Ittner and Larcker (1998), study whether non-financial measures, namely customer satisfaction, can be leading indicators of financial performance. By essentially combining three different studies, they analyze if customer satisfaction measures are leading indicators of accounting performance, is the economic value of satisfaction fully reflected in the accounting book values, and does announcing customer satisfaction measures provide new information to the stock market.

By using customer and business-unit data, Ittner and Larcker find modest support for their hypotheses, according to which customer satisfaction measures are leading indicators of customer purchase behavior (measured in retention, revenue and revenue growth), growth in the number of customers, and in accounting performance (measured in revenues, profit margins and return on sales). Additionally, based on their results, the researchers claim that firm level customer satisfaction measures can be economically relevant to the stock market, but are not fully reflected in accounting book values.

In their comprehensive study, Morgan and Rego (2006) examine the effect of six different customer feedback metrics on future financial performance. Their sample contains observations for 80 U.S. firms over a seven-year period from 1994 to 2000. The researchers analyze six different customer feedback metrics, including, among others, average satisfaction score and top2box satisfaction. They measure financial performance through six different financial variables, which are Tobin's Q, net operating cash flows, total shareholder returns, annual sales growth, gross margin percentage, and market share. For both of the satisfaction metrics, the relation with all the financial variables was to found to be significant and positive.

The results of Anderson et al. (1994, 2004) indicate that quality has a positive effect on satisfaction, and, in turn, on profitability. Additionally, they show that a significant relation exists between customer satisfaction and shareholder value. However, the researchers conclude that this relation seems to vary considerably across industries and firms. Anderson et al. (1994) argue that firms are willing to invest in improving customer satisfaction only if they are able to show effects of sufficient size through traditional accounting methods. Fornell et al. (2006), claim that less is known about how the satisfaction affects security prices and the knowledge about associated risks is even scarcer.

Wyatt (2008) argues that reliability of survey data can possibly explain the mixed evidence of the prior studies, which have examined the relation between customer based non-financial metrics and financial performance. In addition, Wyatt claims that as existing studies have provided evidence about the value-relevance of customer based metrics (see Gupta and Zeithaml, 2006, for a comprehensive summary); this remains an important research area.

Nayyar (1995) investigates how the stock market reacts to customer service announcements. By using news reports from a period of 1981-1991, he finds that customer service increases (decreases) are significantly and positively (negatively) associated with cumulative abnormal returns within a three-day event window. Interestingly, Nayyar suggests that attempts to increase customer service before the actual purchase, such as offering better guarantees or lower price, are more strongly valued by the stock market than attempts to increase service after purchase, such as providing cheaper maintenance costs. Specifically, Nayyar (1995) shows that the stock market values very favorably announcements related to improved guarantees and increasing the number of customer service outlets.

Customer satisfaction, and its relation to stock returns, has been of particular interest in research (O'Sullivan et al., 2009). For instance, research by Anderson et al. (2004), and Gruca and Rego (2005), identify that customer satisfaction is positively and significantly associated with future stock returns. Some studies, however, find contrary results. Ittner and Larcker (1998) and Fornell et al. (2006) both conclude that stock market does not react to customer satisfaction announcements within an event window of 8-10 days.

Jacobson and Mizik (2009) study whether customer satisfaction is associated with future abnormal stock returns. They conclude that the relation between satisfaction, measured from the ACSI index, and future-term abnormal stock returns appears to be limited to a small group of computer and internet firms. Findings of O'Sullivan et al. (2009) give additional support for the results of Jacobson and Mizik, and the researchers conclude that the stock market does not seem to be inefficient in reacting to changes in customer satisfaction announcements, and customer satisfaction based investment strategies thus do not seem to provide investors with opportunities to beat the market. Wyatt (2008), on the other hand, argues that customer satisfaction measures might not change enough to be value-relevant on an annual level, but might be relevant in a wider time frame.

Many existing studies, which examine customer satisfaction and performance, base the analysis on national satisfaction barometers. For instance, Bernhardt et al. (2000), Anderson et al. (2004), Matzler et al. (2005), and Fornell et al. (2006), among many others, utilize the American Customer Satisfaction (ACSI), whereas Anderson et al. (1994) examine the Swedish satisfaction index. Similar studies have also been conducted with national satisfaction indices from Germany, Norway and the United Kingdom. In comparison to studies that utilize large national indices, a large body of research uses smaller scale satisfaction surveys. Moreover, although much of the earlier research has been conducted in the Northern America or in Europe, research is emerging elsewhere as well. For instance, Zhang and Pan (2009) provide recent evidence from China related to customer satisfaction and profitability. The researchers study satisfaction levels from 78 stated owned enterprises and conclude that satisfaction seems to be associated with future profitability in their sample.

In their study, Banker et al. (2000) find that customer satisfaction measures of a hotel chain are significantly positively (and negatively, respectively) associated with future financial performance measured in individual business unit revenues and operating profits. Furthermore, their evidence suggests that the effect of satisfaction is related more to a long-term financial performance, and the effects are less visible in short-term.

Aksoy et al. (2008) examine the impact of customer satisfaction of firm valuation. They analyze 3600 firm-quarter observations of the ACSI index from a period of 1996-2006 and link this data to stock price data. Their results indicate that investing in firms with high or increasing satisfaction earns risk-adjusted cumulative abnormal returns on short-term, but the stock market adjusts in the long run, which diminishes usefulness of this trading strategy.

Bernhardt et al. (1999) conduct a longitudinal study on an American nationwide fast-food restaurant chain, and they find that although employee satisfaction is significantly and positively linked to customer satisfaction in any given time period, such relation does not exist between employee nor customer satisfaction and financial performance. However, the researchers find a significant, positive relation between these factors on a longer time frame. Thus, the authors are able to conclude that the impact of an increase in customer satisfaction on profits is significant in the long run although it is obscured in the short run due to many factors.

2.4. Customer Retention

Customer retention is the activity a company undertakes in order to decrease the number of defected customers. It is a continuous process, which involves all the activities a company considers relevant in encouraging its existing customers to continue the relationship with the company and to make additional purchases. As a concept, customer retention is closely related with customer loyalty, and retention can be considered as an intermediary stage towards loyalty.

Oliver (1997) defines loyalty comprehensively and takes into account both behavioral and psychological aspects of customer loyalty. He claims that loyalty is:

> a deeply held commitment to re-buy or patronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same-brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior.

Although retention and loyalty are closely inter-related terms, Gupta and Zeithaml (2006) aptly point out that that whereas consumer retention is directly observable, consumer loyalty is not. Therefore, in the context of this study, I employ a straightforward approach on consumer retention and measure it in terms of retention rate.

Customer retention rate can be defined as the probability of a customer to continue to have a relation with a firm. Retention rate measures what percentage of consumers who were active in period t has stayed with the company also to the period $t+1$. The mathematical formula of retention rate is provided later on in Section 6.3.2.

Customer retention can be relatively easily measured in contractual settings, where consumers will indicate when they terminate the relationship. An example of a contractual setting could be a bank account or a broadband subscription. However, in a non-contractual setting, like buying groceries or purchasing mobile phones without an operator deal, a firm must infer whether customers are still active. Generally, non-contractual settings are more common than contractual settings, but measuring retention rates in non-contractual settings can prove to be difficult. As regards to this study, retention rates for mobile handset manufacturers are obtained indirectly via a consumer survey. From a mobile handset provider's perspective, a purchase of a mobile phone usually represents a non-contractual transaction and therefore retention rates cannot be obtained directly.

2.4.1. Customer retention and financial performance

In the past, the main focus of companies has often been to acquire new customers, and retaining existing customers has not been considered as equally important. However, during the past few decades, companies have started to understand the value of appropriate retention strategies. This development has much to thank for the findings by the academic community.

Various studies show that acquiring new customers cost generally much more than retaining existing customers. This means that customer retention has a direct impact on profitability and as companies operate with limited resources, they should focus on retaining their existing customers rather than acquiring new ones. For instance, Reichheld and Teal (1996) stress the importance of customer retention and report that, according to some studies, average retention rate for U.S. companies is about 80%. In other words, this would mean that, on average, 20 % of companies' customers defect every year. Roughly speaking, this number indicates that an average company loses the equivalent of its entire customer base in about five years. Indeed, several existing studies show that retention rate is closely linked with financial performance.

Fleming and Asplund (2007) study retention rates of different companies by estimating the impact of engaged customers and employees to firms' profitability. Interestingly, they find that engaged customers generate approximately 1.7 times more revenue compared to normal customers. Additionally, Fleming and Asplund show that if companies had both engaged customers and engaged employees, they were, on average, able to generate 3.4 times more revenue compared to others. Moreover, Rucci et al. (1998) examine relations between employees, customers and profits at Sears and show that higher employee retention is positively associated with customer retention, which in turn has a positive effect on profitability.

Reichheld and Markey (2000) study retention rates and profits of companies in a wide array of industries. The researchers conclude that companies with the highest retention rates also seem to earn the best profits and retention rates explain changes in profits extremely well. In addition, they argue that not only loyalty is inextricably linked to the creation of value, but loyalty also initiates second order economic effects. As customer loyalty (retention) increases, revenues and market share increase as well. Moreover, customer acquisition costs shrink and servicing new customers becomes cheaper. Finally, Reichheld and Markey argue that customer retention eventually leads into increased employee satisfaction and retention, which turns into better service for customers and leads to higher revenues.

Unlike some other non-financial metrics, customer retention is inherently linked to company performance. In fact, market share of a company can be theoretically derived from its retention and acquisition rates. This means that changes in retention rates should be eventually reflected in market shares. The relation between market shares and retention rates are provided in Appendix 1.

Although the previous argument would seem to suggest that companies should aim at 100% customer retention, Gupta and Lehmann (2005) argue that this is not an optimal strategic goal, since the cost of retaining existing customer increase dramatically as the company reaches high levels of retention. In such a situation, it is very likely that a company would be overinvesting in its customers, not charging them enough or ignoring potential customers by focusing on too narrow segment. Therefore, it is not usually optimal for companies to aim at 100% retention rate.

Finally, the earlier research provides a large body of evidence on the chain from satisfaction to retention/loyalty all the way to profitability. This causal relation is rather straightforward in theory. It is assumed that satisfied consumers make continues purchases and became more loyal, which in turn has a positive effect on profits. For instance, Anderson and Sullivan (1993) and Bolton (1998) provide empirical evidence on the positive link between satisfaction and retention, whereas Anderson et al. (1994) and Loveman (1998) examine the whole chain from satisfaction to loyalty and performance. Additionally, Anderson and Mittal (2000) claim that the link from satisfaction to retention and onwards to increased profits is often asymmetric and non-linear and depends on variety of contextual factors. Albeit this causal chain is an important research area as such, the focus of this study is more on the individual relations between different customer-driven non-financial metrics and performance and less on how these measures are associated with each other.

2.5. Net Promoter Score

A customer loyalty metric called a Net Promoter Score has gained considerable attention in the corporate world in recent years. Loyalty consultant Frederick Reichheld introduced the concept of the Net Promoter Score (NPS) in his seminal Harvard Business Review (HBR) article in 2003, after which numerous prominent companies have adopted the metric.

The NPS is obtained by asking customers a single question, on a 0-10 scale, of whether they would recommend company ‘X’ to a friend or colleague? Based on the answers, customers are divided into three groups: Promoters (9-10 rating), Passives (7-8 rating) and Detractors (0-6 rating). Then, the percentage of detractors is subtracted from the percentage of Promoters to obtain a Net Promoter Score.

According to Reichheld, the NPS measures customer loyalty accurately, correlates significantly with company growth can be easily communicated across an organization (Reichheld, 2003). He continues by stating that the NPS ‘is the best predictor of growth’, and the ‘only number you [companies] need to grow’. In addition, it is noted that companies that garner world-class loyalty, have a Net Promoter Score of 75-80% (Reichheld 2003, 2006).

The empirical work, which led to the introduction of the NPS, was started in 2001. Reichheld, in collaboration with Bain Consulting and Satmetrix, conducted a study of 400 U.S. companies, which represented over a dozen industries, about the relation between growth rates and the Net Promoter Scores. Their results show that the NPS seems to explain relative growth rates significantly well, and Reichheld concludes that getting customers enthusiastic enough to recommend a company appears to be crucial for growth for most companies in most industries. Indeed, the numbers Reichheld reports are impressive. Based on his results, Reichheld claims that companies, which lead in the NPS, are, on average, able to grow 2.5 times faster than their competitors. Moreover, considering how well the NPS scores explain the growth rates, Reichheld is able to report R^2s that range from 0.68 to 0.93 (Reichheld, 2006).

Since the publication of the seminal HBR article, numerous large companies have adopted the Net Promoter Score, and managers are widely embracing this metric. Prominent companies, such as, GE, Intuit, Hertz, Walmart, American Expresss, Microsoft (Keimingham et al. 2007; Schneider et al., 2008), and Nokia are all using the Net Promoter Score. Allianz (Allianz, 2009), Aviva (Aviva, 2010), and Standard Chartered (Standard Chartered, 2010), have even included the NPS as a part of their yearly reporting. Also, several top managers are talking about the metric with almost surprising confidence:

> ‘I have little doubt that this will be as big and long-lasting for GE as Six Sigma was.’ - Peter McCabe, Chief Quality Office, GE Healthcare (McGregor, 2006).
>
> ‘All companies should ask their customers what Fred [Reichheld] calls the ultimate question.’ - Ken Chenault, Chairman and CEO of American Express (quoted in Reichheld, 2006)
>
> ‘And a couple of years ago we started really organizing a lot of things around the net promoters score. I won’t talk through the calculation again, but it is basically an all-in score of customer satisfaction.’ - Patrick Byrne, CEO of Overstock.com (Overstock.com, 2007, earnings conference call).
>
> ‘Net Promoter is core to the company…it is part of who I am as a leader.’ - Brad Smith, CEO, Intuit (Smith, 2009)

> ‘For Philips, however, the NPS metric and results are as important as market shares and our financial results.’ - Geert van Kuyck, Chief Marketing Officer, Philips (Roberts, 2009)

Although the success of the NPS has been tremendous and the metric is widely adopted in the corporate world, only a few independent studies have examined the relation between the NPS and performance. Moreover, the bold claims of Reichheld et al. have not been confirmed exclusively. As a matter of fact, several noted researchers question the power of the NPS and its empirical foundation.

2.5.1. Net Promoter Score and financial performance

One of the only independent studies providing evidence about the positive link between the NPS and performance is one of Marsden et al. (2006). They assess the financial value of word-of-mouth activities and compare the Net Promoter Scores and company sales growth rates. Marsden et al. find that the NPS is positively and significantly correlated with growth. Their study is one of moderate size, as the dataset consists of telephone answers from only 1,200 consumers in the United Kingdom. They examine only correlation between the NPS and growth rates without conducting a more rigorous empirical testing. Additionally, Keimingham et al. (2007) criticize their study by noting that the Net Promoter Scores were linked on prior period growth rates. The existing independent research that would confirm Reichheld’s findings is extremely scarce, but some earlier evidence exists that casts doubt on his results.

Lawrie et al. (2006) study the relation between the NPS and market share changes, and they conclude that the NPS is statistically insignificant in explaining changes in market share. They also note that the NPS seems to be a lagging indicator of market share, which suggests that the metric might help in learning about the success of word-of-mouth activities, but is of limited value in predicting future performance. Lawrie et al. (2006) do not fully reveal their research data, but they claim that the analysis is based on eleven years of data, from hundreds of companies from the fields of banking & finance, logistics, telecommunications, and healthcare.

Morgan and Rego (2006) examine the effect of six different customer metrics, including the Net Promoter Score, on future financial performance measured through six performance proxies. They conclude that customer loyalty metrics, the NPS and number of recommendations, have little or no value in predicting financial outcomes for firms. Keimingham et al. (2008), however, argue in their response to Morgan and Rego's article that neither of the loyalty measures was actually appropriately measured and that conclusions about their predictive qualities cannot be made based on the analysis conducted.

Probably one of the most rigorous studies examining the NPS and growth is one of Keimingham et al. (2007). They conduct a longitudinal study of 21 Norwegian companies, in order to replicate the results of Reichheld. They conclude that no support was found for the claim that the NPS is the 'single most reliable indicator of a company's ability to grow'. Additionally, the researchers suggest the NPS score is not superior to other metrics, such as customer satisfaction. Schneider et al. (2008) suggest that managers are widely in a belief that the NPS is based on solid analytical research, and this belief has had a significant effect on the tremendous growth of the metric. Keimingham et al. (2007) also note that false believes about the power of the NPS might potentially result in misallocation of resources and thus affect firm performance, and ultimately shareholder wealth. Finally, Sharp (2008) heavily criticizes Reichheld's results, and argues that compelling slogans based on incorrect findings have made terribly many managers to buy this 'fallacy'.

Several factors are likely to contribute to the strong critique that Reichheld and the NPS metric have faced. First of all, although Reichheld makes bold claims about the power of the NPS, while downplaying other non-financial metrics, he does not provide details about the methodology or the data he examines. Specifically, according to Schneider et al. (2008), the data from the Reichheld’s study is not publicly available for replication, the study does not feature levels of statistical significance for the results, and although the research data was originally collected from over 400 companies, only 50 of them were included in the final analysis, which could suggest that the sample is biased. In addition to this, Reichheld reports that the ‘would recommend’ scores were tracked starting in 2001, whereas the average growth rates were obtained over a three-year period of 1999-2002. This suggests that Reichheld correlates a priori Net Promoter Scores with posteriori growth rates. Thus, it seems that some evidence exists, which would lend support for a claim, according to which the relation between the Net Promoter Scores and growth rates would have been intentionally constructed.

To sum up, a significant number of companies have adopted and are embracing the Net Promoter Score. The very compelling nature of the metric and its claimed superiority over other metrics has surely boosted its growth. Also, according to Schneider et al. (2008) the simplicity and scientific rigor by which the metric has been presented, has had a remarkably positive effect on its success. However, many researchers claim that Reichheld’s findings are not analytically sound, and that the NPS should, at least, not be treated as the single most important indicator for growth. Remarkably, independent evidence, which would support Reichheld’s original claims, is extremely scarce. Finally, and most importantly, the NPS score, nevertheless, deserves more research, since it has been so widely adopted in the corporate world.

2.6. Non-financial metrics and performance in the context of telecommunications industry

The purpose of this subsection is to shortly review the earlier evidence considering the telecommunications industry, and to shed light on the question, why the selected non-financial measures, especially satisfaction and retention, are of relevance in the telecommunications industry.

Non-financial metrics and firm performance in the context of telecommunications industry has not been extensively studied previously. Most of the earlier research, which is relevant regarding this study, examines how satisfaction, retention, and loyalty are associated rather than linking them straightly to financial or performance data. In addition to this, several studies, however, consider these issues indirectly in the context of telecommunications industry, as the datasets of some studies cover a good number of industries including the telecommunications sector. Notably, a great majority of existing research utilizes data from cellular service providers, i.e. network operators, such as AT&T, Vodafone, or China Telecom, whereas the focus of this study is on mobile handset manufacturers. Next, I will shortly present earlier evidence from the telecommunications industry.

Amir and Lev (1996) study a 10-year panel data for 14 publicly traded U.S. cellular operators. By utilizing an event window technique, the researchers examine value-relevance of non-financial and financial information on security valuation. Their findings suggest that accounting based measures, such as earnings or cash flows, are alone largely irrelevant to security valuation. On the other hand, non-financial information seems to be relevant. Finally, Amir and Lev conclude that financial information combined with non-financial information contributes to the explanation of stock prices.

As the study of Amir and Lev was conducted already 15 years ago, their measure of population size in certain areas, a proposed indicator for growth of a licensed operator, seem to be partly outdated by now. Currently, mobile penetration rates are well above 100 percent in virtually all western countries, which means that population size would not work as a good proxy for growth potential. However, this metric is still of relevance in the developing markets. Moreover, the other metrics Amir and Lev utilize, such as subscriber bases and customer churn rates are still relevant and tracked widely by operators.

Gerpott et al. (2001) analyze causal links between customer satisfaction, loyalty, and retention by utilizing consumer survey data from German cellular operator customers. They do not directly examine how non-financial metrics affect performance, but apparently, the underlying notion is that there is a strong positive correlation between these two. The researchers conclude that customer satisfaction leads to customer loyalty, which in turn shows in increased customer retention. More evidence on customer satisfaction and customer retention, provide, for instance, Kim et al. (2004) and Eshghi et al. (2007). Kim et al. (2004) show how mobile telecommunication service provider can increase customer loyalty by maximizing customer satisfaction and switching barriers, which makes changing service provider difficult and costly. Eshghi et al. (2007) continue by arguing that customer satisfaction plays and important role in determining customer’s propensity to stay with a service provider.

Often, regulatory environment can have a significant impact on companies’ customer strategies. Until recently, American mobile service subscribers faced significant switching costs when changing service provider in the United States. As a result, a large portion of consumers tended to stay with their existing operator regardless of their satisfaction with the service. However, in 2003 a new law was introduced that allowed customers to keep their existing mobile phone numbers while changing a service provider. This change reduced customers’ switching costs tremendously and forced cellular service providers to shift their focus from customer acquisition to customer retention strategies (Eshghi et al., 2007).

Some researchers argue that non-financial information might be of greater relevance in fast changing, technology based industries, since financial measures tend to be retrospective. Additionally, the aforementioned development in the U.S. and the continuous nature of cellular subscription contracts, which make retention rates rather easy to gauge, are likely to partly explain the strong emphasis on customer retention metrics in the telecommunications industry. Finally, to the best of my knowledge, this is the first academic study to examine the Net Promoter Score solely and directly in the context of telecommunications industry.

3. Hypotheses

This section presents the research hypotheses and discusses how they are linked with the earlier literature. The focus of this thesis is to examine, how a set of customer-driven non-financial metrics is associated with company performance. Previous literature on the link between non-financial metrics and financial performance advocates mainly customer satisfaction and loyalty metrics. Earlier studies suggest that both customer satisfaction and customer loyalty are positively linked to various performance measures, such as return-on-investment, stock returns, market shares and size of the cash flows. In this study, I examine the relation between value shares and three customer based metrics – customer satisfaction, customer retention, and the Net Promoter Score.

According to theory, consumption experiences that exceed pre-purchase expectations cause satisfaction. Intuitively, more satisfied customers are more likely to make subsequent purchases from the same supplier and they are also more likely to engage in worth-of-mouth activities and recommend products to others. This hypothesized causal chain from customer satisfaction to customer retention and loyalty should eventually lead to increased competitiveness and turn into enhanced financial performance. Indeed, the main rationale for managers to utilize non-financial metrics is that they are believed to be leading indicators of financial performance. Links between the individual non-financial metrics are beyond the scope of this study, but the logic behind the research hypotheses largely stems from this causal chain. Therefore, my research hypotheses are defined as follows:

***H1**: Customer satisfaction is positively linked to company performance*

***H2**: Customer retention is positively linked to company performance*

***H3**: Net Promoter Score is positively linked to company performance*

3.1. H1: Customer satisfaction is positively linked to company performance

The first hypothesis suggests that customer satisfaction has a positive link to financial performance of a company. This relation has been extensively studied by the previous literature. Studies by, for instance, Anderson et al. (1994, 2004), Jones and Sasser (1995), Kaplan and Norton (1996, 2001), and Ittner and Larcker (1998), provide evidence that there exists a positive and significant link between customer satisfaction to financial performance.

In this thesis, I will try to provide more evidence about this relation by studying an extensive sample of companies and countries from the telecommunications industry. Specifically, I will test the customer satisfaction hypothesis by analyzing average customer satisfaction and top2box satisfaction scores' effect to value shares and try to understand whether they provide incremental information that helps to assess future company performance.

3.2. H2: Customer retention is positively linked to company performance

The second hypothesis claims that customer retention is positively associated with company performance. Likewise with customer satisfaction, also customer retention has faced substantial interest in the academic community before. In general, customer retention can be regarded as a sign of loyalty. However, many researchers argue that true loyalty is more than just continues purchases from the same provider (see Reichheld, 2003, for instance). Nevertheless, many companies have applied the concept of customer retention in practice, and especially in the telecommunications industry, operators and phone manufacturers are keen on measuring it.

The majority of previous studies, which examine customer retention and financial performance, have relied on attitudinal measures, such as intention to purchase. Although positive intensions of purchasing have been proved to be associated with higher economic returns, they are still only proxies for actual purchasing behavior, and are thus more volatile in nature. In this study, I will try to overcome some of the weaknesses related to attitudinal measures and analyze actual retention rates acquired through customer surveys. Optimally, I would be able to examine actual purchases of individual customers from an accounting system, but such data is scarcely available, and is often considered as a business secret. Therefore, I examine how retention rates and value shares of telecommunication companies are associated. The applied definition of retention rate is later provided in Section 6.3.2.

3.3. H3: Net Promoter Score is positively linked to company performance

According to the third hypothesis, the Net Promoter Score is positively associated with company performance. As previously discussed in this study, mixed evidence exists on this issue. Originally, the Net Promoter Score was claimed of being able to capture customer loyalty better than some other loyalty measures. The existing research proposes various loyalty metrics, including repurchase rates and amounts, cross-category purchases, intension to purchase again, and word-of-mouth measures. However, the Net Promoter Score has raised considerable attention, especially in the corporate world, and a significant number of top managers have publicly advocated the metric. Interestingly, however, the Net Promoter Score has not received significant attention in the academic world, and independent previous studies made on the subject claim that the NPS is not, by any means, a superior non-financial metric as originally suggested by Reichheld.

This confrontation between Reichheld and other researchers, as well as the significant popularity of the Net Promoter Score metric in the business world, provides an interesting starting point to further study if the metric truly deserves its place among the key indicators of company performance.

In the context of this study, I will closely follow Reichheld's approach in measuring the Net Promoter Score, and define it as follows: 'If someone you know was looking to buy a mobile phone, how likely would you be to recommend your current brand?' Notably, there is a minor difference between the definitions of this study and Reichheld's. In my study, the exact wording of the question slightly points towards possible recommendation action, which would incur after someone has indicated that she is looking to buy a new product, whereas Reichheld defines the NPS simply as: 'How likely is it that you would recommend our company to a friend or colleague?'. Therefore, Reichheld's definition is slightly more neutral and does not spoke out whether recommending is triggered by a knowledge that someone is actually looking for a new phone. However, I firmly believe that this minor difference does not jeopardize comparisons between my results and the results of the existing studies.

4. Data description and sources

This section describes the data sources utilized in the empirical part of this study. I will start by introducing the three data sources individually and continue by discussing the data collection and adjustments made to the data. Finally, I will provide descriptive statistics of the dataset.

In this study, data from several sources are brought together. An extensive consumer survey and a retail sales tracking database, which follows volumes and prices of mobile phone globally, form a basis for the analysis. In addition to these primary data sources, I acquire mobile phone manufacturers' financials from Thomson One Banker. Specifically, my final dataset is a two-dimensional panel, which consists of observations over multiple time periods over the same individual units, brand-country groups in my case. Next, I will discuss individually about these different data sources.

4.1. Consumer survey

The first dataset is an extensive consumer survey collected by Nokia. The survey has been running since 2004 and every year almost 200,000 mobile phone users are interviewed globally through face-to-face interaction or via online surveys. The study started off with 10 countries, and to-date covers 25 key markets globally with records from 178 different mobile handset providers in total. The countries included in the study represent a comprehensive picture of the mobile phone market both in terms of the size of the countries relative to the global economy as well as in terms of their geographical reach.

The survey is conducted on a quarterly basis and each respondent, who has purchased a mobile handset during the previous four months, is presented with more than a hundred of questions, which can be further divided in four dimensions. The study features questions related to respondent's current and previous mobile phone, purchasing behavior, mobile phone usage and satisfaction, as well as segmentation and demographic variables. The survey responses have been weighted to represent population structure in terms of age and gender in each market. Appendix 2 specifies the survey questions utilized in the context of this study.

In particular, my dataset covers a period from the beginning of the second quarter of 2007 until the end of the first quarter of 2011. For this period, the initial dataset consists of responses from

569,692 individuals. In order to a handset provider and a single market to be included in my sample, I require that there are at least eight successive quarterly observations from a single market. Additionally, I require that a single brand has to have a value share of over one percent during some of those eight quarters in some market. As some countries have been added to the consumer survey more recently, my final dataset consists of 19 countries, out of which 10 countries have a maximum of 10 successive quarterly observations, and nine have a maximum of 16 successive quarterly observations.

4.2. GfK market tracking data

The second primary dataset is provided by GfK Group, which is one the largest market research companies in the world. GfK is tracking handset sales to consumers in retail outlets globally, and collecting information on retail sales volumes and prices by product, country and month. The GfK dataset covers 65 countries globally, but as the consumer survey delimits the data, which can be utilized, the final dataset, where the consumer survey and GfK data have been combined, covers 19 countries from the beginning of the second quarter, 2007 until the end of the first quarter of 2011. For this time period, the GfK dataset has in total of 760,330 observations, covering 1164 different brand names and 20,665 different mobile phone model names. The GfK provides all the figures on a monthly basis, but for the purposes of this study, I aggregate the figures on country, brand and quarterly levels. The aggregation produces a total of 16,187 country-brand-year-quarter observations.

GfK provides non-subsidized retail sell-out prices and as GfK cannot capture every singly retail outlet in each country, they provide a coverage estimate for each market on a monthly basis. The sell-out volumes are readily extrapolated in the dataset to correspond to the “true” market volumes, and the extrapolation is based on GfK’s estimates on its retail sales coverage. Appendix 4 provides the estimates of the retail sales coverage per country. Based on the pricing data and volumes, I form value share figures for each brand in each country on a quarterly level. Next, I will discuss the performance proxy of value share more in detail.

4.2.1. Definition of value share

In this study, I use value share as a proxy for company performance. Value share is defined as:

$$\mathrm{VS}_{ikt} = \frac{\mathrm{Value}_{ikt}}{\mathrm{Value}_{kt}} \,, \tag{1}$$

where VS_{ikt} is the value share for company *i* in country *k* for period *t*. Value_{it} denotes the net sales of company *i* in country *k* for period *t* and Value_{kt} is the total market value in country *k* for period *t*. Value share resembles closely a more conventional term of market share as the only difference between these two is that the value share is measured in terms of net sales rather than in terms of volume.

The value share is selected as a proxy for company performance due to several reasons. First of all, accounting based items visible in balance sheet or income statement are not conventionally split into geographical dimensions and thus would not allow one to fully utilize the panel dataset. Secondly, capital market items, such as stock price, are available only on a company level and several companies of my dataset are not listed in any stock exchange. Thirdly, as the value share data comes from an external source, disclosure practices or regulatory considerations between different countries and companies do not distort or complicate the analysis. Fourthly, the use of value share allows me to strictly limit the analysis on the performance of the mobile handset business. Several companies in my dataset operate in many industries and some other performance proxies would not allow separating mobile handset business from other branches. Finally, the value share is favored over market share, since volume based measures can be inaccurate proxies for profitability. Particularly in the telecommunications market, it is common that companies with the highest volumes are not the most profitable ones.

4.3. Other data sources

In addition to the primary data sources discussed above, I acquire company specific financial information through Thomson One Banker. These items include quarterly data from the beginning of 2007 until the end of first quarter 2011 about net sales, net income and total assets. As the database does not contain every item for all the quarters and companies, I fetch the missing information manually from individual companies' financial reports. The tables presented later on show only total assets variable, since it was found to be the most reliable indicator for controlling the company size effect.

4.4. Descriptive statistics of the data sources

In total, the final dataset, where the consumer survey and the GfK market tracking dataset have been combined, consists of 2032 quarterly observations for 19 countries and has records from 19 different mobile phone manufacturers. Table 1 provides a summary of the final dataset in a country dimension, and Table 2 presents descriptive statistics about the mobile phone manufacturers included in the analysis. Additionally, Appendix 3 lists all the mobile phone manufacturers per country.

The dataset I am examining covers an extensive selection of countries all over the world. As regards to an individual country, the consumer survey has been running either since Q2/2007 or Q4/2008, and the dataset contains observations from each market accordingly. All of the countries have observations until the end of the first quarter 2011. On average, there are observations from eight mobile phone manufacturers in each country. As Table 2 shows, all the largest mobile phone brands are present in the dataset, and additionally, the dataset contains observations from over a dozen of smaller manufacturers. Essentially, the dataset examined in this study is a combination of 161 individual brand-country panels.

TABLE 1: DESCRIPTION OF COUNTRIES

Table 1 provides a summary for a dataset, where Nokia consumer survey and the GfK market tracking dataset have been combined. Start period column shows, when a country has been added to the consumer survey. All the countries have observations until the end of the first quarter, 2011. The Quarters per country section presents quarterly observation statistics per country.

Country	Start Period	End Period	Total # of Brands	Quarters per Country				
				Min.	Max.	Avg.	Mode	Median
Argentina	Q4/2008	Q1/2011	7	10	10	10.00	10	10
Brazil	Q2/2007	Q1/2011	9	14	16	15.78	16	16
China	Q2/2007	Q1/2011	12	9	16	14.08	16	16
Egypt	Q2/2007	Q1/2011	8	14	16	15.75	16	16
France	Q4/2008	Q1/2011	10	10	10	10.00	10	10
Germany	Q4/2008	Q1/2011	8	10	10	10.00	10	10
India	Q2/2007	Q1/2011	9	10	16	15.33	16	16
Indonesia	Q4/2008	Q1/2011	7	9	10	9.86	10	10
Italy	Q2/2007	Q1/2011	10	14	16	15.80	16	16
Mexico	Q2/2007	Q1/2011	8	12	16	15.00	16	16
Nigeria	Q2/2007	Q1/2011	8	13	16	15.63	16	16
Poland	Q4/2008	Q1/2011	7	10	10	10.00	10	10
Russia	Q4/2008	Q1/2011	8	10	10	10.00	10	10
Saudi Arabia	Q4/2008	Q1/2011	7	8	10	9.43	10	10
South Africa	Q4/2008	Q1/2011	8	10	10	10.00	10	10
Spain	Q4/2008	Q1/2011	9	10	10	10.00	10	10
Thailand	Q2/2007	Q1/2011	9	9	16	15.00	16	16
Turkey	Q4/2008	Q1/2011	9	9	10	9.78	10	10
United Kingdom	Q2/2007	Q1/2011	8	14	16	15.75	16	16

Table 2 indicates that there is considerable variation in average net sales or volume figures regarding individual brands. For instance, the lowest average global quarterly volume figure (Siemens) is only 51 thousand, whereas the highest one is almost 60 million (Nokia). This, however, only reflects the existing mobile phone market structure, where a small number of brands control some 99% of the global market. In addition, the mobile phone market has undergone tremendous changes in recent years, and the climbs and declines are also clearly present in the dataset.

TABLE 2: DESCRIPTION OF BRANDS

Table 2 shows descriptive statistics for the dataset in brand dimension. Figures in the table represent quarterly values. Retention rate has been omitted from the table, since it cannot be summarized meaningfully in this sort of dimension. Presence in countries column shows from how many countries each brand has observations in the data. Avg. volume figure is based on GfK market tracking data and thus does not represent global sales volume. Avg. net sales figure is acquired through Thomson One Banker and represents quarterly income statement figure. NPS stands for Net Promoter Score index. The right hand side of the table shows average yearly changes in value shares per brand. The Avg. column shows an average yearly percentage point change in value share over all the countries from the first period until the last period in data. The max and min columns depict highest and lowest changes over all the countries respectively.

						Avg. annual percentage point changes in value share		
Brand	Presence in countries	Avg. volume (t)	Avg. net sales (t)	Avg. satisfaction	Avg. NPS	Avg.	Max.	Min.
Alcatel	7	523	22 888	3.18	-0.03	0.161	0.477	-0.348
Apple	14	1 461	105 018	4.17	0.59	4.209	14.495	0.005
Bird	1	619	53	3.50	-0.25	-0.531	-0.531	-0.531
Haier	1	338	1 076	4.21	0.51	-0.128	-0.128	-0.128
HTC	11	503	24 142	3.74	0.38	1.195	3.632	-0.587
Huawei	3	1 892	13 418	3.33	-0.05	0.218	0.810	-0.367
I-Mobile	1	283	58	3.98	0.05	0.345	0.345	0.345
Lenovo	1	1 634	2 889	3.54	-0.09	-0.218	-0.218	-0.218
LG	19	10 338	148 658	3.79	0.22	-0.270	3.791	-4.919
Motorola	18	8 063	62 216	3.78	0.17	-1.841	-0.121	-4.991
Nokia	19	59 085	171 036	3.99	0.38	-3.249	2.265	-10.284
Philips	3	515	14 013	3.62	-0.12	-0.168	0.097	-0.410
RIM	16	1 448	25 454	3.62	0.43	4.337	14.610	0.084
Sagem	3	209	6 947	3.56	-0.01	-0.852	-0.398	-1.091
Samsung	19	27 079	329 380	3.92	0.30	0.421	6.517	-7.368
SE	19	8 637	30 661	3.96	0.34	-3.197	-0.083	-8.430
Sharp	1	154	5 099	4.08	0.33	0.526	0.526	0.526
Siemens	1	51	19 403	4.09	0.45	-0.572	-0.572	-0.572
ZTE	4	1 461	5 394	3.41	0.14	-0.024	0.368	-0.907

The right hand side of Table 2 shows average annual percentage point changes in value shares for different brands. The dataset exhibits relatively large growth rates, but also significant drops in value share. For instance, Apple and RIM have been able to generate over four percentage point average annual growth rates since 2007, compared to Nokia and Sony Ericsson, who have witnessed tremendous declines, and show average annual growth rates of -3.25 and -3.2 percentage points, respectively. These statistics confirm the observation that the telecommunications industry, especially the mobile phone part of it, has been in great turmoil recently. Next, I will consider shortly how the data looks like as regards to the non-financial metrics of interest.

Although the changes in the mobile phone market have been tremendous, the non-financial metrics are not understandably as volatile as volume or sales figures. Nevertheless, Table 2 shows, how out of all brands, Apple has the highest Net Promoter Score of 0.59 and its average satisfaction score is also extremely high, being above four. Apple has experienced a staggering growth in recent years, and is to date the most valuable technology company in the world. Just by looking at these figures, one could easily argue that high customer satisfaction could have been an important driver of the growth. A more general statistics of the main regression variables are provided next in Table 3.

TABLE 3: DESCRIPTIVE STATISTICS FOR REGRESSION VARIABLES

Table 3 presents a summary of regression variables. Abbreviations are as follows: Avg. CS = average customer satisfaction, top2box CS = the percentage of respondents, who answered “4” or “5” for the satisfaction question in the consumer survey, RR = retention rate, NPS index = net promoter score index.

Variable		Mean	Std. Dev.	Min.	Max.
Value share	overall	0.11	0.15	0.00	0.87
	between		0.14	0.00	0.72
	within		0.04	-0.07	0.37
Avg.CS	overall	3.81	0.88	0.00	5.00
	between		0.47	2.02	4.73
	within		0.74	-0.22	6.20
Top2box.CS	overall	0.67	0.25	0.00	1.00
	between		0.17	0.08	0.98
	within		0.20	-0.18	1.31
RR	overall	0.22	0.22	0.00	1.00
	between		0.18	0.00	0.87
	within		0.12	-0.35	1.15
NPS.index	overall	0.29	0.34	-1.00	1.00
	between		0.27	-0.43	0.90
	within		0.21	-1.25	1.26
Total assets	overall	25401	23023	101	101554
	between		22426	133	92930
	within		5106	7163	55251

2032 observations
161 groups

Table 3 indicates that based on the data, consumers seem to be rather satisfied as the mean for average satisfaction variable is 3.81 and for the top2box variable 0.67, respectively. This implies that a significant proportion of the respondents claim to be either satisfied, or very satisfied considering their experience as a whole. The average figure of 3.81 is likely to be slightly higher than the true average for consumer satisfaction, as only consumers, who have acquired a mobile phone during the previous four months, were included in the survey sample of each quarter. Regarding average retention rates, only some 20 percent of consumers seem to retained ones. In other words, based on the sample, 80 percent of consumers, who owned one brand at period t-1, changed their phone brand before period t.

5. Methodology

This section discusses different methodologies utilized in the empirical part of this study. In order to properly analyze, how non-financial metrics and company performance are associated, I employ two different econometric techniques: Granger causality testing and a distributed lag panel regression model. Before introducing the techniques more in detail, it is, however, beneficial to shortly consider the structure of panel data and panel data analysis in general.

A panel dataset is one, where a sample of individuals or groups is observed over time. A panel dataset combines both spatial and temporal dimensions and thus offers more possibilities for econometric analysis than either of the dimensions would offer alone. Specifically, according to Baltagi (2005), panel data offers various advantages over pure cross-section or time-series data. One of the most important advantages of panel data is that one is able to control individual heterogeneity, which does not vary between groups or across time, whereas such treatment is not possible with solely cross-section or time-series data.

In the context of this study, spatial or cross-sectional units are brand-country groups, and the temporal dimension consists of sequential quarterly observations for these cross-sections. Various econometric techniques exist for analyzing panel data, which is sometimes also known as time-series cross-sectional data. In this study, I will consider two prominent techniques: fixed effects and random effects models. Before introducing the fixed and random effects model, I will discuss the Granger causality testing, which has also been applied in a panel framework in several studies. In the context of this study, the Granger causality testing will be utilized in addition to the distributed lag panel regression models to form a comprehensive picture about the relations between the non-financial metrics and company performance.

5.1. Granger causality testing

Granger causality refers to a statistical hypothesis test, which tries to determine whether one time series causes another. The seminal work of Clive Granger in 1969 formally introduced the idea of Granger causality, although Weiner apparently discussed the underlying notion several decades before. Aside from the fact that Granger causality, nor any statistical test for that matter, can truly confirm causal relations, it is a widely used technique, which can help in uncovering how some variables are related. According to Granger (1969) a variable X is said to (Granger)-cause variable Y, if Y can be better predicted by using all the information available, that is the histories of both X and Y, than using the history of Y alone. Granger causality is normally tested by regressing a dependent variable with its own lags and lags of independent variables. Adapting from Seth (2007), let us consider a simple, bivariate linear autoregressive model with two variables, Y_t and X_t:

$$\mathrm{Y}_t = \alpha_1 + \sum_{j=1}^{\mathrm{J}} \beta_j \mathrm{Y}_{t-j} + \sum_{k=1}^{\mathrm{K}} \gamma_k \mathrm{X}_{t-k} + \varepsilon_{1t}\,, \tag{2}$$

$$\mathrm{X}_t = \alpha_2 + \sum_{j=1}^{\mathrm{J}} \beta_{\mathrm{j}} \mathrm{X}_{t-j} + \sum_{k=1}^{\mathrm{K}} \gamma_k \mathrm{Y}_{t-k} + \varepsilon_{2t}\,, \tag{3}$$

where α_1 and α_2 are intercepts, β_j and γ_k are coefficients of the model, and ε_t's are the residuals for each time series. Considering the first equation, for instance, if the variance of the residual, ε_t, is strongly reduced by the inclusion of the X_t, then it is said that X_t Granger causes Y_t. By definition, X_t Granger causes Y_t if coefficients, γ_{k}'s, are jointly significantly different from zero. This can be examined by conducting a simple F-test with a null hypothesis that γ_{k}'s = 0. Similarly, one could test, whether Y_t Granger causes X_t. It is frequently found that the Granger causality runs in both directions, which researchers refer to as an existence of a feedback system.

It remains important to note that an existence of a Granger causality relation from X to Y does not imply that Y is the result of X. The Granger causality concept only measures precedence and information content, but cannot confirm causal relations between two or more variables. Next, I will present the Granger causality equations analyzed in this study. The Granger causality equation pairs examined in this study are specified as follows:

$$\mathrm{VS}_{it} = \alpha_i + \alpha_1 \mathrm{NFM}_{it-1} + \ldots + \alpha_l \mathrm{NFM}_{it-l} + \beta_1 \mathrm{VS}_{it-1} + \ldots + \beta_l \mathrm{VS}_{it-l} + \varepsilon_{it}\,, \tag{4}$$

$$\mathrm{NFM}_{it} = \alpha_i + \alpha_1 \mathrm{VS}_{it-1} + \ldots + \alpha_l \mathrm{VS}_{it-l} + \beta_1 \mathrm{NFM}_{it-1} + \ldots + \beta_l \mathrm{NFM}_{it-l} + \varepsilon_{it}\,, \tag{5}$$

where VS stands for quarterly value share, $\propto_i$ is a brand-country group specific intercept, β's are coefficients, NFM is one of the non-financial metrics, average satisfaction, top2box satisfaction, retention rate or the Net Promoter Score. As the theory behind the Granger causality is based on an observation that all past information might be of relevance, the number of time lags should equal the maximum number of periods one could assume to have an effect. Therefore, I conduct the Granger causality testing with up to six quarterly lags.

The concept of Granger causality has been widely utilized in several different fields of science, including economics, political science, and neuroscience. However, to the best of my knowledge, I am not familiar with any previous studies examining the relation between non-financial measures and company performance that would utilize the Granger causality testing. Nonetheless, the Granger causality analysis has a solid potential to further help to assess how non-financial measures and company performance are associated.

5.2. Fixed effects panel regression

As discussed in the introduction of Section 5, panel data consists of both spatial and temporal dimensions. Specifically, according to Baltagi (2005) we can consider a simple linear regression model with a set of independent variables,

$$Y_{it} = \beta_0 + \beta X_{it} + u_{it} , \quad (6)$$

where, Y_{it} is the dependent variable, β_0 is an intercept, X_{it} presents a set of independent variables, u_{it} is a disturbance term and β is a vector of coefficients of the independent variables. Usually, the disturbance term of u_{it} is a one-way error component model of:

$$u_{it} = \mu_i + v_{it} , \quad (7)$$

where μ_i is an unobservable, time-invariant individual specific effect and v_{it} denotes the remaining disturbance, which can vary across time and individuals.

If we then consider the characteristics of a fixed effect model, we assume that the μ_i is a fixed parameter and that the v_{it} term is independent and identically distributed. Additionally, we assume that X_{it} is independent of the v_{it} for all i and t (Baltagi, 2005). In other words, when employing a fixed effects model, one assumes that the fixed individual specific effects can be correlated with the explanatory variables.

The fixed effects model tries to overcome the problem of omitted variable bias. In non-experimental studies, there is always a possibility that some of the key covariates are left out from a model specification which, in turn, can severely bias the estimates for the variables included. In non-experimental situations, independent variables normally vary both within and between individuals. Also, in the context of this study, it is reasonable to assume that the non-financial metrics of interest vary both between the cross sectional units of brand and country, and also across time.

A fixed effects model assumes that unobservable factors, which might simultaneously affect both independent and dependent variables are time in-variant. In other words, if there exist factors, which would have effect on both sides of the regression equation simultaneously, then these effects are treated as if they did not vary across time. For this reason, the fixed effect model bases regression coefficient estimates only within group variation. Although this approach usually increases sampling variability and produces higher standard errors relative to random effects method, for instance, as it takes into account only within group variation, one can control all the omitted variables as long as they do not vary in time. Essentially, using fixed effects technique is a tradeoff between sampling variability and reduced omitted variable bias.

Like all the statistical methods, also the fixed effects models have both advantages and some drawbacks. As already discussed, the biggest advantage of fixed effects models is that it allows one to control for all the fixed individual unit characteristics, as long as they do not vary across time. This means that one can better capture the net effect of the independent variables as the time-invariant factors are cleaned out. However, a potential drawback of the fixed effects models is that may not be utilized if there does not exist enough variation within groups. Additionally, group-wise heteroscedasticity or autocorrelation across time might also affect negatively coefficient estimates.

5.3. Random effects panel regression

In contrast to fixed effects models, the random effects models assume that a random process causes the variation across cross-sectional units and the variation is uncorrelated with the independent variables. Similarly to the fixed effects models, also the random effects model could be modeled as an equation:

$$\mathrm{Y}_{it} = \beta_0 + \beta\mathrm{X}_{it} + \mathrm{u}_{it}\ , \tag{8}$$

where, Y_{it} is the dependent variable, β_0 is an intercept, X_{it} presents a set of independent variables, u_{it} is a disturbance term and β is a vector of coefficients of the independent variables. However, in contrast to fixed effects models, we also assume that the error components are independent:

$$\mu_i \sim \text{i.i.d. } N(0, \sigma_\mu^2) \tag{9}$$

$$v_{it} \sim \text{i.i.d. } N(0, \sigma_\varepsilon^2) \tag{10}$$

In addition, we assume that X_{it} is independent of both μ_i and v_{it}, for all i and t (Baltagi, 2005). Therefore, the random effect model imposes more strict requirements than the fixed effect model. On the other hand, the random effects model has the advantage of allowing factors, which do not vary across time (like gender) to be included as independent variables. In the fixed effects model, the gender effect, for instance, would be part of the intercept. Therefore, according to Torres-Reyna (2011), random effects models should be favored if there is a reason to believe that differences across entities have an effect to the dependent variable. Unlike the fixed effects models, the random effects models enable us to generalize the regression estimates to apply to the whole population. Probably the most significant drawback of the random effects models is that if data on those time-invariant variables is not available, one has to face a problem of omitted variable bias.

The question of whether a fixed or a random model should be applied is naturally a significant one based on the discussion above. In general, a fixed effects model might be favored over the random effects one, since it works as a precaution against omitted variable bias and the strict assumptions of the random effects model are rather difficult to satisfy. Additionally, a more conservative way is to assume that the unobserved effect can be correlated with the independent variables, and thus favor a fixed effects model. However, there are also statistical tests developed to determine which model should be applied. A key consideration in choosing between a fixed and random effects model, is to determine whether μ_i, the unobservable, time-invariant individual specific effect and X_{it}, the independent variables, are correlated. Probably the most famous method to test this assumption is called a Hausman specification test.

The Hausman specification test compares two alternative estimators, under a null hypothesis that the time-invariant individual specific effects are uncorrelated with the regressors (Hausman, 1978). If the null hypothesis is rejected, then correlation exists, and a random effects model produces biased estimates and violates Gauss-Markov assumptions. However, if the null is not rejected, then one favors a random effects model over a fixed effects model. In order to determine, which model should be applied in the context of this study, I conduct the Hausman tests for different model specifications individually. I will return the question of model choice in Section 6, where I will present the results of the empirical analysis. Next, I will introduce a concept of distributed lag panel regression model.

5.4. Distributed lag panel regression model

The idea behind distributed lag models is that both current and past period values of independent variables might contain relevant information and help to explain variation of a dependent variable. In other words, one allows for a possibility that time might elapse between a change in the independent variable and the effect in the dependent variable. Throughout this study, I refer to this time between cause and effect with a term lag.

The distributed lag models can only be applied to time series data, since past values of independent variables are used to construct additional regression variables. Let us consider a simple distributed lag model of one dependent variable and one independent variable with k lags:

$$\mathrm{Y}_t = \alpha + \beta_0 \mathrm{X}_t + \beta_1 \mathrm{X}_{t-1} + \beta_2 \mathrm{X}_{t-2} + \ldots + \beta_k \mathrm{X}_{t-k} + \varepsilon_t \, , \qquad (11)$$

where Y_t is the dependent variable, α is an intercept, X is the independent variable, X_{t-k} variables are lagged values of X, β's are regression coefficients, and ε_t is an error term. Here, we explain the variation in Y with both current and past values of X.

As discussed earlier in the second section, several customer based assets are believed to have a lagged effect on performance. For instance, Bernhardt et al. (1999) find that increase in customer satisfaction is associated with profits on long-term although obscured in the short-term. Their findings therefore suggest that past values of customer satisfaction might be relevant in assessing future performance. Specifically, in the context of this study, the lag-model is specified as follows:

$$\text{Value share}_{it} = \propto_i + \sum_{k=0}^{K} \beta_k \text{NFM}_{it-k} + \text{Total Assets}_{it} + \mu_t + \varepsilon_{it}\,, \qquad (12)$$

where quarterly brand-country group specific value share is the dependent variable, $\propto_i$ is a group specific intercept, β_k is coefficient, NFM_{it-k} is one of the non-financial metrics , either average satisfaction, top2box satisfaction, retention rate or the Net Promoter Score. Total Assets_{it} is a quarterly balance sheet item for each mobile phone manufacturer and thus not vary between countries. μ_t is a dummy variable for each period, and ε_{it} is an error term. I estimate the model with up to six lags, meaning that k runs from 0 to 6. Next, I will introduce the results from the empirical analysis.

6. Empirical results

In this section, the empirical results of the study are reviewed. I will start by describing how individual non-financial metrics, customer satisfaction, customer retention and the Net Promoter Score, are associated with company performance based on the dataset. Then, I will review more in detail the results of the Granger causality testing and the distributed lag panel regression models, after which I will discuss aspects related to robustness of the applied methodology. Finally, I will present concluding remarks about to the empirical findings of this study.

6.1. General characteristics of regression variables

I begin the empirical part of the analysis by following a conventional route of correlating regression variables with each other. Although correlations as such cannot be used to infer causal relations between variables, they however, provide a good starting point for the analysis, and may indicate, whether existence of more profound links are to be expected. Table 4 shows a Pearson correlation matrix for different regression variables.

TABLE 4: CORRELATION MATRIX FOR REGRESSION VARIABLES

Table 4 presents Pearson correlations between the main regression variables used in the empirical analysis. Coefficients with significance levels of 5% have asterisks. The abbreviations in the table are as follows: Value share is each company's proportion of market's total sales in each quarter in each market. Total value denotes the total net sales of all the companies in one market in one quarter, CS = customer satisfaction, Top2box CS = the percentage of respondents, who answered "4" or "5" for the satisfaction question in the consumer survey, RR = retention rate. NPS = Net Promoter Score. Total assets variable represents quarterly balance sheet items for each company in each quarter and the figures are retrieved through Thomson One Banker.

	Value share	Market share	Total value	Avg. CS	Top2box CS	RR	NPS index	Total assets
Value share	1.00							
Market share	0.97*	1.00						
Total value	0.51*	0.48*	1.00					
Avg. CS	0.16*	0.12*	0.08*	1.00				
Top2box CS	0.14*	0.1*	0.05*	0.84*	1.00			
RR	0.72*	0.67*	0.39*	0.27*	0.24*	1.00		
NPS index	0.18*	0.11*	0.02	0.49*	0.64*	0.25*	1.00	
Total assets	0.37*	0.40*	0.26*	0.10*	0.06*	0.21*	0.06*	1.00

Obs=2032

Table 4 clearly indicates that almost all the variables are positively and significantly correlated with each other. This is an interesting finding, which gives an early support for the research hypotheses, according to which the three non-financial metrics of interest and company performance are positively associated.

Regarding the individual non-financial measures, it does not come to a surprise that the average satisfaction and top2box satisfaction metrics exhibit a strong positive correlation, since they are derived from the same consumer survey question. However, the inclusion of both of these metrics should not be considered redundant, but rather to view them as complementary to each other. Moreover, the satisfaction metrics and the NPS seem to also exhibit a relatively strong positive correlation. This is likely partly due to the fact that all the consumer metrics are based on the same survey data, but there is also a clear rationale behind this finding. It is reasonable to assume that satisfied consumers are more likely to engage in positive word-of-mouth activities, which in turn would show as higher Net Promoter Scores. If we assume that the NPS measures customer loyalty accurately, this result is firmly in line with the existing studies, which provide evidence on the link between satisfaction and loyalty.

Regarding the correlations between the non-financial metrics and company performance measures, we see that the retention rate is clearly more strongly correlated with value share than other metrics. Retention rate shows a correlation of 0.72 with value share, compared to the other metrics, which all exhibit a correlation below 0.2. However, the link between retention rates and value shares is also conceptually different from the other non-financial metrics. Market share, a metric closely related to value share, is in fact a liner combination of acquisition and retention rates. This means that, in theory market share of a company could be derived based on the number of acquired and retained customers. Naturally, this proves to be difficult in practice and although market shares and value shares are closely correlated, the correlation is not still perfect. The theoretical relation between retention and acquisition rates and market shares of companies is provided in Appendix 1.

Based on the discussion above, it would easy to conclude that the retention rate is more strongly associated with value share development than other consumer metrics, but one must bear in mind that the correlation matrix reflects only relations between variables measured at the same period. In fact, a more interesting question is that if we take into account also the history of different non-financial metrics, as well as the performance history, are we then able to say more about the relation between the different metrics and performance? Next, I will try to shed more light on this issue by reviewing results from the Granger causality analysis.

6.2. Results of Granger causality testing

In this sub-section, I will review the results from the Granger causality analysis. However, before a Granger causality analysis can be conducted, one must first check that the data meets the requirements of the test. In particular, it is important to examine, whether the time-series are stationary and thus do not contain unit roots. In addition, a conventional approach is also to test the level of cointegration of the time-series. Although the Granger causality could be analyzed with non-stationary time-series as well, it would surely add a complicating factor to the analysis and make the results harder to interpret. Therefore, let us first define, what is a unit root, and after that turn to discuss cointegration.

If a time series has a unit root, then the joint probability distribution of the series evolve over time, which also means that the mean and variance of the series change when time passes. In particular, time-series, which contain unit roots, are called non-stationary series. In order to detect, whether the time-series of interest in this study are stationary, i.e. do not contain unit roots, I conduct a battery of slightly differing unit root tests. Specifically, I ran Levin-Lin-Chu, Im-Pesaran-Shin, Fisher-ADF, and Fisher-PP unit root tests. The results from the unit root tests are provided in Appendix 5. The results indicate that the different non-financial metrics or the value share time-series do not seem to contain unit roots. Therefore, one can apply conventional panel Granger causality methods. Next, I will introduce the concept of cointegration.

Two time series are said to be cointegrated if they share a common stochastic (random) drift. In probability theory, the stochastic drift is defined as the change of the average value of a stochastic process. Specifically, X_t and Y_t are said to be cointegrated, if a parameter α exists, such that

$$U_t = Y_t - \alpha X_t \tag{13}$$

is a stationary process (Sorensen, 2005). If cointegration exists, there must also be a Granger causality relation present. However, vice versa is not true.

Hoover (2003) uses an apt analogy to describe the concept of cointegration. He depicts a situation, where a drunk wanders around, but his loyal friend follows his steps closely to make sure he does not hurt himself. If we first consider the steps of the drunk, they look like a product of a random process. If we then consider the steps of the friend, they also look like a random walk, if viewed in isolation. However, the steps of the sober person are largely predictable, as long as we have knowledge about the steps of the drunken person. The paths of the two persons are an example of cointegration.

In order to conduct the cointegration tests in a panel framework, I follow a method developed by Westerlund (2007). The underlying idea is to test for the absence of cointegration by inferring whether the individual panel members are error correcting (Persyn and Westerlund, 2008). The Westerlund’s approach consists of four different cointegration tests, which are based on structural rather than residual dynamics, and have a null hypothesis of no cointegration. Specifically, according to Persyn and Westerlund (2008), the tests are general enough to allow a large degree of heterogeneity both in the short and long run cointegrating relationships, as well as across cross-sectional units. Westerlund (2007) shows in a Monte Carlo simulation study that the tests have limiting normal distributions, are consistent, and more powerful than other residual-based cointegration tests.

Table 5 shows results of the cointegration tests, which are conducted with a fixed of number of lags and based on Akaike information criterion (AIC). The fixed number of lags is selected to be five, since it is the largest number of lags for which the tests can be carried out with this specific dataset. Additionally, five lags correspond closely to six lags, which will be used as the largest number of lags later on in the Granger causality testing and in the distributed lag regressions. Also, I ran the cointegration tests based on the AIC, which suggests that lags of 1.74-1.81 are of relevancy depending on the non-financial metric. Overall, the test statistics, which are based on the AIC, clearly indicate that all the four non-financial metrics are cointegrated with the value share. The tests, which are conducted with a fixed number of lags point to the same direction although the results are not quite as strong.

In addition, I also conduct the tests other way around, to see whether the time-series are cointegrated to the other direction. In brief, the results from these tests strongly suggest that the value shares are not cointegrated with the non-financial metrics in the other direction. Appendix 6 provides a summary of the other-way cointegration tests. Next, I will discuss the results of the Granger causality analysis.

TABLE 5: COINTEGRATION TESTS

Table 5 shows results from cointegration tests developed by Westerlund (2007). 'Gt' and 'Ga' denote group mean tests, which test an alternative hypothesis that at least one unit is cointegrated. 'Pt' and 'Pa' denote panel tests statistics, which pool information over all the cross-sectional units and test an alternative hypothesis that the panel is cointegrated as a whole. The right hand side of the table shows results from the tests, where the number of lags is specified to be five. The left hand column shows the test results, where the number of lags is based on Akaike information criterion. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively. Abbreviations are as follows: RR = retention rate, CS = satisfaction, NPS = Net Promoter Score.

		Lag = 5		Lag = avg. AIC lag length		
Variable	Statistic	Value	Z-value	Value	Z-value	Lag
RR	Gt	-	-	4.51**	-38.76	1.8
	Ga	-1.1e+14**	-2.6e+14	-810000**	-1900000	
	Pt	-1.611	16.880	-45.37**	-26.31	
	Pa	-1.8e+06**	-5.0e+6	-13.63**	-25.66	
Avg.CS	Gt	-	-	-5.25**	-49.3	1.74
	Ga	-5.5e+6**	-1.3e+7	-10.79**	-8.4	
	Pt	-429.338**	-405.352	-59.27**	-40.04	
	Pa	-38.901**	-95.528	-16.41**	-33.33	
Top2box.CS	Gt	-	-	-6.16**	-62.34	1.81
	Ga	-7.7e+13**	-1.8e+14	-11.58**	-10.25	
	Pt	-6.217	12.333	-39.96**	-20.97	
	Pa	-7.6e+6**	-2.1e+7	-11.21**	-18.96	
NPS	Gt	-	-	-5.83**	-57.61	1.8
	Ga	-1.6e+7**	-3.7e+7	-10.15**	-6.9	
	Pt	-5.948	12.598	-37.91**	-18.95	
	Pa	-1.6e+7**	-4.4e+7	-11.79**	-20.57	

Table 6 shows the results from the Granger causality tests. If the F-statistics presented in the table are significant, it is an indication of Granger causality relation. Regarding individual non-financial metrics and their relation on value share, we can conclude from the table that both average and top2box satisfaction seem to Granger-cause the value share. This means that by utilizing both the histories of satisfaction and value share, one is better able to explain the variation of value share than using the history of value share alone. If we consider the inverse relation, we can see from the table that three lags (out of 12) of the satisfaction metrics are significant on a 5 percent level. This could be interpreted as an indication of an existence of a feedback system. However, the Granger causality method is somewhat susceptible to a correct selection of lags, and as the inverse relation does not seem to be persistent over both satisfaction metrics and over time, I am able to conclude with firm confidence that a Granger causality runs only from satisfaction to value share.

TABLE 6: GRANGER CAUSALITY TESTING

Table 6 shows results for the Granger causality analysis. The left hand column presents Granger causality null hypotheses, according to which each variable does not Granger-cause another variable. For instance, the H_0 of the NPS – VS -row reads as follows: NPS does not Granger-cause Value share. Rejection of the null hypothesis indicates that there exists a Granger causality relation, which runs from the first to the second variable. The reported F-statistics are Wald statistics for a joint hypothesis that all the betas equal zero. The right hand side columns show results for different time lag specifications. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Granger causality relationship	1 Lag	2 Lags	3 Lags	4 Lags	5 Lags	6 Lags
RR - VS	7.02**	4.32*	3.63*	3.52**	3.84**	3.07**
VS - RR	337.55**	83.21**	30.5**	20.24**	14.2**	14.51**
Number of obs.	1719	1545	1384	1230	1079	930
Avg.CS - VS	15.59**	7.69**	4.91**	4.04**	3.42**	3.15**
VS - Avg.CS	3.49	3.3*	2.14	1.76	1.10	1.18
Number of obs.	1793	1627	1464	1302	1140	978
Top2box.CS - VS	11.44**	6.17**	4.49**	3.82**	3.14**	2.92**
VS - Top2box.CS	6.35*	3.89*	2.29	1.73	1.38	1.64
Number of obs.	1883	1721	1559	1397	1235	1073
NPS - VS	14.52**	7.99**	5.59**	3.83**	3.03*	2.5*
VS - NPS	7.36**	4.09*	3.24*	1.99	1.47	1.92
Number of obs.	1800	1632	1468	1306	1144	982

As regards to retention rate, the results shown in Table 6 indicate that there is a two-way Granger causality relation between retention rate and value share. In other words, both the histories of value share and retention rate seem to be relevant in explaining value share development, but similarly both of the histories are relevant also in explaining retention rate development. Unlike with the customer satisfaction metrics, here the existence of a feedback system seems more plausible, since the F-statistics are significant on a one percent level and the effect is persistent over time. Therefore, based on the Granger causality results, one is unable to determine if the value share comes before the retention rate, or vice versa. This finding does not seem counter-intuitive as it may well be that the causality runs in both directions also in reality. Successful retention efforts might show in better performance, but an increased performance relative to competitors might as well result in higher brand visibility and eventually lead to increased customer retention. I will return to this question later in the next subsection, where results from the distributed lag model analysis are presented.

Additionally, the results presented in Table 6 suggest that the NPS Granger causes the value share and the effect is persistent over time. However, the results also give an indication that the recent history of the value share is of relevancy if one is trying to explain the development of the NPS. Here, the causality might thus run in both directions, similarly than with the retention rate, which was discussed earlier.

Based on the Granger causality and cointegration tests, one can conclude that the value shares and the non-financial metrics are clearly associated. The results show that all of the metrics Granger causes the value share, and there is also evidence, especially as regards to the retention rate, which suggests that the inverse relation is also true. Finally, I must point out that as the Granger causality tests conducted in this study do not incorporate explanatory variables beyond the non-financial metrics, I am unable to control away possible omitted variable bias. However, I will try to overcome this problem later on by conducting another set of econometric tests.

6.3. Results from the distributed lag-model analysis

In the following subsections, I will review and discuss the results from the lag-model analysis. Specifically, I test four different model specifications, with lags ranging from zero to six. In other words, I estimate four panel regressions with varying number of lags, where the dependent variable is a value share percentage, and the main explanatory variable is one of the non-financial metrics, either average satisfaction, top2box satisfaction, retention rate, or the Net Promoter Score. The model specification is presented in Section 5.4. In order to determine, whether a fixed or random effects model should be applied in each case, I conduct the Hausman test for each model and lag specification individually. The results from the specification tests are reviewed in Section 6.4, where various aspects related to robustness of the study are discussed. The lag-model analysis is conducted in Stata 11, which has been tweaked with additional statistical packages in order to conduct tests not provided in the software by default.

6.3.1 Customer satisfaction and performance

My first research hypothesis suggests that customer satisfaction is positively associated with financial performance. As previously discussed in length, this relation has been of significant interest among the academic community already for several decades. Results by Ittner and Larcker (1998), Kaplan and Norton (2001) and Anderson et al. (2004), for instance, lend support to the claim that increasing satisfaction leads to better performance, and that customer satisfaction might work as a leading indicator for financial performance. Several existing studies confirm that customer satisfaction is indeed positively linked to performance, and a noticeable body of research also suggests that there might be a time lag effect between customer satisfaction and company performance.

One of the studies examining time lags of customer satisfaction is one by Matzler et al. (2005), where they study how customer satisfaction is associated with shareholder value. Matzler et al. examine a dataset, which contains observations for 99 U.S. based companies for a period from 1994 to 2002. Their conclusion is that satisfaction is positively associated with Tobin's q of companies and that the strongest effect of customer satisfaction is delayed by three quarters from the measurement time. In addition to the findings of Matzler et al., a study by Bernhardt et al. (2000) gives additional support for the lagged effect of customer satisfaction. Bernhardt et al. find no relation between current period customer or employee satisfaction and various financial performance measures, but they conclude that a time-series analysis reveals a significant and positive relation between these two. Finally, Evanschiztky et al. (2007) investigate this relation with a dataset from a large European do-it-yourself (DIY) retailer's 119 outlets over a two-year period. Their results indicate that customer satisfaction directly affects profits, as well as that there is a six month time lag from customer satisfaction to a performance measure of turnover per customer.

Based on the discussion above, it seems that albeit time lag effects of customer satisfaction on profitability are discussed widely, rather limited empirical evidence exist about this relation. Next, I will try to contribute to the existing evidence and present the results from the distributed lag model analysis, where a value share is a dependent variable and customer satisfaction the main independent variable.

Table 7 presents panel regression results for a model specification, where the average satisfaction is used as an explanatory variable. In addition to average satisfaction, I have included a total assets variable to control for a possible company size effect. Furthermore, I include a period dummy in the model as specified in Section 5.4. The estimates for the period dummies and intercepts are omitted from the following tables due to their unimportance as regards to the analysis and in order to save space.

TABLE 7: DISTRIBUTED LAG MODEL REGRESSION OF AVERAGE SATISFACTION

Table 7 reports results from the distributed lag model regression, where average satisfaction is the main independent variable. The left hand column shows the model specification, where L* stands for a lagged variable of average satisfaction. 'Assets' is a balance sheet item of total quarterly assets for each manufacturer. The model specification also includes period dummies and intercepts, as shown in Section 5.4, in Equation 12. The dummies and intercepts have been omitted from the table. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Model specification	Coefficient	Robust std. error	R-squared, within	R-squared, between	R-squared, overall	Number of obs.	Number of groups
Avg_CS	0.0035*	0.00157	0.1419	0.1473	0.1410	2032	161
Assets	0**	0.00000					
Avg_CS	0.00209*	0.00096	0.1443	0.1505	0.1451	1871	161
L1.Avg_CS	0.00258	0.00144					
Assets	0**	0.00000					
Avg_CS	0.00276*	0.00134	0.1427	0.1564	0.1516	1710	161
L1.Avg_CS	0.00071	0.00080					
L2.Avg_CS	0.00323*	0.00143					
Assets	0**	0.00000					
Avg_CS	0.00212	0.00121	0.1395	0.1639	0.1594	1549	161
L1.Avg_CS	0.00204	0.00107					
L2.Avg_CS	0.00086	0.00064					
L3.Avg_CS	0.00411**	0.00152					
Assets	0**	0.00000					
Avg_CS	0.00152	0.00103	0.1414	0.1716	0.1684	1388	161
L1.Avg_CS	0.00195*	0.00094					
L2.Avg_CS	0.00184	0.00100					
L3.Avg_CS	0.00239*	0.00093					
L4.Avg_CS	0.00349*	0.00150					
Assets	0**	0.00000					
Avg_CS	0.00120	0.00091	0.1674	0.1737	0.1756	1227	161
L1.Avg_CS	0.00166	0.00092					
L2.Avg_CS	0.00134	0.00086					
L3.Avg_CS	0.00354**	0.00135					
L4.Avg_CS	0.00159*	0.00078					
L5.Avg_CS	0.00391*	0.00158					
Assets	0**	0.00000					
Avg_CS	0.00042	0.00126	0.1611	0.1753	0.1815	1066	161
L1.Avg_CS	0.00177	0.00095					
L2.Avg_CS	0.00104	0.00092					
L3.Avg_CS	0.00308*	0.00123					
L4.Avg_CS	0.00286*	0.00116					
L5.Avg_CS	0.00271**	0.00083					
L6.Avg_CS	0.00288	0.00153					
Assets	0**	0.00000					

The figures presented in Table 7 are based on a random effects panel regression with robust standard errors. The random effects model was favored over a fixed effects model based on the Hausman specification test, which will be further discussed in Section 6.4. As previously mentioned, the random effects model assumes that there is no correlation between the unit specific error and explanatory variables. Regarding the analysis of the satisfaction metrics, this means making an assumption that fixed brand-country specific errors are not correlated with the satisfaction metrics. Thus, we assume that no (significant) fixed brand-country specific factors exist that would affect satisfaction and value share variables simultaneously.

We can conclude from Table 7 that current period average satisfaction seems to be positively and significantly associated with value share development in the first three model specifications. However, if one adds more than two lags of average satisfaction, the current period satisfaction variable becomes insignificant. This finding suggests that although the current period satisfaction variable seems to be relevant at first hand, adding more lags to the model shows that the current period variable is picking up some effect of the lagged variables.

Lags of one or two periods (i.e. one or two quarters), do not seem to be statistically significant. Interestingly, however, lags from three up to five are significant, which suggest that these lagged variables seem to hold some explanatory power, and thus should be included in the regression model. In other words, based on the presented results, satisfaction seems to have a lagged effect on performance.

As regards to the regression variables, the value share is a continuous one and it runs from zero to 1, whereas the average satisfaction varies between zero and five. Regarding the coefficient estimates, if we consider the first model, it suggests that if the average satisfaction would rise by one unit, from three to four, for instance, we would see a 0.35 percent point change in value share, other things being equal. On the other hand, regarding the last specification with six lags of average satisfaction, based on the data, we see that if a company would be able to increase its average satisfaction by one unit now, and hold the satisfaction stable for six quarters, it would result in a total effect of 1.47 percent points on value share. A post-estimation Wald test confirms that the coefficient estimates in the models of three or more lags are, as a combination, statistically significant. Additionally, throughout the table, the coefficient estimates for the total assets variable are positive and significant, although the effect of size on value share is very small.

I also run the same model with lags for the top2box satisfaction variable. The results of this analysis are provided in Appendix 7. The results partly support the conclusions, which were based on the analysis of the average satisfaction metric. First of all, the findings confirm that satisfaction has a lagged effect on performance. However, the current period top2box satisfaction seems to pick the effect of lagged variables even more than the average satisfaction metric, as the current period top2box coefficient estimate is only significant, when there are no lagged variables included. However, if one adds one even one lagged variable, the current period coefficient estimates turn insignificant. As the scale of the top2box variable differs from the average satisfaction variable, the coefficient estimates of Appendix 7 make more sense, when divided by 10, for instance. This transformation would show the effect of 10 percentage point change of top2box satisfaction compared to the estimates provided in the table that currently reflect changes in value share, if the top2box satisfaction would change by one unit - that is from zero to one.

In summary, the results from the average satisfaction and top2box satisfaction models suggest that customer satisfaction seem to be positively and significantly associated with value share development. The finding that current period satisfaction as such is linked positively to performance is in line with the previous studies. However, the result that the current period satisfaction seems to pick up effect from the history has not been analyzed extensively by the previous research, but some studies do suggest that satisfaction might have a lagged effect on performance. As previously discussed, to the best of my knowledge, only few previous time-series studies exist that examine the relation between satisfaction and performance. My results therefore contribute to the scarce body of existing research by giving additional support for the claim that satisfaction seems to have a lagged effect on company performance.

6.3.2. Customer retention and performance

Customer retention is the activity a company undertakes in order to decrease the number of defected customers. As previously discussed, in theory, it is rather straightforward to define, whether a customer has retained or not. Naturally, measuring retention in practice is more difficult to accomplish, especially with goods, which are not based on a contract, such as buying milk. In the context of this study, I define retention rate following a conventional practice. Therefore, retention rate (RR) for a brand X at time t is defined as:

$$\mathrm{RR(X)}_t = \frac{\mathrm{X}_t}{\mathrm{X}_t + \mathrm{Y}_{t.}}, \qquad (14)$$

where X_t= the number of consumers, whose current and previous mobile phone was of brand X. Y_t = the number of consumers, whose previous model was of brand X but current mobile phone is of brand Y. The retention rates obtained for the analysis are based on the consumer survey answers. Appendix 2 specifies the survey question form.

Whereas customer satisfaction has been widely examined by the previous research, retention rate, in contrast, has emerged later as a concept, and has been studied less extensively. A majority of studies, which examine retention rates' effect on performance, has considered changes in purchase intentions, rather than measuring actual retention. In this study, however, another approach on retention is utilized. Here, retention rates are obtained based on survey answers, which should reflect actual purchasing behaviour. Although this approach is not equal of calculating retention rates based on actual purchase data from a financial system, it does, however, provide a better visibility to true retention than using a proxy of purchase intentions.

The second research hypothesis suggests that retention rate is positively associated with company performance. This claim is in line with previous studies, which provide evidence that retention rates and financial performance seem to be positively correlated. In order to further analyse this relation, I utilize the distributed lag regression model, which is presented in Section 5. Table 8 provides a summary of the conducted regressions.

Unlike with customer satisfaction metrics, I employ a fixed effect regression for modeling retention rates. This choice is based on the Hausman specification test, whose results will be further discussed in the next section. Interestingly, the Hausman test suggests a different model for retention rate than for the satisfaction metrics or the NPS. This might imply several things. First of all, based on the test's results, retention rate seems to be different from the non-financial metrics. Specifically, as the fixed effects model is utilized, one assumes that a fixed factor exists that correlates with retention rate and value share, but not with the other non-financial measures of interest in this study. Such a factor might be existing operator relations, for instance. It is reasonable to assume that such relations might explain persistent differences in value shares between different country-brand groups, and that the strength of these relations would correlate with retention rates, but not with the other non-financial metrics. This assumption is supported by the fact that market share, a metric closely related to value share, is actually a function of acquisition and retention rates.

TABLE 8: DISTRIBUTED LAG MODEL REGRESSION OF RETENTION RATE.

Table 8 reports results from the distributed lag model regression, where retention rate is the main independent variable. The left hand column shows the model specification, where L* stands for a lagged variable of retention rate. 'Assets' is a balance sheet item of total quarterly assets for each manufacturer. The model specification also includes period dummies and intercepts, as shown in Section 5.4., in Equation 12. The dummies and intercepts have been omitted from the table. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Model specification	Coefficient	Robust std. error	R-squared, within	R-squared, between	R-squared, overall	Number of obs.	Number of groups
RR	0.07705**	0.01700	0.1876	0.2748	0.2628	2032	161
Assets	0**	0.00000					
RR	0.07399**	0.01665	0.2091	0.3559	0.3424	1871	161
L1.RR	0.0485**	0.01131					
Assets	0**	0.00000					
RR	0.07182**	0.01754	0.2169	0.4278	0.4130	1710	161
L1.RR	0.04646**	0.01232					
L2.RR	0.03789**	0.00999					
Assets	0**	0.00000					
RR	0.073**	0.01747	0.2142	0.4968	0.4812	1549	161
L1.RR	0.04297**	0.01311					
L2.RR	0.03398**	0.00957					
L3.RR	0.03264**	0.01035					
Assets	0**	0.00000					
RR	0.06563**	0.01617	0.2221	0.5500	0.5391	1388	161
L1.RR	0.0479**	0.01473					
L2.RR	0.03845**	0.01236					
L3.RR	0.03245**	0.01075					
L4.RR	0.03043**	0.01018					
Assets	0**	0.00000					
RR	0.05461**	0.01516	0.2320	0.5313	0.5315	1227	161
L1.RR	0.03966**	0.01349					
L2.RR	0.04005**	0.01290					
L3.RR	0.03174*	0.01260					
L4.RR	0.02997**	0.00978					
L5.RR	0.02226	0.01341					
Assets	0**	0.00000					
RR	0.0521**	0.01552	0.2127	0.5443	0.5543	1066	161
L1.RR	0.03005*	0.01253					
L2.RR	0.03667**	0.01205					
L3.RR	0.03572*	0.01526					
L4.RR	0.03315**	0.01006					
L5.RR	0.01937	0.01280					
L6.RR	0.01850	0.01537					
Assets	0**	0.00000					

Table 8 shows that all coefficient estimates for retention rates and its lags up to four are positive and statistically significant on a five percent level. This finding suggests that not only the current values of RRs are positively associated with value shares, but also RRs' history values hold explanatory power. Interestingly, however, the coefficient estimates turn insignificant after the fourth lag. This finding seems to indicate that the explanatory power of RR's history becomes less significant more than a year back.

Although the results from the fixed and random effects model cannot be directly compared without restrictions, RR still seems to have a smaller effect on value share development, than the customer satisfaction metrics discussed earlier. The coefficient estimates presented in Table 8 show how much a value share would change, if the retention rate would change by one unit. Regardless, it does not make a whole lot of sense to examine what would happen if RR would, for instance, increase from zero to one. Therefore, if one divides the coefficient estimates by ten, we can see, what is the expected effect to value share if RR changes by 10 percentage points.

The regression results indicate that a ten percent point increase in RR would, on average and depending on the number of lags included, seem to have a positive, 0.8-2.1 percentage point effect on value share, other things being equal. If we are to consider, how current period non-financial metrics are associated with value shares, we can conclude that, based on the results, a one unit increase in average satisfaction roughly equals the effect of 10 % change in retention rate. RR models, however, have a better goodness of fit than the satisfaction metrics do. Therefore, from a business perspective, the retention rate seems to have a larger effect on value share development than the satisfaction metrics.

6.3.3. Net Promoter Score and performance

Table 9 shows a summary of a set of random effects panel regressions, where the dependent variable is a value share of a company and the main independent variable is the Net Promoter Score. In order to select a statistical method to model this relation, I follow a similar approach as with the other non-financial metrics, and conduct the Hausman specification test, which suggests a random effects model should be favored over the fixed effects one.

A quick overview of Table 9 shows that the different lag specifications of the NPS are not statistically significant on a five percent level. This result indicates that neither the current period values of the NPS nor its history values seem to be strongly associated with the value share development. This is an interesting finding by several ways.

First, as previously shown in Table 4, the value share and the NPS are significantly correlated, with a correlation factor of 0.18, which is higher than between value share and customer satisfaction metrics, for instance. Moreover, as discussed in Section 6.2., the NPS seems to Granger-cause the value share. At first hand, it looks the results of the distributed lag regression would be contradictory to the results from the Granger causality testing. However, if we look at things more closely and run a distributed lag regression analysis without the control variables of period dummies and total assets, we identify that the coefficient estimates of the NPS and the lags of it become significant on a five percent level. As mentioned in Section 6.2., the Granger causality analysis conducted in this study is unable to capture the effect of the control variables. Although all the non-financial metrics seem to be positively associated with value shares based on the Granger causality analysis, the NPS is the only metric, which loses its significance if one includes the control variables in the distributed lag model. Therefore, the results of the distributed lag model analysis suggest that the NPS is not significantly associated with the value share development, while controlling for the time effect and the company size effect.

TABLE 9: DISTRIBUTED LAG MODEL REGRESSION OF NET PROMOTER SCORE

Table 9 reports results from the distributed lag model regression, where the Net Promoter Score is the main independent variable. The left hand column shows the model specification, where L* stands for a lagged variable of the NPS. 'Assets' is a balance sheet item of total quarterly assets for each manufacturer. The model specification also includes period dummies and intercepts, as shown in Section 5.4., in Equation 12. The dummies and intercepts have been omitted from the table. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Model specification	Coefficient	Robust std. error	R-squared, within	R-squared, between	R-squared, overall	Number of obs.	Number of groups
NPS	0.00894	0.00599	0.1399	0.1485	0.1419	2032	161
Assets	0**	0.00000					
NPS	0.00539	0.00493	0.1409	0.1516	0.1457	1871	161
L1.NPS	0.00564	0.00532					
Assets	0**	0.00000					
NPS	0.00759	0.00535	0.1372	0.1579	0.1523	1710	161
L1.NPS	0.00135	0.00448					
L2.NPS	0.00626	0.00540					
Assets	0**	0.00000					
NPS	0.00684	0.00526	0.1314	0.1670	0.1613	1549	161
L1.NPS	0.00385	0.00515					
L2.NPS	0.00006	0.00385					
L3.NPS	0.01156	0.00591					
Assets	0**	0.00000					
NPS	0.00507	0.00462	0.1294	0.1756	0.1709	1388	161
L1.NPS	0.00421	0.00471					
L2.NPS	0.00098	0.00431					
L3.NPS	0.00544	0.00424					
L4.NPS	0.01139	0.00623					
Assets	0**	0.00000					
NPS	0.00711	0.00432	0.1494	0.1793	0.1795	1227	161
L1.NPS	0.00220	0.00424					
L2.NPS	0.00107	0.00422					
L3.NPS	0.00688	0.00458					
L4.NPS	0.00619	0.00472					
L5.NPS	0.01066	0.00618					
Assets	0**	0.00000					
NPS	0.00705	0.00445	0.1381	0.1841	0.1888	1066	161
L1.NPS	0.00560	0.00471					
L2.NPS	-0.00012	0.00439					
L3.NPS	0.00839	0.00514					
L4.NPS	0.00780	0.00560					
L5.NPS	0.00807	0.00511					
L6.NPS	0.00762	0.00638					
Assets	0**	0.00000					

Regarding the existing research on the NPS, my results are in line with the findings of Keimingham et al. (2007) and Lawrie et al. (2006) who find that the NPS is not significantly associated with company performance or superior to other non-financial metrics. However, it must be pointed out that my findings are contradictory to the results of Reichheld et al. (2003). As previously discussed in length, the strong claims of Reichheld about the power of the NPS have not been confirmed in any independent, peer-reviewed, large-scale studies to-date. Interestingly, despite of the criticism stemming from the academic world, the NPS has witnessed a tremendous popularity in the corporate world, and is widely embraced by many top managers. Finally, I will shortly consider possible reasons behind the observation that the NPS seems to be less capable of explaining company performance than the other non-financial metrics of this study.

Schneider et al. (2008) suggest that the measurement of the Net Promoter Score might not be optimal. They aptly note that the NPS seeks to measure a unipolar construct, likelihood to recommend a company on a scale of 0-100%. They claim, however, that the previous research has shown that unipolar constructs are measured most reliably on a five-point scale. In addition, they argue that rating scales yield most reliable results when all the scale points are fully labeled with descriptions. In the NPS metric, only the first and the last options are labeled, compared for instance to the satisfaction metric of this study, where all the options are labeled. Moreover, Schneider et al. (2008) claim that placing the ‘neutral’ option in the middle of the scale in the NPS question might be problematic, since an answer of five or six in fact means that there is a 50% change of recommending a product that is clearly not the same as ‘neutral’ or ‘indifferent’. Also, respondents who select a middle point answer of 5, 6 or 7 might not necessarily be detractors of a brand as such; rather they abstain from making any recommendation. Finally, as the formation of the NPS index (i.e. how the data is manipulated and divided into groups) is not by any way visible for respondents, the description of the scale might confuse them, as well as those who interpret the results.

The NPS is obtained by deducting a percentage of detractors from a percentage of promoters, which means that there are several different answer distributions, which will all yield a same index score. This might be problematic if solely looking at the index scores, since an NPS of 0 consisting of 50/50 ‘promoters’ and ‘detractors’, will surely imply different things than a 0 score consisting 80% of ‘passives’ and 10% of both ‘detractors’ and ‘promoters’. In addition to this, a possible drawback of the metric is that it does not distinguish between positive and negative recommendations, nor does not directly incorporate the strength of recommendation likelihood as the index is based on different proportions of respondents rather than their actual answers.

To shed more light on the question, whether the formation of the NPS index distorts the data somehow, I form an average variable from the original Net Promoter Score -question answers and conduct a panel regression analysis, where I include the average ‘raw’ NPS as the main explanatory variable following the same approach as with the other non-financial metrics. As the raw scores are not available for the whole time period of Q2/2007-Q1/2011, I need to restrict the analysis on time period of Q4/2008-Q1/2011. In addition to the raw score analysis, I also run regressions, where I include proportions of different NPS classes (promoters/passives/detractors) as well as various combinations of them as the main explanatory variables. The results from the average ‘raw’ NPS panel regressions are provided in Appendix 8.

The results presented in Appendix 8 lend some supporting evidence for an argument, according to which the way the NPS index is formed might distort information as regards to how the NPS question is associated with value share development. The regression analysis shows that some lagged variables of the average raw NPS seem to be significant although none of them are significant throughout the different model specifications.

As the duration of the dataset was altered, I re-run regressions for the NPS index, as well. However, the results confirm the previous evidence and provide additional support for the conclusion that the NPS index is not significantly associated with company performance. If we compare the results from the NPS index and the average raw score NPS regressions, we can conclude that there is a possibility that the formation of the index might distort the data, and have a negative impact on the explanatory power as regards to company performance. However, more research is needed in order to answer this question conclusively.

6.4. Robustness checks

The panel regression model presented in the equations (4) and (5) assumes that the disturbances are homescedastic, meaning they have a constant variance. However, according to Baltagi (2005), this might be a restrictive assumption for panel data, where cross-sectional units may vary in terms of size and thus exhibit different variation. Additionally, Baltagi (2005) notes that assuming homescedastic disturbances in a situation where heteroscedasticity is present will result in consistent estimates, but the estimates are not efficient and the standard errors are biased.

In order to detect, whether my dataset contains group-wise heteroscedasticity, I conduct a modified Wald test for time-series cross-sectional data by following a method developed by Baum (2000). According to Baum (2000), the modified Wald test follows strictly an approach of Greene (2000). The test has a null hypothesis of homoscedasticity, i.e. that $\sigma_i^2 = \sigma_{iN}$, when N is the number of cross-sectional units, brand-country groups in my case. The test indicates a presence of heteroscedasticity in all of the models, and I therefore apply Huber/White robust estimates of variance, which also result in robust estimates for standard errors. The requirement of robust estimates usually results in larger standard errors and p-values, which is the case also in my dataset.

Regarding the applied methodology, the Hausman specification tests largely dictate whether a fixed or random effects model is applied in each situation. The results from the Hausman specification tests are provided in Appendix 9. Appendix 9 shows that, based on the Hausman tests, models, where retention rate is the main explanatory variable, should be conducted by using a fixed effects regression. On the other hand, the test suggests that all the other non-financial metrics should be modeled through a random effects regression.

Finally, I check whether the dataset contains serial correlation. By following an approach of Wooldridge (2002), I conduct a Wald test under a null hypothesis of no serial correlation in the residuals. I identify that my time-series contain first order auto-correlation, which means that the standard error estimates I have previously obtained might be smaller than the true standard errors. However, the presence of serial correlation does not affect the un-biasedness or consistency of my estimates.

7. Conclusions

The purpose of this study was to examine, how a set of non-financial customer-driven measures are associated with company performance. I have analyzed how three non-financial measures, namely customer satisfaction, customer retention and a loyalty measure of Net Promoter Score, are linked to value shares of companies in the telecommunications industry. In this study, a particular focus has been on discovering whether changes in these specific non-financial metrics are reflected in performance only after a while, meaning that they have a lagged effect on performance.

The motivation for the study has been three-folded. First of all, I have pursued to provide fresh and up-to-date empirical knowledge on the relation between non-financial measures and company performance on a general level. Secondly, the aim has been to quantify the magnitude and strength of these relations, especially as regards to the telecommunications industry. Finally, I was motivated by the intriguing situation around the NPS. The metric has had a tremendous success in the corporate world and several prominent companies are widely embracing it, while at the same time, several noted researchers have questioned the power and the whole empirical foundation of the metric.

The empirical analysis conducted in this study is based on two longitudinal datasets from the telecommunication industry covering a period of Q2/2007-Q1/2011. The first dataset is an extensive consumer survey, conducted on a quarterly basis in 19 countries, and worked as a source for the non-financial metrics. The second dataset provides information on mobile handset prices and volumes on a country and brand level, and enabled me to form performance proxies of value shares for different brands in different countries, respectively. Next, I will briefly summarize the findings of the study, after which I will consider some limitations related to this research. Finally, I will present concluding remarks and propose suggestions for further research.

7.1. Research findings summarized

In order to properly tackle the question of how the aforementioned non-financial metrics are associated with company performance, I formed three research hypotheses, one for each metric. Largely based on the existing evidence, I hypothesized that all the three non-financial metrics are positively and significantly linked to company performance. To test these research hypotheses, I have utilized two different econometric techniques; Granger causality testing and distributed lag panel regression model. As a result of the empirical analysis, I am able to conclude that I find supporting evidence for my first and second research hypotheses, according to which customer satisfaction and customer retention are positively associated with company performance, but I reject the third hypothesis and conclude that, based on the results, the Net Promoter Score does not seem to be significantly associated with company performance. Table 10 provides a summary of the results from the empirical analysis.

TABLE 10: SUMMARY OF RESEARCH FINDINGS

Table 10 presents a summary of the research findings. Abbreviations are as follows: CS = customer satisfaction, RR = retention rate, NPS = Net Promoter Score.

Method	Metric	Findings	Relationship with hypotheses
Granger-causality testing	CS	One-way Granger-causality relationship exists from satisfaction to value share.	Support for H1
	RR	Both-way, feedback, Granger-causality relationship is found between retention rate and value share.	Support for H2
	NPS	One-way Granger-causality relationship exist from the NPS to value share. Also some evidence supporting another way relationship with lags up to three or less.	Support for H3
Distributed lag panel regression	CS	Satisfaction metrics seem to have a lagged effect on performance . Time-lags of 3,4,5 quarters are significant, but time-lags of 1 and 2 quarters are not. One unit change in Avg.CS has 0.4-1.5 % point effect on value share. 10 % point change in top2box.CS has 0.1-05 % point effect on value share.	Support for H1
	RR	Retention rate is strongly and positively associated with value share, with up to 4 lags (4 quarters) being significant. 10% change in retention rate has 0.8-2.1 percentage point effect on value share.	Support for H2
	NPS	Net Promoter Score is not significantly associated with value share.	Rejection of H3

My findings show that customer satisfaction seems to have a lagged effect on performance. Specifically, changes in customer satisfaction are reflected in performance only after two quarters, and changes hold explanatory power for up to five quarters. Secondly, customer retention is shown to be positively and significantly associated with company performance. Based on my results, current period customer retention rates are positively associated with value shares, and lagged variables of retention rates are of relevance for up to one year, or four quarters. Finally, my results indicate that the Net Promoter Score is not significantly associated with performance. Albeit the Granger causality testing would suggest that the NPS is positively linked to company performance, the distributed lag panel regression analysis confirms that if time and company size effects are controlled, the significance disappears.

The findings of this study are largely consistent with previous research as regards to customer satisfaction and retention. Ittner and Larcker (1998) report that customer satisfaction might work as a leading indicator for financial performance and they find that satisfaction has a lagged effect on performance. Banker et al. (2000) conclude that satisfaction measures are significantly and positively linked to future financial performance measured in business unit revenues and operating profits. Moreover, Banker et al. suggest that the effect of satisfaction is more related to long-term performance and the effect is less visible in short-term. Regarding customer retention, Reichheld and Markey (2000) show that relatively small positive shifts in retention rates have a considerable effect on profits and Rucci et al. (1998) lend additional support for the positive relationship between retention and performance.

However, the existing evidence on the Net Promoter Scores’s effect on performance is rather mixed. Reichheld et al. (2003) make bold claims about the power of the NPS in predicting business performance and growth, but Lawrie et al. (2006) and Keimingham et al. (2007) among others, criticize these findings and report that the NPS is not significantly related to performance. The findings of my study are contradictory to the ones of Reichheld et al. (2003), but lend support for the claim that the NPS is not strongly associated with company performance.

7.2. Limitations of the study

I acknowledge that there are several limitations to the study. To begin with, the dataset I have examined consists of companies operating in the field of telecommunications. As the data is restricted to observations from only one industry, the results from this study cannot be generalized to other industries without restrictions. Secondly, I have used only one proxy variable, a value share, to capture company performance due to reasons discussed earlier in Section 4. Optimally, I would have been to utilize selection of differing metrics, which would have provided a more comprehensive visibility to company performance.

Moreover, although my dataset covers an extensive set of firms from the field of telecommunications, the duration of the time-series could have been somewhat longer, which would have enabled a richer analysis of changes over time. Currently, the dataset offers visibility to a period, during which the whole telecommunications industry has undergone some tremendous changes, and it is probable that the same analysis would offer differing results should it be conducted during some other period in history or in the future. Finally, the analysis of geographic differences has been beyond the scope of this study, but naturally such differences are likely to exist, and the analysis of them could be a fruitful area for further research.

7.3. Implications and suggestions for further research

The relation between non-financial metrics and company performance has attracted significant attention in the academic world already for decades. There is a strong consensus among researchers on the usefulness and value of non-financial information in supplementing accounting based financial information and enriching companies’ understanding of the complicated business environment. This study adds on to the existing body of research by providing additional evidence on the relation between customer satisfaction, customer retention and the Net Promoter Score on company performance. Specifically, the main contribution of this study stems from the analysis of lagged effects of non-financial metrics to performance.

Traditional accounting based financial measures are often accused of being retrospective in nature. On the contrary, non-financial metrics are suggested to be more forward-looking and possibly better indicators of longer-term performance. My results lend additional support for this view and in specific, show that customer satisfaction and customer retention metrics are of relevance in predicting future company performance. However, based on this research, the NPS does not seem to be able to explain current or future period changes in company performance, here measured in value share development. Next, suggestions from continuing this study are put forward.

First of all, more research is needed to better quantify the duration and strength of the identified lagged effect between customer satisfaction and retention to performance. This study has utilized data from only one industry and possible further studies could employ information from several industries as well as examine additional proxies for financial performance. Moreover, it is extremely likely that in the future companies are able to track their customers' behavior more accurately than what is currently possible. This development will be especially distinctive as regards to the telecommunication industry. Naturally, the value-relevance of non-financial information is then also likely to increase.

Additionally, the widespread use of the NPS in the corporate world warrants more independent, peer-reviewed, large-scale research. It is evident that the index score as such should not guide decision-making, but rather one ought to analyze and understand the underlying answer distributions. From this perspective, possible avenues of future research could be to examine, whether the formation of the NPS distorts the usefulness of the 'raw' data or to compare performance of the NPS to other customer based metrics. Although the NPS index most definitely has appeal, it may well be that some other treatment for the 'raw' answer data could be of additional value.

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9. Appendices

A1: RELATION BETWEEN MARKET SHARE AND RETENTION RATE

Appendix 1 shows how market shares and retention rates are theoretically related on a hypothetical market of two players. The proof of this relation is modified from Platzer (2011).

T	**xN**	**Xc**
Nx	NN	Nc
Cx	CN	CC
Fx	FN	FC

,

where

T = Number of consumers, who purchased a product at time *t*
Nx = Number of consumers, who owned brand N previously, and purchased a product at time *t*
Cx = Number of consumers, who owned brand C previously, and purchased a product at time *t*

Fx = Number of consumers, who did not own a product previously, but purchased a product at time *t*
xN =Number of consumers, who purchased brand N at time *t*
xC = Number of consumers, who purchased brand C at time *t*

NN = Number of consumers, who previously owned brand N, and also purchased brand N at time *t*
NC = Number of consumers, who previously owned brand N, and purchased brand C at time *t*
CN = Number of consumers, who previously owned brand C, and purchased brand N at time *t*
CC = Number of consumers, who previously owned brand C, and purchased brand C at time *t*
FN = Number of consumers, who did not own a product previously, but purchased brand N at time *t*
FN = Number of consumers, who did not own a product previously, but purchased brand C at time *t*

T = xN + xC = Nx + Cx + Fx
Nx = NN + NC
Cx = CN + CC
Fx = FN + FC
xN = NN + CN + FN
xC = NC + CC + FC

Retention Rate: RR = NN / Nx

Acquisition Rate: AR = CN / Cx

First Time Buyers Rate: FR = FN / Fx

Market Share = (Nx/T) * RR + (Cx/T) * AR + (Fx/T) * FR

A2: CONSUMER SURVEY QUESTIONS

Appendix 2 lists the consumer survey questions, which have been examined in the empirical part of the study.

Current phone question:

"What brand of mobile phone handset have you most recently bought/received? We are interested in the manufacturer of the handset rather than the network operator/carrier?"

Then a respondent is presented with a list of brands

Previous phone question:

"Before talking about your (*current make/model),* we'd like to talk about the previous phone that you owned – ie. the main mobile phone that you used before you got your *(current make/model)."*

"What was the brand of the previous mobile phone handset that you owned? If you didn't previously own a mobile phone, please select 'This is my first mobile phone'"

Then a respondent is presented with the same list of brands previously showed in the current phone question, plus "not sure" and "this is my first mobile phone" -options.

Satisfaction question:

What is your overall satisfaction with your *(current make/model),* taking everything into account, including how it looks, feels and works?

1 = Not all satisfied, 2 = Somewhat satisfied, 3 = Satisfied, 4 =Very satisfied, 5 = Completely satisfied, 98 = Don't know/ not sure.

Loyalty question:

If someone you know was looking to buy a mobile phone, how likely would you be to recommend your current brand?

0 = Definitely would not recommend, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 = Definitely would recommend

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A3: MOBILE PHONE MANUFACTURERS PER COUNTRY

Appendix 3 lists mobile phone manufacturers per country in the dataset. Abbreviations are as follows: RIM = Research in Motion, SE = Sony Ericsson.

Country	Brand
Argentina	Alcatel, LG, Motorola, Nokia, RIM, Samsung, SE
Brazil	Apple, LG, Motorola, Nokia, RIM, Samsung, SE, Siemens, ZTE
China	Apple, Bird, Huawei, Lenovo, LG, Motorola, Nokia, Philips, Samsung, SE, Sharp, ZTE
Egypt	Alcatel, HTC, LG, Motorola, Nokia, RIM, Samsung, SE
France	Alcatel, Apple, HTC, LG, Motorola, Nokia, RIM, Sagem, Samsung, SE
Germany	Apple, HTC, LG, Motorola, Nokia, RIM, Samsung, SE
India	Haier, Huawei, LG, Motorola, Nokia, RIM, Samsung, SE, ZTE
Indonesia	Huawei, LG, Motorola, Nokia, RIM, Samsung, SE
Italy	Alcatel, Apple, HTC, LG, Motorola, Nokia, RIM, Sagem, Samsung, SE
Mexico	Alcatel, Apple, LG, Motorola, Nokia, RIM, Samsung, SE
Nigeria	Alcatel, LG, Motorola, Nokia, RIM, Sagem, Samsung, SE
Poland	Apple, HTC, LG, Motorola, Nokia, Samsung, SE
Russia	Apple, HTC, LG, Motorola, Nokia, Philips, Samsung, SE
Saudi Arabia	Apple, LG, Motorola, Nokia, RIM, Samsung, SE
South Africa	Apple, HTC, LG, Nokia, RIM, Samsung, SE, ZTE
Spain	Alcatel, Apple, HTC, LG, Motorola, Nokia, RIM, Samsung, SE
Thailand	Apple, HTC, I-Mobile, LG, Motorola, Nokia, RIM, Samsung, SE
Turkey	Apple, HTC, LG, Motorola, Nokia, Philips, RIM, Samsung, SE
United Kingdom	Apple, HTC, LG, Motorola, Nokia, RIM, Samsung, SE

A4: GFK DATABASE - ESTIMATES OF RETAIL SALES COVERAGE PER COUNTRY

Appendix 4 shows GfK's estimates for retail sales coverage per country. Coverage estimates column shows an average of monthly coverage estimates for a period of 2007-1Q2011. "Nielsen" marked countries are collected by Nielsen, and coverage estimates from these countries are not available.

Country	Coverage estimate (%)
Argentina	80
Brazil	84
China	90
Egypt	72
France	39
Germany	85
India	68
Indonesia	73
Italy	94
Mexico	Nielsen
Nigeria	72
Poland	78
Russia	91
Saudi Arabia	70
South Africa	82
Spain	78
Thailand	Nielsen
Turkey	93
United Kingdom	84

A5: PANEL UNIT ROOT TESTS

Appendix 5 presents results from a set of unit root tests. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively. Probabilities for Fisher testes are computed using an asymptotic Chi-square distribution, whereas other tests assume asymptotic normality. The optimal lag length is selected automatically on based on Schwarz information criterion of 0 to 2.

Variable	Levin-Lin-Chu	Im-Pesaran-Shin W-stat	ADF - Fisher Chi-square	PP - Fisher Chi-square
Value share	-36.45**	-6.33**	509.6**	498.33**
Avg.CS	-13.74**	-8.93**	581.33**	724.61**
Top2box.CS	-14.4**	-9.87**	639.75**	792.93**
RR	-16.68**	-11.4**	707.19**	792.18**
NPS index	-17.14**	-10.4**	677.44**	764.39**

A6: COINTEGRATION TESTS

Appendix 6 shows results from cointegration tests developed by Westerlund (2007). ‘Gt’ and ‘Ga’ denote group mean tests, which test an alternative hypothesis that at least one unit is cointegrated. ‘Pt’ and ‘Pa’ denote panel tests statistics, which pool information over all the cross-sectional units and test an alternative hypothesis that the panel is cointegrated as a whole. The right hand side of the table shows results from the tests, where the number of lags is specified to be five. The left hand column shows the test results, where the number of lags is based on Akaike information criterion. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively. Abbreviations are as follows: RR = retention rate, CS = satisfaction, NPS = Net Promoter Score.

		Lag = 5		Lag = avg. AIC lag length		
Variable	Statistic	Value	Z-value	Value	Z-value	Lag
RR	Gt	-	-	-3.16**	-19.48	1.83
	Ga	-1.061	14.378	-5.45	4.09	
	Pt	-4.432	14.095	-12.59	6.04	
	Pa	-7.799**	-9.521	-3.39	2.68	
Avg.CS	Gt	-	-	-7.82**	-86.01	1.86
	Ga	-0.073	16.690	-5.55	3.86	
	Pt	-8.014	10.559	-10.57	8.03	
	Pa	-2.641	4.741	-2.95	3.88	
Top2box.CS	Gt	-	-	-3.39**	-22.74	1.88
	Ga	-0.178	16.445	-5.47	4.06	
	Pt	-1.946	16.549	-18.08	0.63	
	Pa	-0.915	9.515	-4.97*	-1.71	
NPS	Gt	-	-	-4.25*	-35.1	1.84
	Ga	-0.607	15.441	-7.09	0.25	
	Pt	-24.603**	-5.816	-14.42	4.24	
	Pa	-11.475**	-19.688	-3.57	2.19	

A7: DISTRIBUTED LAG MODEL REGRESSION OF TOP2BOX SATISFACTION

Appendix 7 reports results from the distributed lag model regression, where the main independent variable is top2box satisfaction. The left hand column shows the model specification, where L* stands for a lagged variable of the NPS. 'Assets' is a balance sheet item of total quarterly assets for each manufacturer. The model specification also includes period dummies and intercepts, as shown in Section 5.4., in Equation 12. The dummies and intercepts have been omitted from the table. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Model specification	Coefficient	Robust std. error	R-squared, within	R-squared, between	R-squared, overall	Number of obs.	Number of groups
T2B_CS	0.01192*	0.00566	0.1411	0.1473	0.1409	2032	161
Assets	0**	0.00000					
T2B_CS	0.00690	0.00382	0.1435	0.1508	0.1453	1871	161
L1.T2B_CS	0.00995	0.00536					
Assets	0**	0.00000					
T2B_CS	0.00717	0.00463	0.1407	0.1563	0.1513	1710	161
L1.T2B_CS	0.00543	0.00351					
L2.T2B_CS	0.00979	0.00531					
Assets	0**	0.00000					
T2B_CS	0.00603	0.00443	0.1357	0.1638	0.1590	1549	161
L1.T2B_CS	0.00735	0.00411					
L2.T2B_CS	0.00445	0.00239					
L3.T2B_CS	0.0126*	0.00566					
Assets	0**	0.00000					
T2B_CS	0.00348	0.00375	0.1381	0.1721	0.1688	1388	161
L1.T2B_CS	0.00873*	0.00408					
L2.T2B_CS	0.00591	0.00323					
L3.T2B_CS	0.00774*	0.00353					
L4.T2B_CS	0.01388*	0.00593					
Assets	0**	0.00000					
T2B_CS	0.00333	0.00343	0.1623	0.1745	0.1762	1227	161
L1.T2B_CS	0.00674	0.00373					
L2.T2B_CS	0.00637*	0.00322					
L3.T2B_CS	0.00845	0.00440					
L4.T2B_CS	0.00926**	0.00332					
L5.T2B_CS	0.0135*	0.00597					
Assets	0**	0.00000					
T2B_CS	0.00116	0.00381	0.1550	0.1767	0.1829	1066	161
L1.T2B_CS	0.00825*	0.00384					
L2.T2B_CS	0.00416	0.00320					
L3.T2B_CS	0.00785	0.00458					
L4.T2B_CS	0.01136**	0.00440					
L5.T2B_CS	0.01045**	0.00353					
L6.T2B_CS	0.01129	0.00592					
Assets	0**	0.00000					

A8: DISTRIBUTED LAG MODEL REGRESSION OF AVERAGE NPS

Appendix 8 reports results from the distributed lag model regression, where the main independent variable is an average, which is based on raw answers of Net Promoter Score -question. The left hand column shows the model specification, where L* stands for a lagged variable of the Avg_NPS. 'Assets' is a balance sheet item of total quarterly assets for each manufacturer. The model specification also includes period dummies and intercepts, as shown in Section 5.4., in Equation 12. The dummies and intercepts have been omitted from the table. Coefficients with significance levels of 5% and 1% are marked with * and **, respectively.

Model specification	Coefficient	Robust std. error	R-squared, within	R-squared, between	R-squared, overall	Number of obs.	Number of groups
Avg_NPS	0.0046*	0.00191	3.0000	9.8000	10.0000	1584	161
Assets	0**	0.00000					
Avg_NPS	0.00327	0.00183	2.0000	8.8000	9.0000	1422	161
L1.Avg_NPS	0.00366*	0.00174					
Assets	0**	0.00000					
Avg_NPS	0.00375	0.00198	1.0000	7.8000	8.0000	1260	161
L1.Avg_NPS	0.00258	0.00183					
L2.Avg_NPS	0.00249	0.00160					
Assets	0**	0.00000					
Avg_NPS	0.00402*	0.00195	3.0000	6.9000	7.0000	1098	160
L1.Avg_NPS	0.00371	0.00195					
L2.Avg_NPS	0.00094	0.00165					
L3.Avg_NPS	0.00521**	0.00182					
Assets	0**	0.00000					
Avg_NPS	0.00290	0.00174	1.0000	5.9000	6.0000	937	160
L1.Avg_NPS	0.00479*	0.00189					
L2.Avg_NPS	0.00087	0.00195					
L3.Avg_NPS	0.00380	0.00209					
L4.Avg_NPS	0.00369	0.00208					
Assets	0**	0.00000					
Avg_NPS	0.00205	0.00146	1.0000	4.9000	5.0000	777	159
L1.Avg_NPS	0.00346*	0.00163					
L2.Avg_NPS	0.00174	0.00199					
L3.Avg_NPS	0.00411	0.00234					
L4.Avg_NPS	0.00214	0.00230					
L5.Avg_NPS	0.00465*	0.00210					
Assets	0**	0.00000					
Avg_NPS	0.00256	0.00149	1.0000	3.9000	4.0000	618	158
L1.Avg_NPS	0.00348	0.00187					
L2.Avg_NPS	0.00113	0.00213					
L3.Avg_NPS	0.00627**	0.00235					
L4.Avg_NPS	0.00175	0.00252					
L5.Avg_NPS	0.00352	0.00256					
L6.Avg_NPS	0.00388	0.00247					
Assets	0**	0.00000					

A9: HAUSMAN MODEL SPECIFICATION TESTS

Appendix 9 shows results from the Hausman model specification tests. Each model specification (introduced in Section 5.4., in Equation 12) is tested by running both fixed and random effects regression. Then, the results from these tests are compared under a null hypothesis of "difference in coefficients not systematic".

Model specification	Chi-squared	Prob. > Chi-squared
Avg_CS	4.69	0.999
L1.Avg_CS	0.08	1.000
L2.Avg_CS	5.63	0.992
L3.Avg_CS	4.98	0.996
L4.Avg_CS	3.26	1.000
L5.Avg_CS	5.79	0.990
L6.Avg_CS	5.03	0.996
T2B_CS	5.73	0.995
L1.T2B_CS	5.27	0.994
L2.T2B_CS	4.37	0.998
L3.T2B_CS	2.59	0.999
L4.T2B_CS	2.65	0.999
L5.T2B_CS	3.97	0.999
L6.T2B_CS	3.97	0.999
RR	N/A	N/A
L1.RR	N/A	N/A
L2.RR	551.15	0
L3.RR	296.47	0
L4.RR	164.05	0
L5.RR	168.24	0
L6.RR	119.54	0
NPS	6.78	0.986
L1.NPS	7.14	0.971
L2.NPS	6.65	0.979
L3.NPS	3.71	0.999
L4.NPS	4.1	0.999
L5.NPS	5.32	0.994
L6.NPS	4.24	0.998