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A New Valuation Approach

INTEGRATING BIG DATA ANALYTICS TO FORECAST CUSTOMER BEHAVIOR AND DRIVING SHAREHOLDER VALUE

PIETER LIEVENSE

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Erasmus University Rotterdam
Erasmus School of Economics
Burgemeester Oudlaan 50, 3062 PA Rotterdam, the Netherlands

✉ pieterlievense@me.com ✆ +31 643 546 466

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"A New Valuation Approach – Integrating Big Data Analytics to Forecast Customer Behavior and Driving Shareholder Value"

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Abstract

The most important intangible asset of a firm are its customers. Why? Because ultimately, paying customers provide the expected future cash flows which determine the value of a firm. As such, it follows to take the individual relationship as a starting point for firm valuation. The process of valuation is well established in finance. The most common used methodology among practitioners and academics is the discounted cash flow approach. Against all odds, the discounted cash flow methodology does not take the individual customer as central object of analysis, and instead applies an aggregated 'product-centric' analysis in forecasting cash flows. Traditionally, the role of the marketing department is to advocate the customer within the firm. As a consequence, the department is well informed on detailed information on every individual relationship it has with its customers. Driven by the rise of big data, marketers can now analyze and accurately forecast the development of the individual future relationship with the customer. This forms the foundation for valuation of every individual customer relationship with the firm. The objective of this study is to develop a new valuation method by integrating big data analytics to forecast customer behavior and drive shareholder value, bridging the gap between marketing and finance. It demonstrates this new approach in valuation, based on a combination of existing methods and techniques in finance and quantitative marketing. For this purpose, it combines publicly available data and big data on customer behavior. This study is successful in finding a substantial and positive correlation between customer equity and shareholder value. In addition, the analysis, forecast and valuation of individual customer behavior, leads to an accurate firm valuation in terms of obtained shareholder value compared to a well calibrated discounted cash flow valuation. It also delivers new insights on value creation. An example is that the largest customer behavior value driver, in terms of total SHV contribution is 'retention,' ranging between EUR 6.7–10.4b. Another insight example comes from improving the customer probabilities for the customer behavior value driver 'defection.' An improvement in this value driver of 1% yields an incremental SHV of EUR 360–596m. Overall, the results show that the integration of big data analytics into a valuation context, valuing individual customer relationships linked to shareholder value is successful, accurate and insightful.

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List of abbreviations

BS	Balance sheet
BSP	Brand segment product
CAPEX	Capital expenditures
CBB	Customer behavior based
CBV	Customer-based valuation
CE	Customer equity
CF	Cash flow
CFO	Cash flow from operations
CLV	Customer lifetime value
CV	Continuing value
DCF	Discounted cash flow
DV	Dependent variable
EBITDA	Earnings before interest, taxes, depreciation, and amortization
EMH	Efficient market hypotheses
EV	Enterprise value
FCF	Free cash flow
IV	Independent variable
KPI	Key performance indicator
MARKET CAP	Market capitalization
NOA	Non-operating assets
NOPLAT	Net operating profit less adjusted taxes
NPV	Net present value
NWC	Net working capital
P&L	Profit & loss
PP	Planning period
PV	Present value
ROIC	Return on invested capital
RONIC	Return on new invested capital
SHV	Shareholder value
SOW	Share of wallet
YOY	Year on year

1. Introduction

"Customers are the pulse; they provide cash flows – the vital sign of life in a firm" [1]

Pieter Lievense (2013–2014)

Originally this is a quote from Jack Welch, retired CEO of General Electric Inc. (1981–2001). However, it is rewritten to what I believe really is the pulse of a firm: its customers! Ultimately, its them paying bills and thus providing CFs to the firm. This makes customers the most important intangible asset of a firm, and therefore should be carefully managed and valued (Gupta & Lehmann 2003). Valuing assets is traditionally a specialty within the finance domain which is underlined by one of its principles: "if it doesn't create cash flow, it doesn't create shareholder value" (Koller et al. 2010). In addition to finance, the marketing domain is emerging as the specialist in valuing individual customers, as described in the relatively recent emerged CBV literature; introducing concepts like 'CLV.' Therefore, this study aims to develop a new approach in valuation, combining methods from both quantitative marketing and finance, integrating big data. The main model, an algorithm driven valuation model, analyzes, forecasts and values customer behavior, directly linking customers to SHV.

Problem background | The main challenge for senior executives is to create sustainable *SHV* (Koller et al. 2010). This is accomplished by developing successful *strategies* that drive future CFs (Koller et al. 2010). In order to determine the impact of future strategies on CFs, senior executives have to continuously translate and understand how their strategic choices affect SHV (Koller et al. 2010; Srinivasan & Hanssens 2009). This process is called '*the firm value adjustment process'* (Koller et al. 2010; Srinivasan & Hanssens 2009). First, based on their strategic options the value per share is determined for each scenario, commonly using a DCF valuation model (Koller et al. 2010). Next, based on the estimated outcome(s) senior executives start *managing the expectations* of the investor community (Koller et al. 2010). However, based on their personal view and interpretation of strategic choices investors develop their own expectation on future CFs (Srinivasan & Hanssens 2009). Different earning expectations lead to trading activity, resulting into the firm's share price, hence SHV (Koller et al. 2010; Srinivasan & Hanssens 2009). A down trending share price is perceived as a failure of senior executive strategic decision making (Koller et al. 2010). An upwards trending share price is perceived as the opposite (Koller et al. 2010). However, this comes with the risk of getting trapped in the so called '*expectations treadmill*' (Koller et al. 2010). Managing down market expectations, or 'damage control' is a very hard task (Koller et al. 2010). This 'thin line' between 'success' and 'failure' creates the need for *data driven decision making* (Manyika et al. 2011). According to Manyika et al. (2011) sophisticated *big data analytics* can substantially improve the senior executive decision making process. This potentially improves senior executives' strategy development, future value assessment and expectations management, ultimately increasing SHV creation (Manyika et al. 2011). A very promising development in big data analytics is that every day big data becomes bigger and analysis gets more sophisticated (Arthur 2013). More information on customer preference and other types of *customer behavior* becomes available together with the increase of computing and applications power. This makes big data analytics increasingly important (Arthur 2013), which is also recognized by the World Economic Forum (Davos, Switzerland 2012). The forum declared big data as a new asset class (Lohr 2012), underlined by that year's payoff: "big data, big impact." That the impact and applications of big data analytics are no longer ignored is confirmed by the study of the McKinsey Global Institute – MGI and McKinsey's Business Technology Office (Manyika et al. 2011). Manyika et al. (2011)

[1] The original quote reads: "cash flow is the pulse – the vital sign of life in a firm."

conclude that: "the analysis of big data analytics, is a key basis of competition, underpinning new waves of productivity growth, innovation and consumer surplus," based on several key insights derived from studying big data analytics developments. First of all, big data analytics is already an important factor of production, alongside labor and capital (Manyika et al. 2011). It is used to improve the development of next generation of products and services (Manyika et al. 2011). As a result, it is becoming a key basis for competition and growth (Manyika et al. 2011). But most importantly, it can create significant value; sophisticated big data analytics substantially improves decision-making, making information transparent and usable at much higher frequency (Manyika et al. 2011). The key drivers of big data analytics are the rise of social media and the use of mobile devices, resulting in a tremendous growth of big data that is being generated (Arthur 2013; Manyika et al. 2011). As a result of this development, marketing departments are currently transforming into being more technical and analytical (Verhoef & Leeflang 2009). Therefore, the marketing department is better than ever able of contributing to the value creation assessment, as part of the continuous value adjustment process resulting from senior executive strategic decision making (Koller et al. 2010; Verhoef & Leeflang 2009). As a result, this is the moment for marketing that it should move beyond tactical decisions into strategic approaches (Verhoef & Leeflang 2009). In addition, it is time to reclaim a seat at the boardroom table, and thereby reverse the current trend in which senior executives most often are disappointed in their chief marketing officer (Nath & Mahajan 2008). All in all, big data analytics is the connective tissue that can bridge the gap between marketing, finance, the boardroom and the investor community driving SHV (Arthur 2013). However, before the full potential of big data analytics can be utilized, still more work remains to be done on its integration within the firm (Arthur 2013).

Problem statement | This study focusses on the integration and calibration of valuation concepts on the marketing-finance interface, as part of the continuous firm value adjustment process. The traditional DCF valuation model in finance particularly uses aggregated data as input for the forecast of future cash flows. In addition, the forecast itself is largely depending on the analyst's view on the development of the business. In contrast, CBV models in marketing forecast future cash flows on the individual customer level, where the forecast itself is algorithm driven. In essence, both approaches are two sides of the same coin and therefore should result similar valuations. However, there is a gap in knowledge on how traditional DCF valuation and CBV models perform compared to each other in terms of a SHV forecast, given their fundamentally different forecast approach.

Study purpose | The purpose of this study is to analyze, forecast and value customer behavior by integrating big data analytics, ultimately driving SHV. In addition, it aims in further supporting the alignment of top and bottom of the firm and bridging the gap between marketing and finance. Therefore, this study has a quantitative design. The DV is individual customer EBITDA and the IVs comprises of nine customer behavior value drivers, relationship age, SOW and various other customer characteristics. The population consists of about 4.5 million CM customer, 650.000 BM customers and 6.5 million potential customers.

Study significance | The significance of this study stems from the need for data driven decision making throughout the entire firm. As more data from new big data sources comes available, the continuous increase of computing power and new and increasingly powerful applications supporting these analyses are being developed. The importance is to understand whether a new approach in valuation, which is the key input for investment decision making, is able to deliver comparable valuation results to the traditional model. First of all, this will make the new valuation approach as reliable. But most important, a new data driven valuation approach will increasingly deliver new manageable insights improving decision making for senior executives, but also marketing, finance and many other departments, ultimately supporting the common goal of SHV creation.

Academic relevance | As far as my knowledge of the concerning academic literature reaches there has never been a comparison of a DCF valuation model and a CBV model. Therefore, the academic relevance of this study stems from its focus on 'finalytics,' the point where analytics and finance meet. This study demonstrates a new valuation approach based on when the best of both academic worlds in quantitative marketing and corporate finance meet. It combines and integrates value relevant concepts, methods and models from both fields. Or in other words, the advance in science from this study comes from the merger of a DCF valuation model and a CBV model, complementing each other. However, the real advance in science stems from the fact that researchers have not shown a direct link between the forecast of individual customer behavior and its impact on SHV.

Central question | The central question of this study in developing and calibrating a new approach in valuation that integrates big data analytics, bridging the gap between marketing and finance, is:

DOES INDIVIDUAL CUSTOMER BEHAVIOR DRIVE SHAREHOLDER VALUE?

Sub-questions | Before answering this central question more investigation is required, resulting in various sub-questions. It is important to understand the concept of value, how value is build up and how the traditional DCF valuation model in finance determines SHV, thus resulting in the sub-questions:

What is shareholder value?
How is it driven?
How is it derived?

Given that the marketing department is the customer's ambassador within the firm, and its ultimate goal is to maximize individual customer profitability, the sub-question is:

Does marketing drive shareholder value?

Given the recently emerged literature stream of CBV in marketing, it is important to understand the concept of customer-based valuation, what drives customer value and how it can be determined. Therefore, the associated sub-questions are:

What is customer based value?
How is it driven?
How is it derived?

Given that customer behavior drives customer profitability and customer profitability drives value, the final sub-questions are:

What is customer behavior?
How does it drive value?

Research design | This study uses two main sources of data. On the one hand it uses publicly available firm financials and on the other hand it heavily relies on large quantities of big data containing customer behavior. The collection of data from the firm's various data sources is conducted through database software Microsoft SQL. Five of the firm's top data specialists and myself have built an integrated customer centric dataset, combining about 12 million customers (CM: 4.5m; BM: 0.6m and potential: 6.5m), 4 brands, 2 market segments and 29 products. These main data sources serve as input for two main models. First, a traditional DCF valuation model is used to forecast future cash flows during a 4-year PP (2015–2018) and derive SHV. The valuation process comprises of four steps: (1) understanding industry dynamics, (2) understanding competitive position and strategy, (3) analyzing historical performance and (4) discounting and valuing cash flows. The focus of the first main model in this study is on the last part of the process. This consist of (4a) identifying key value drivers, (4b) forecasting operating value drivers (P&L, BS and CF), (4c) determining the WACC, (4d) estimating the CV, and finally (4d) estimating the EV and equity value. In addition, sensitivity analysis is applied by computing three different scenarios. The second model is an algorithm driven model, analyzing, forecasting and valuing customer behavior. This so called CBB valuation model is developed based on various concepts in CBV, rooted in recently emerged marketing literature. The forecast of the model is driven by 18 estimated behavior logit models and 2 profit regression models. The number of predictors for the different models varies between approximately 60–115. The 18 behavior logit models forecast customer behavior, which serves as input for the forecast of customer profitability in both profit regression models. The behavior logit and profit regression models are complemented with additional predictors based on customer characteristics like: relationship age, SOW and many more. The model forecasts customer behavior and profitability during a 4-year PP (2015–2018) for 3 different scenarios. This results in the calculation of 216 different equations, producing 2 billion estimated probabilities. Ultimately, for every individual customer an EBITDA forecast is obtained which is finally translated into SHV, hence equity value. In addition, the second model delivers new and highly valuable insights for senior executives and managers in their challenge to increase the creation of SHV.

Assumptions | Several assumptions underlie the DCF valuation model. First of all, it assumes that the firm is all equity financed, so that the financing effects are incorporated in the valuation through the WACC. Then, in determining the CV it assumes that the firm maintains a competitive advantage in the near future, thus generating a RONIC higher than the WACC. Finally, in determining the WACC the r_f is set to 1.5%; it assumes that current yield on a ten year German government bond is too low and thus will overestimate the CV of the firm, as it is expected that yields will rise in the future. Also several assumptions underlie the intermediate CBB status quo valuation model. It assumes that the EBITDA realized at time t (2014) simply remains constant during the planning period (2015–2018). Then, there are also assumptions underlying the algorithm driven CBB valuation model. First, there are several assumptions with regards to the new developed integrated customer centric dataset. The dataset contains on average for 88% of unique customers, as it has a location based structure. Therefore, it assumes that each location equals a unique customer. In determining the DV it assumes that the historical EBITDA-margins remain stable overtime. It also assumes that for each year of the PP the outlier EBITDA grows by the forward looking inflation rate fixed at 1.5%. In addition, it assumes that the customers driving the outlier EBITDA remain with the firm during the PP, so that incorporating the retention rate (r) is not needed. Then, concerning the CBB valuation model itself it assumes that for the forecast all customer characteristic predictors (relationship age, SOW, etc.), observed in 2014, remain stable over time. The final assumption underlies the forecast of the CE model, it assumes a forward looking retention rate ($r_{t+1\,to\,+4}$), discount rate ($d_{t+1\,to\,+4}$) and growth rate ($g_{t+1\,to\,+4}$).

Scope | The geographical scope of this study concerns the market in which the firm is active in. Only the firm's four major brands are included, excluding four relatively small brands. As a result, the generalizability of the study is very limited.

Summary | This study aims to develop a new approach in valuation, by integrating big data analytics in order to analyze, forecast and value customer behavior driving SHV. Therefore, it covers four areas. The data that is used as input for both main models DCF valuation and CBB valuation is discussed, in addition elaborates on the challenges concerning the development of the integrated customer-centric dataset. It continuous by presenting the used methodologies in finance and marketing. It also describes how the different models are integrated and merged with each other. The results present highly valuable new insights arising from this new approach in valuation, driving improved strategic decision making and the execution of tactics. It ends by concluding and comparing both models, its pros and cons and the limitations of the study. It also describes directions for future studies. However, it will start next with discussing origins of SHV and how its driven on the various levels of the firm. This is followed by a brief review of the most frequently used approach by practitioners and academics in valuation: the DCF valuation model, rooted in finance literature. Then, it moves on to the marketing section of this study where the contribution of this domain to SHV is discussed. This includes a review and application of the fundamentals of CLV and CE, forming the building blocks of CBV. In addition, the value drivers in customer behavior are presented and discussed, complemented by a review of brand choice behavior and customer characteristics. Finally, the conceptual model is presented, resulting from the theoretical framework.

2. Theoretical framework and hypotheses

"Integrating big data analytics to forecast customer behavior and driving shareholder value"

The theory chapter will broadly cover two literature streams. First, from a finance perspective it describes the concept of SHV, its drivers and how it can be derived. Then, from a marketing perspective it describes the concept of CLV and CE, their drivers and how both can be derived. It is remarkable how similar both theoretical concepts are, however in practice they tend to be far apart. Therefore, the objective of this chapter is to bridge the gap between both domains. More specific, while describing both subjects it builds the practical link between the concept of CE and SHV by integrating big data analytics. In doing so, it starts with finance theory describing SHV and its fundamental value drivers, followed by a brief introduction to DCF valuation theory. A more detailed description on the DCF valuation method will be covered in the methodology chapter. Then, it switches to marketing theory describing the empirical findings of marketing's contribution to SHV. First, it reviews CBV theory, covering the concepts of CLV and CE. Then, the fundamental value drivers in customer purchase-behavior are discussed. CBV heavily relies on large quantities of data containing these behaviors. The concept of big data and its relation to valuation and the boardroom's relation to value are described previously. Finally, it concludes by presenting the conceptual model derived from theory. It visualizes the parallelism between the conceptual models of DCF and CBB valuation; two sides of the same coin in determining and driving SHV.

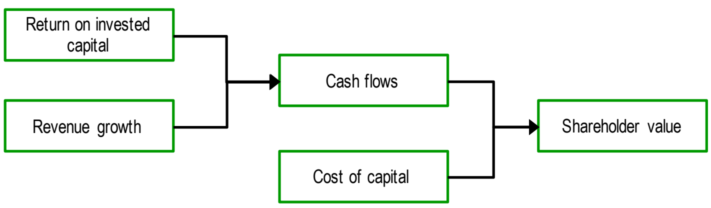
2.1 Shareholder value and value drivers

"Shareholders value value"

Koller et al. (2010)

Shareholder value | SHV as a metric is what defines the bottom-line performance of a firm (Koller et al. 2010). Investors analyze and assess the amount and the ability of a firm in creating SHV (Koller et al. 2010). As a consequence, this challenges senior executives to find the balance between short-term performance in order to satisfy investors, and long-term value creation in order to ensure continuity of the firm (Koller et al. 2010).

Figure 1 Shareholder value drivers (Koller et al. 2010)



Source: McKinsey & Company, Koller et al. (2010)

Cash flows | CFs drive SHV (Figure 1) (Koller et al. 2010). Therefore, the primary task for senior executives is to create SHV by generating future CFs (Koller et al. 2010). These CFs indirectly arise from capital that has been invested, such that the return on them must exceed the cost of the invested capital, in order to create value (Berk &

DeMarzo 2007). Modigliani & Miller (1958) showed that senior executives should focus on increasing CFs. They argue that changes in capital structure that do not change the overall CFs generated by the firm, do not affect SHV. This is in accordance with a quote of Koller et al. (2010): "if you can't pinpoint the tangible source of value creation, you're probably looking at an illusion." However, if tax deductibility of debt related interest payments changes the firms CFs, then this does create value (Koller et al. 2010). Creating value, by generating future CFs is surrounded by uncertainty, which needs to be taken into account (Koller et al. 2010).

Cost of capital | The COC reflects the price of future CF risk (Koller et al. 2010), resulting from the time value of money on future CFs (Berk & DeMarzo 2007). The COC, also known as the discount rate, represents at the firm side the cost of invested capital, as to investors it represents the expected return on invested capital (Berk & DeMarzo 2007). The returns to both equity and debt suppliers are weighted, this results in the WACC (Berk & DeMarzo 2007).

Return on invested capital | Improving ROIC relative to the COC drives SHV (Koller et al. 2010). A good *strategy* is the foundation for improvements in ROIC (Marshall 1890; Porter 1980). Senior executives who have developed a successful strategy deliver the firm a *competitive advantage* (Koller et al. 2010). The process of continuously seeking and exploiting new sources of competitive advantage is vital for long-term SHV creation (Koller et al. 2010). This enables the firm to charge a *price premium* or to produce with a *cost and capital efficiency*[2] or a combination of both, and hence drive ROIC (Koller et al. 2010). Koller et al. (2010) argue drivers of competitive advantage; five driving price premium and four driving cost and capital efficiency, as reported in Table 1.

Table 1 Competitive advantage drivers (Koller et al. 2010)

Price premium	Cost and capital efficiency
1. **Innovative products**: Difficult-to-copy or patented products, services or technologies	1. **Innovative business method**: Difficult-to-copy business method that contrasts with established industry practice
2. **Quality**: Customers willing to pay a premium for a real or perceived difference in quality over and above competing products or services	2. **Unique resources**: Advantage resulting from inherent geological characteristics or unique access to raw material(s)
3. **Brand**: Customers willing to pay a premium based on brand, even if there is no clear quality difference	3. **Economies of scale**: Efficient scale or size for the relevant market
4. **Customer lock-in**: Customers unwilling or unable to replace product or service they use with a competing product or service	4. **Scalable product/process**: Ability to add customers and capacity at negligible marginal cost
5. **Rational price discipline**: Lower bound on prices established by large industry leaders through price signaling or capacity management	

Source: McKinsey & Company, Koller et al. (2010)

Growth | Improving growth drives SHV (Koller et al. 2010). A good *strategy* also drives improvements in growth (Koller et al. 2010). However, there is an interaction between growth and ROIC. In fact, growth at rates of ROIC below the COC will destroy SHV (Koller et al. 2010). In order to maximize SHV, senior executives need to understand what drives growth and what makes it value-creating (Koller et al. 2010). Viguerie et al. (2008) disaggregate overall growth into three main components: portfolio momentum, market share performance and mergers and acquisitions (M&A). In their study, they find that portfolio momentum and M&A explain most of the difference in growth. Koller et al. (2010) argue eight drivers of growth, resulting from the firm's strategy as reported in Table 2.

Table 2 Growth drivers (Koller et al. 2010)

1. **New products** can create new markets	5. **Bolt-on acquisitions** to accelerate product growth
2. **Sell more** convincing existing customers to buy more of a product	6. **Innovation** (incremental) to gain share from rivals
3. **New customers** attracting to the market	7. **Product promotion and pricing** gaining share from rivals
4. **Market share** gain in fast-growing market	8. **Large acquisitions**

Source: McKinsey & Company, Koller et al. (2010)

[2] "Cost efficiency is the firm's ability to sell products and services at a lower cost than the competition, capital efficiency is the firm selling more products per dollar of invested capital than competitors" (Koller et al. 2010).

New products typically create more SHV, while acquisitions typically create the least (Koller et al. 2010). As Koller et al. (2010) say: "the crucial point in creating SHV is that revenue growth is not all that matters, it is the value created per euro of additional revenues that drives the true creation of SHV." SHV, CFs, COC, ROIC and growth are tightly linked (Koller et al. 2010). This relation is mathematically expressed in the key value driver formula (Eq. 1) (Koller et al. 2010):

$$SHV_t = \frac{NOPLAT_{t_{+1}}\left(1 - \frac{E(g_{t_{+1}})}{ROIC_t}\right)}{WACC_t - E(g_{t_{+1}})} \qquad \text{Eq. 1}$$

Where $NOPLAT_{t+1}$ is the next period's net operating profit less adjusted taxes, representing the profits generated from the firm's core operation after subtracting the income taxes related to these operations (a proxy for CF) and $E(g_{t_{+1}})$ is the expected growth rate in perpetuity. As Jiang & Koller (2007) say: "the right balance between growth and ROIC is critically important to SHV creation."

2.1.1 Discounted cash flow valuation

"If it doesn't increase cash flow, it doesn't create value[3]"

Koller et al. (2010)

As has become clear the creation of SHV is the primary task of a firm (Koller et al. 2010). Senior executives should focus on increasing CFs by investing capital at a ROIC larger than the COC (Koller et al. 2010; Modigliani & Miller 1958). In order to determine the amount of SHV generated by the firm, forecasted future CFs need to be discounted with a discount rate (Berk & DeMarzo 2007; Koller et al. 2010).

Discounted cash flow valuation | DCF valuation is based on the key value driver formula (Eq. 1), representing the concept governing the theory of valuation (Koller et al. 2010). However, in practice this formula is not used for firm valuation (Koller et al. 2010). It is too restrictive; it assumes a constant ROIC and growth rate going forward (Koller et al. 2010). For firms whose key value drivers are expected to change, the DCF valuation model offers more flexibility in forecasting (Koller et al. 2010). DCF valuation is used for valuing firms, projects or assets using the concept of the time value of money (Berk & DeMarzo 2007). In his book 'theory of interest', Fisher (1930) expressed as first DCF valuation in modern economic terms. Since then, several valuation methods have emerged, nevertheless DCF valuation still remains favorite of practitioners and academics (Koller et al. 2010). It relies solely on CFs in and out of the firm rather than on accounting based earnings, which explains its popularity according to Koller et al. (2010).

Discounted cash flow valuation process | The DCF valuation process for valuing a firm's common equity is described by Koller et al. (2010) in a three-part process. First, the *value of the firm's operations* (Eq. 2) needs to be derived, consisting of the PV of the estimated future FCFs during the PP (Koller et al. 2010):

$$Value\ of\ operations = \sum PV\left(FCF_{during\ PP}\right) \qquad \text{Eq. 2}$$

[3] Assuming there are no changes in the firm's risk profile, reflected in the cost of capital.

The forecast on CFs is driven by the forecast on key and operating value drivers (Koller et al. 2010). These CFs are discounted at the WACC in order to obtain their PV (Berk & DeMarzo 2007). The sum of all these future CFs, both incoming and outgoing, is the NPV (Berk & DeMarzo 2007). Second, the value of the discounted CFs after the planning period is a perpetuity based CV, denoted as the key value driver formula (Eq. 1). The estimation of the CV is essential to any valuation because it accounts for at least 56% (up to 125%) of the firm's total value (Koller et al. 2010). In other words, a firm's CV is highly dependent on the forecast of ROIC and growth, which has important implications for valuing a firm (Koller et al. 2010). The EV results from the sum of the value during the planning period and the CV (Koller et al. 2010) (Eq. 3):

$$EV = Value\ of\ operations + CV \qquad \text{Eq. 3}$$

Third and last, in order to derive the value of common equity (or equity value) (Eq. 4), *NOA*[4] need to be identified, valued and added to the EV (Koller et al. 2010). In addition, the value of all *debt and non-equity financial claims*[5] need to be identified, valued and subtracted from the EV (Koller et al. 2010):

$$Equity\ value = EV + NOA\ - Debt \qquad \text{Eq. 4}$$

The obtained equity value equals the market price of common equity (Koller et al. 2010), implied by the EMH (Fama 1991). It states that: "investors fully and accurately incorporate any new information that has value relevance" (Fama 1991). This implies that the firms market cap (Eq. 5), the ultimate metric of SHV, equals the equity value.

$$Equity\ value = Market\ cap = Share\ price * Shares\ outstanding \qquad \text{Eq. 5}$$

Or (Eq. 6):

$$\frac{Equity\ value}{Shares\ outstanding} = \frac{Market\ cap}{Shares\ outstanding} \qquad \text{Eq. 6}$$

Thus, the following is expected:

H1: The value per share estimated by DCF valuation, approximates the price per share.

2.2 Marketing and shareholder value

"Marketing is all about building the intangible assets of the firm"

Srinivasan & Hanssens (2009)

The first part of literature review has revealed that the finance domain is specialized in the valuation process, and that DCF valuation methodology enables the option to account for changes in key value drivers (Koller et al. 2010).

[4] "NOA consist of excess marketable securities, nonconsolidated subsidiaries, and other equity investments" (Koller et al. 2010).
[5] "Non-equity financial claims consist of fixed-rate and floating-rate debt, unfunded pension liabilities, employee options and preferred stock" (Koller et al. 2010).

The change in value drivers is caused by changes of strategy (Koller et al. 2010), hence marketing strategy. In short, the firm's marketing strategy particularly affects the demand-side of the firm, affecting ROIC and growth, and thus profitability, hence CFs and ultimately SHV (Koller et al. 2010; Srinivasan & Hanssens 2009).

Marketing's contribution to shareholder value | The challenge for the marketing domain is to assess and communicate its contribution to SHV (Srinivasan & Hanssens 2009). With respect to the EMH[6] (Fama 1991), it is crucial to successfully translate the marketing resource allocation and the impact on performance, into financial and SHV contributions (Srinivasan & Hanssens 2009). However, Srinivasan & Hanssens (2009) question whether short-term impact on SHV can be made visible. This is relevant to investors as they respond to quarterly changes in sales and earnings accordingly (Srinivasan & Hanssens 2009). The complication of this challenge, arises from the fact that marketing is all about building the intangible asset of the firm, aiming for long-term SHV creation (Srinivasan & Hanssens 2009). A first but modest move in the right direction, is a specific request to investors. The marketing domain asks them to adopt an investment perspective on marketing spending's, similar to R&D spending's (Srinivasan & Hanssens 2009). The general constant pressure on the marketing domain is an additional complication in accomplishing this challenging task (Gupta 2009). The comparatively short tenure of chief marketing officers underlines this pressure (Nath & Mahajan 2008).

Finance literature supports in the marketing-SHV-relevance-challenge | Srivastava et al. (1998) argue that marketing impacts the magnitude, ability and volatility of the generation of future CFs. In addition, Rao & Bharadwaj (2008) argue that marketing affects the shape of the probability distribution of future CFs. This impacts the firm's future cash needs, hence working capital requirements (Rao & Bharadwaj 2008). However, Lev (2004) reports that 'intangible-intensive' firms are systematically undervalued. This indicates that the building of the intangible asset by marketing is not recognized by investors (Lev 2004). Or in other words, investors do not recognize the relevance of marketing on SHV (Lev 2004). This is potentially the start of a vicious circle, as undervaluation may lead to a higher COC, resulting in reduced investments in intangibles (Lev 2004). This has a negative impact on the generation of future CFs, leading to higher risk for investors (Lev 2004). A higher risk means a higher compensation, such that investors demand a higher return (Myers 2003). However, it could be that the EMH (Fama 1991) is not entirely complete and accurate on the prediction of investor response mechanisms (Srinivasan & Hanssens 2009). More work on investigating the marketing-SHV-relevance-challenge is required, due to these contradictive findings in finance.

Four factor model | Therefore, marketing academics have integrated finance theory in their empirical studies. Much of this work builds on finance literature, in particular the four-factor model (Carhart 1997). This is an explanatory financial model for the expected returns on shares and is buildup from several previous models in finance. The most fundamental model underlying the four-factor model is the CAPM (Fama 1965). The CAPM recognizes the random-walk nature of share prices, as the model is expressed as if the return on shares are stationary (Fama 1965). This first factor in the four-factor model captures this phenomenon (Srinivasan & Hanssens 2009). The second fundamental model is an extension of the CAPM; the three-factor model (Fama & French 1992; 1996), adding two more factors to the CAPM model. The final extension of the model comes from Carhart (1997), resulting in the four-factor model as expressed (Eq. 7):

$$R_{it} - R_{rf,t} = \alpha_i + \beta_i\left(R_{mt} - R_{rf,t}\right) + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{it} \qquad \text{Eq. 7}$$

[6] Marketing actions are publicly observable which makes the semi-strong EMH the most appropriate.

Where R_{it} is the stock return for firm i at time t, $R_{rf,t}$ is the risk-free rate of return in period t, R_{mt} is the average market rate of return in period t (Carhart 1997). Then, $R_{mt} - R_{rf,t}$ is the CAPM market risk factor (Fama 1965). This factor captures the excess return on a broad market portfolio (Fama 1965). The size risk factor (SMB_t) captures the difference in return between a large-cap and a small-cap portfolio (Fama & French 1992; 1996). The value risk factor (HML_t) captures the difference in return between high and a low book-to-market portfolio (Fama & French 1992, 1996). The momentum factor UMD_t captures the difference in return between a portfolio that has performed well in the recent past and continues to do so, and a portfolio that has performed poor in the recent past and continues to do so as well (Carhart 1997). Then, α_i is the model intercept, β_i, s_i, h_i, and u_i are parameter estimates of the factors and ε_{it} is the error term (Carhart 1997). Where β_i is a measure of the firms sensitivity to market changes; the stock market as a whole has a β_i of 1 (Carhart 1997). If the firm's share performs 'normally,' then the four-factor model captures the variation in R_{it}, so that α_i is zero (Carhart 1997). Therefore, α_i is the abnormal return associated with firm i, and ε_{it} captures additional abnormal (excess) returns in period t (Carhart 1997).

Risk and return | Finance theory describes the risk-return tradeoff; a higher risk results in a higher return (Berk & DeMarzo 2007). Where the total return equals the sum of expected return and abnormal return (Koller et al. 2010). And total risk, which is a fundamental metric in finance (Hamilton 1994), equals the sum of systematic risk and *idiosyncratic risk* (unsystematic or firm-specific) (Koller et al. 2010). The factors in the four-factor model capture the variability in returns originating from the firm's systematic risk (Carhart 1997). It follows that, marketing studies on the SHV-relevance-challenge, focus on the variability in returns (excess returns) originating from the firm's idiosyncratic risk, that cannot be explained by changes in average market portfolio returns (Srinivasan & Hanssens 2009). Hence, these studies focus on the unanticipated component of stock returns, where abnormal returns are captured in α_i (the hunt for alpha) and excess returns are captured in ε_{it} (Srinivasan & Hanssens 2009).

Empirical findings | A study on the marketing–finance interface, with respect to the SHV-relevance-challenge, using solely the four-factor (Carhart 1997) model is from McAlister et al. (2007). Other studies use different methods that, from a finance perspective, complements the four-factor model. A summary of these studies is presented by Srinivasan & Hanssens (2009) including: 'event studies' (Chaney et al. 1991), 'the calendar portfolio method' (Sorescu et al. 2007), 'stock return models' (Mizik & Jacobson 2004) and 'persistence modelling' (Pauwels et al. 2004). The empirical findings on the marketing–finance interface, with respect to the SHV-relevance-challenge are reported in Table 3 based on the summary from Srinivasan & Hanssens (2009).

Table 3 Marketing assets and actions contribution to shareholder value (Srinivasan & Hanssens 2009)

Marketing assets	Marketing actions
▪ **Customer equity:** improvements in customer equity are significantly related to SHV	▪ **Advertising:** affects intangible SHV and lowers systematic market risk
▪ **Brand equity:** improvements in brand equity have a significant, positive impact on SHV	▪ **New product introduction:** firm innovativeness is predominantly positively related to SHV
▪ **Customer satisfaction:** levels of customer satisfaction are significantly related to SHV	▪ **Price promotions:** are negatively related to SHV in the long run
▪ **R&D and product quality**: improvements in consumer appraisal in terms of perceived quality, particularly for new products, are significantly related to SHV	▪ **Channels of distribution:** on average, the opening of new distribution channels is positively related to SHV

Source: Srinivasan & Hanssens (2009)

Srinivasan & Hanssens (2009) conclude from their literature review that all marketing assets are linked to SHV. However, they note that marketing performance metrics are slow-moving and therefore not immediately visible to investors (Srinivasan & Hanssens 2009). In contrast, they also note that marketing actions are typically immediately observable but their impact on SHV is more ambiguous, as they are not outcome variables (Srinivasan & Hanssens

2009). Srinivasan & Hanssens (2009) finally note that preliminary evidence suggests that changes in firm value drive some marketing actions. Or in other words, they acknowledge that at times there is a reverse causality effect of marketing actions (Srinivasan & Hanssens 2009). The ultimate evidence of marketing's-SHV-relevance-challenge is provided by the impact of marketing related exogenous variables in the four-factor model (Carhart 1997), demonstrating how marketing related managerial actions contributes to SHV (Srinivasan & Hanssens 2009).

2.2.1 Customer-based valuation

"Customers are the central object for valuing a firm"

Gupta et al. (2004)

As has become clear previously, the marketing department is in charge of building the intangible assets. This requires them to assesses and communicate the (incremental) value of those assets. Recently, a new stream of valuation literature has emerged in marketing, making the individual customer the central object of analysis.

Customer-based valuation | According to Schulze et al. (2012) CBV is a concept that values firms based on information about their customer base. In addition, Gupta et al. (2004) argue that CBV is the term that describes all approaches in which customers are the central object for valuing a firm. The premise of CBV in valuing the current and future customer base of a firm is simple (Gupta et al. 2004). If the growth in number of customers can be forecasted accurately, then the CLV framework can estimate the long-term value of a customer (Gupta & Lehmann 2003). CBV provides a good alternative approach for the forecast of future CFs of a firm (Gupta et al. 2004). Especially in the situation where a firm has negative CFs, such that the DCF valuation method can't be applied (Gupta et al. 2004; Koller et al. 2010). Or the situation in which a firm has no earnings such that the traditional P/E (price/earnings) ratio can't be applied either (Gupta et al. 2004; Koller et al. 2010). In addition, CBV can provide useful insights and guidelines to investors, given that the firm's overall value stems to a large extent from its customer base (Hogan et al. 2002; Kim et al. 1995). CBV has even found its way into investment banking, which is the industry that is specialized in valuation (Gupta et al. 2006). In this example the investment banking department of Credit Suisse based a valuation case largely on the estimation of CLV (Gupta et al. 2006). In essence this valuation case was about forecasting the number of new customers and the future parameters of a CLV model (Gupta et al. 2006).

Marketing studies on customer-based valuation | Various marketing studies with regards to CBV have been conducted. Libai, Muller & Peres (2009) and Rust et al. (2004) compare the value of current and future customers against SHV. Kumar & Shah (2009) regress measures of CE on the share price of firms. The best-known example of a CBV study is the one by Gupta et al. (2004). Their CBV approach was based on publicly available information of five firms to estimate the after-tax value of the customer bases (Gupta et al. 2004). Their results show that the sum of CLVs approximates market value of three firms very well (Gupta et al. 2004). For two firms total CLV is significantly below their market values (Gupta et al. 2004). However, the results suggest either that they have unaccounted for growth opportunities or that the market overvalued both firms (Gupta et al. 2004).

Customers as assets | "Customers have become the ultimate scarce resource" (Peppers & Rogers 2005), and are the most important intangible asset of a firm (Gupta & Lehmann 2003). Lev (2001) has shown that in the US the 500 largest corporations have a market value of almost six times their book value; underlining again the importance of intangible assets. As a result, a wide consensus has emerged around the importance of customers as assets (Gupta & Lehmann 2003; Seybold 2001). Nevertheless, investors still mainly use traditional financial approaches where they implicitly capitalize R&D expenditures, but continue to treat marketing and customer acquisition as an expense (Demers & Lev 2001). In CBV customers are treated as assets, so that customer related (marketing) expenditures are treated as investments (Gupta 2009). Therefore, investor's need to know more about the intangible assets of a firm (Gupta & Lehmann 2003). As a consequence, it is becoming increasingly important to value and manage customers properly (Gupta & Lehmann 2003). According to Seybold (2001), this follows logically as a next step in the already widely accepted importance of a customer-centric firm. However, the acceptance of customers recognized as assets is negatively impacted by the requirements of extensive data and complex modeling (Gupta & Lehmann 2003).

Customer life time value concept | The fundamental building block for CBV of firms is the CLV concept, developed and discussed in marketing literature (Gupta 2009). It is defined as the PV (Berk & DeMarzo 2007) of all future CFs obtained during the relationship of a customer with the firm (Getz & Thomas 2001; Rust et al. 2001). CLV has emerged as an important metric to manage and grow customers, and has gained the attention of senior executives (Gupta 2009) and investors (Jain & Singh 2002) due to its link to SHV. Its acceptance in the boardroom stems from its intuitive methodology very similar to DCF valuation, with two key differences (Gupta & Lehmann 2006). First, as the name implies CLV is estimated at the individual customer level (Gupta & Lehmann 2006), where its acceptance and use of it in customer management is driven by the 'individual-aspect' (Gupta & Lehmann 2006). Second, CLV explicitly accounts for the possibility of customer defection (Gupta & Lehmann 2006). However, there have been few attempts to capture a firm's option value (Smit & Trigeorgis 2004), in the development of theoretical CLV models, even though a firm's option value often accounts for a large portion of total value (Gupta and Lehmann 2006; Koller et al. 2010; Smit & Trigeorgis 2004). Gupta and Lehmann (2006) suggest that finance literature may be useful in further developing such CLV models. For now, the proposed CLV models do not capture the entire market value of a firm, but they do provide a strong guideline (Berger et al. 2006). The CLV for a single customer (Eq. 8) (Gupta et al. 2004; Reinartz & Kumar 2003) is denoted as:

$$CLV = \sum_{t=0}^{T} \frac{m_t r_t}{(1+d)^t} - AC \qquad \text{Eq. 8}$$

Where, m_t is the margin on customer purchases at time t, d is the discount rate (the cost of capital) for, r_t is the retention rate at time t, AC are the acquisition costs and T is the time horizon for estimating CLV. At least three of these CLV components are affected by marketing actions: margins, retention rates and acquisition costs (Gupta 2009).

CLV margin | Gupta (2009) notes that there has been limited academic effort put into the forecast of margins (m), such that many studies assume constant customer margins over time. Reinartz & Kumar (2003) and Gupta et al. (2004) base their margins on historical data.

CLV retention rate | The customer retention rate is defined as the probability of the repeat purchase (which can also be defined as one minus the probability of customer defection), also known as "the customer being alive" (Gupta 2009). The retention rate is estimated based on historical data (Bauer et al. 2003). Retention rates are positively correlated with customers' loyalty, customers' share of wallet and customers' word-of-mouth (Reichheld & Sasser 1990; Zeithaml 2000). In their study, Gupta et al. (2004) show that the impact on firm value by improvements in retention rates are by far superior to similar improvements in margins and discount rate.

CLV acquisition cots | Acquisition costs are sunk costs and therefore irrelevant to valuation (Pfeifer et al. 2005). However, these 'costs' are actually relevant investments in future customers and therefore should be included in valuation (Gupta 2009). Though, improvements in acquisition costs have the smallest impact on firm value, among the other CLV components (Gupta et al. 2004).

CLV horizon | Assumptions on the time horizon in CLV are determined to some extent by the product category (Gupta 2009). Several assumptions have been used in studies. Reinartz & Kumar (2000) and Thomas (2001) use an expected customer lifetime, Gupta et al. (2004); Fader, Hardie & Lee (2005) use an infinite time horizon.

CLV growth | Assuming that margins (m) and retention rates (r) are constant over time and the time horizon is infinite and adding an extra growth rate (g) representing 'acquisition growth per existing customer', then CLV simplifies to (Gupta & Lehmann 2003; 2006; Gupta et al. 2004) (Eq. 9):

$$CLV = \sum_{t=0}^{\infty} \frac{mr^t}{(1+d)^t}(1+g) - AC = m\frac{r}{(1+d-r)}(1+g) - AC \qquad \text{Eq. 9}$$

This is a simple CLV premise where the margin (m) is multiplied by a multiple ($r/(1+d-r)*(1+g)$), where (r) is the retention rate, (d) the discount rate, times a growth rate (g) minus the acquisition costs (AC) for new customers. This equation (Eq. 9) is the foundation of CBV that can be used for firm valuation (Gupta et al. 2004).

Customer equity | CE is defined as the sum of all CLVs and has emerged as a key metric to manage and grow customers (Schulze et al. 2012). This concept is intrinsically related with the firm valuation concept as both are two versions of the PV rule (Berk & DeMarzo 2007) of expected future CFs (Srinivasan & Hanssens 2009). This overlap with finance makes marketing financially more relevant and accountable (Schulze et al. 2012). This is demonstrated by Gupta & Lehmann (2003) and Gupta et al. (2004), as their estimated CE in these studies approximate the market value of three out of five firms very well. Although CE does not capture all the sources of market value for a firm, it does provide a strong guideline (Gupta & Lehmann 2003). Thus, the following is expected:

H2: CE and share price are positively correlated.

Gupta & Lehmann (2003) and Gupta et al. (2004) also show the relative impact of similar improvements between the CE drivers. They find among others that a 100 basis points improvement in retention rate results in a 5% increase of CE (Gupta & Lehmann 2003; Gupta et al. 2004). Thus, the following is expected:

H3: Improvements in the retention rate affects CE.

Customer equity to shareholder value | Schulze et al. (2012) incorporate valuation theory in their CE model, in order to account for the effect of NOA and debt on CE in order to obtain SHV (Damodaran 2006; Koller et al. 2010). They propose the following adjustment to CE (Eq. 10):

$$SHV = Equity\ value = CE + NOA - Debt \qquad \text{Eq. 10}$$

Thus, the following is expected:

H4: The EV estimated by DCF valuation, approximates CE estimated by CE valuation.

2.2.2 Customer behavior value drivers and forecasting

"Forecasting is very difficult, especially if it's about the future"

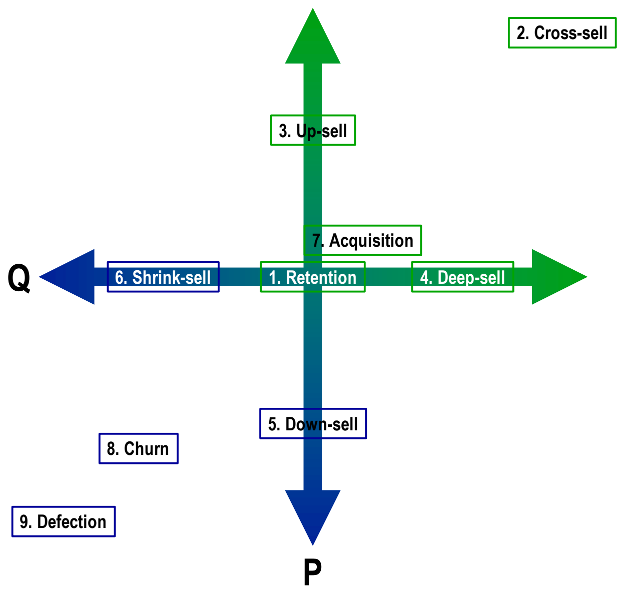
Niels Bohr, Nobel Prize in Physics (1885-1962)

Customer behavior value drivers | The main value drivers of CLV are customer retention, customer development and customer acquisition (Gupta 2009). Most of the CLV studies in marketing have focused on building better models for these customer behavior value drivers (Gupta 2009). This has led to improved decision making and greater accountability of marketing (Wiesel et al. 2008). Given that customer behavior drives CLV (Gupta 2009) and improvements in CE are linked to improvements in SHV (Schulze et al. 2012), equals individual customer behavior driving SHV. Therefore, data on customer purchase behavior with the firm can be used as input into a model forecasting future individual customer behavior, ultimately forecasting profitability (Verhoef & Donkers 2001). Thus, the following is expected:

H5: Customer purchase behavior explains the variance in customer profitability.

Specifying the main behavioral value drivers, customer retention and development, into more detailed forms of customer behavior, results in the customer behavior spectrum[7] displayed in (Figure 2). Where 'P' represents price or monetary value and 'Q' quantity; in essence customer behavior varies in these two dimensions.

Figure 2 Customer behavior spectrum



Source: Gupta (2009), Keiningham et al. (2007), Kim & Kim (1999), Knott et al. (2022), Li et al. (2005), Neslin et al. (2006) and Zakirov & Momtselidze (2015)

[7] The customer behavioral spectrum is described from the firm's perspective. However, the same terminology is used intertwining for describing the customer's perspective. E.g. cross-selling (business perspective), cross-buying (customer perspective).

Customer behavior value driver 1: retention | Keiningham et al. (2007) define customer retention as follows: "the customers' stated continuation of a business relationship with the firm." Customer retention has a large impact on firm profitability (Reichheld & Sasser 1990) and firm value (Gupta et al. 2004). Thus, the following is expected:

H6: There is a positive relation between retention and customer profitability.

Customer behavior value driver 2: cross-sell | Li et al. (2005) define cross-sell (or from the customer perspective: cross-buying) as follows: "the practice of selling additional products or services to existing customers." Cross-sell is of high importance in CBV (Donkers et al. 2007), it mainly drives ROIs (Knott et al. 2002) and improves margins (Gupta 2009). As a result, firms in many industries have put the highest strategic priority to cross-selling (Li et al. 2005). Thus, the following is expected:

H7: There is a positive relation between cross-sell and customer profitability.

Customer behavior value driver 3: up-sell | Kim & Kim (1999) define up-sell (or from the customer perspective: up-buying) as follows: "the firms attempt to sell a similar but more expensive version of the same services or products." Up-selling is an important component of CLV (Kim & Kim 1999) and improves margins (Gupta 2009). Thus, the following is expected:

H8: There is a positive relation between up-sell and customer profitability.

Customer behavior value driver 4: deep-sell | Zakirov & Momtselidze (2015) define deep-sell (or from the customer perspective: deep-buying) as follows: "the attempt to let customers increase their usage of the services and products they currently have." Thus, the following is expected:

H9: There is a positive relation between deep-sell and customer profitability.

The behaviors cross-sell, up-sell and deep-sell imply the existence of a counterpart in the customer behavior spectrum. The following types of customer behavior are exact opposites and are based on economic reasoning within the described theoretical framework thus far.

Customer behavior value driver 5: down-sell | Down-sell (or from the customer perspective: down-buying) can be perceived as the counterpart of customer up-sell; it follows that it can be defined as: 'the firm selling less expensive version of the same services or products.' Thus, the following is expected:

H10: There is a negative relation between down-sell and customer profitability.

Customer behavior value driver 6: shrink-sell | Shrink-sell (or from the customer perspective: shrink-buying) can be perceived as the counterpart of customer deep-sell; it follows that it can be defined as: 'the firm selling less of the same product or service to the same customer.' Thus, the following is expected:

H11: There is a negative relation between shrink-sell and customer profitability.

The types of customer behavior discussed so far are more specified subtypes of both retention and development. In essence these types come down to the fact that the customer is retained in the subsequent period, just that it has changed its behavior in terms of 'quantity' (Q) or 'monetary value' (P) or a combination both. The following (and last) types of customer behavior discussed, are independent customer behavior events within the spectrum.

Customer behavior value driver 7: acquisition | Gupta (2009) defines customer acquisition as follows: "the first-time purchase by new or lapsed customers." Customer acquisition has an important impact on long-term profitability of the firm (Villanueva et al. 2008) and represents an important investment with effect on the future retention rate (Thomas 2001). Moreover, Schulze et al. (2012) show that it affects SHV more than customer retention. However, Reinartz et al. (2005) mention that firms poorly understand the underlying linkage between acquisition and the long-term impact on profitability. Thus, the following is expected:

H12: There is a positive relation between acquisition and customer profitability.

Customer behavior value driver 8: churn | Neslin et al. (2006) define customer churn as follows: "the moment a customer does not stay with a certain product or service of the firm[8]." In their study they conclude that customer churn has a negative impact on CLV. Thus, the following is expected:

H13: There is a negative relation between churn and customer profitability.

Customer behavior value driver 9: defection | Gupta (2009) defines customer defection as follows: "a customer that is lost for good." In addition, he notes that some researchers consider customer defection as 'switching to competitors' as transient, or 'always a share.' The probability of customer defection is explicitly part of CLV (Gupta 2009). Thus, the following is expected:

H14: There is a negative relation between defection and customer profitability.

When observing a single customer's behavior during a certain period, a variety of purchase behavior combinations can occur at once. In the most 'extreme' scenario all types can occur in the same time, apart from acquisition and defection as these are isolated events. Multi-purchase behavior is induced by at least two factors. In the first place this is due to multi-brand, multi-product and multi-segment. Then, cross-sell as a common highest strategic priority (Li et al. 2005) functions as a catalyst for 'multi-purchase-behavior' and encourages customers to be more exposed to firm products, which drives general purchase-behavior activity. The impact of both factors is supported by findings from Donkers et al. (2007) on purchase behavior between two periods among several products within one insurance firm (Donkers et al. 2007). They find high correlations among purchased products for subsequent years, especially on the diagonal (Donkers et al. 2007). This indicates that a product is repurchased and implicitly drives retention (Donkers et al. 2007). But they also find high correlations between different products, indicating cross-sell and or churn (Donkers et al. 2007). Thus, the following is expected:

H15: Observed customer behavior affects future customer behavior.

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[8] The customer remains with the firm purchasing other products or services, but simply ends for example a product in a certain product category.

2.2.3 Customer brand choice behavior and forecasting

"Through the years, customers may come and go, but strong brands will endure"

Leone et al. (2006)

Customers and brands are two sides of the same coin; they both improve the profitability of marketing within the firm (Leone et al. 2006).

Brand equity | In addition to the CE metric, marketing has developed another equity metric for the value measurement of its other major intangible asset: brands (Doyle 2000). Together with other marketing intangibles brand equity accounts on average for 75% of a firm's value (Doyle 2000). Keller (1993) defines customer based brand equity as: "the differential effect of brand knowledge on consumer response to the marketing of the brand." This definition implies that in the end customers drive a brand's success. The firm's marketing department develops brands for customers (Bick 2009) to be attracted, to be reminded (Lemon et al. 2001) and to be connected emotionally to the firm (Lemon et al. 2001; Leone et al. 2006). Brands represent value to customers (Aaker 1996). As a result, this drives customer loyalty and price premiums driving incremental CFs (Leone et al. 2006), hence SHV (Bick 2009; Koller et al. 2010).

Brand choice behavior | Customers need and value brands (Leone et al. 2006). However, in the end a brand is only as good as the customers it attracts (Leone et al. 2006). The associations a customer has with a brand drives the brand experience, affecting customer satisfaction and customer loyalty (Brakus et al. 2009). As loyalty goes down a customer is more likely to switch between brands of which it might derive utility from switching itself and the new brand choice (McAlister & Pessemier 1982; Van Oest & Franses 2005). Ultimately, the customer brand-switching is related to individual customer brand choice behavior (Van Oest & Franses 2005). From a theoretical perspective customer brand choice behavior is complementary to the customer behavior value driver spectrum (Figure 2), as it moderates a customer's movement within the spectrum. Thus, the following is expected:

H16: Customer brand choice affects customer behavior.

H17: Customer brand choice affects customer profitability.

2.2.4 Customer characteristics, relationship age, share of wallet and forecasting

Customer characteristics or socio-demographics, are important predictors (Kamakura et al. 1991). In addition to the traditional variables (e.g. income, age, education, household composition, gender, risk attitude, social class, etc.), the family lifecycle is a good predictor as well (Antonides & van Raaij 1998). Customer characteristics are linked to customer needs (Engel et al. 1995) and customer needs drive the purchase decision process (Hauser & Urban 1986). In addition, Verhoef & Donkers (2001) note that: "as there is hardly ever complete information on needs available, customer characteristics relating to tastes and needs can be used instead." It follows that, to a certain extent customer characteristics drive the movements within the customer behavior value driver spectrum (Figure 2). Thus, the following is expected:

H18: Customer characteristics affect customer behavior.

As customer characteristics are indirectly linked to customer purchase behavior, it follows that customer characteristics are linked to customer profitability. Thus, the following is expected:

H19: Customer characteristics affect customer profitability.

Relationship age | The customer's length of the relationship has a moderating effect on loyalty (Cooil et al. 2007) and is a good predictor for retention probabilities (Donkers et al. 2007). The relationship of the firm with the customer evolves over time, creating a bond between them (Cooil et al. 2007). As a result, this decreases the probability of a customer's defection (Anderson & Sullivan 1993), and creates satisfaction that drives customer loyalty (Anderson & Weitz 1989). The cumulative effect of the customer journey with the firm affects the customer's entire judgement of its relationship (Kalwani & Narayandas 1995). So, when the length of a customer relationship ages, movements in satisfaction have less impact on loyalty (Homburg et al. 2003). In addition, switching costs tend to increase when the relationship length increases (Cooil et al. 2007). Thus, the following is expected:

H20: Relationship age affects customer purchase behavior.

H21: There is a positive relation between relationship age and customer profitability.

Share of wallet | Keiningham et al. (2007) define customer SOW as follows: "the stated percentage of total spending on products or services held at the firm with respect to the total capacity of the customers' wallet." In addition, it measures customer loyalty behavior (Bowman et al. 2000; Bowman & Narayandas 2004; Jones & Sasser 1995). However, measures of loyalty are forward looking, where SOW just summarizes the current situation in a single metric (Oliver 1999). Improvements in customers' SOW results in greater financial impact than customer retention (Keiningham et al. 2007). In combination with retention improvements, this results in ten-times greater value to a firm than customer-retention improvements solely (Coyles & Gokey 2005). Thus, the following is expected:

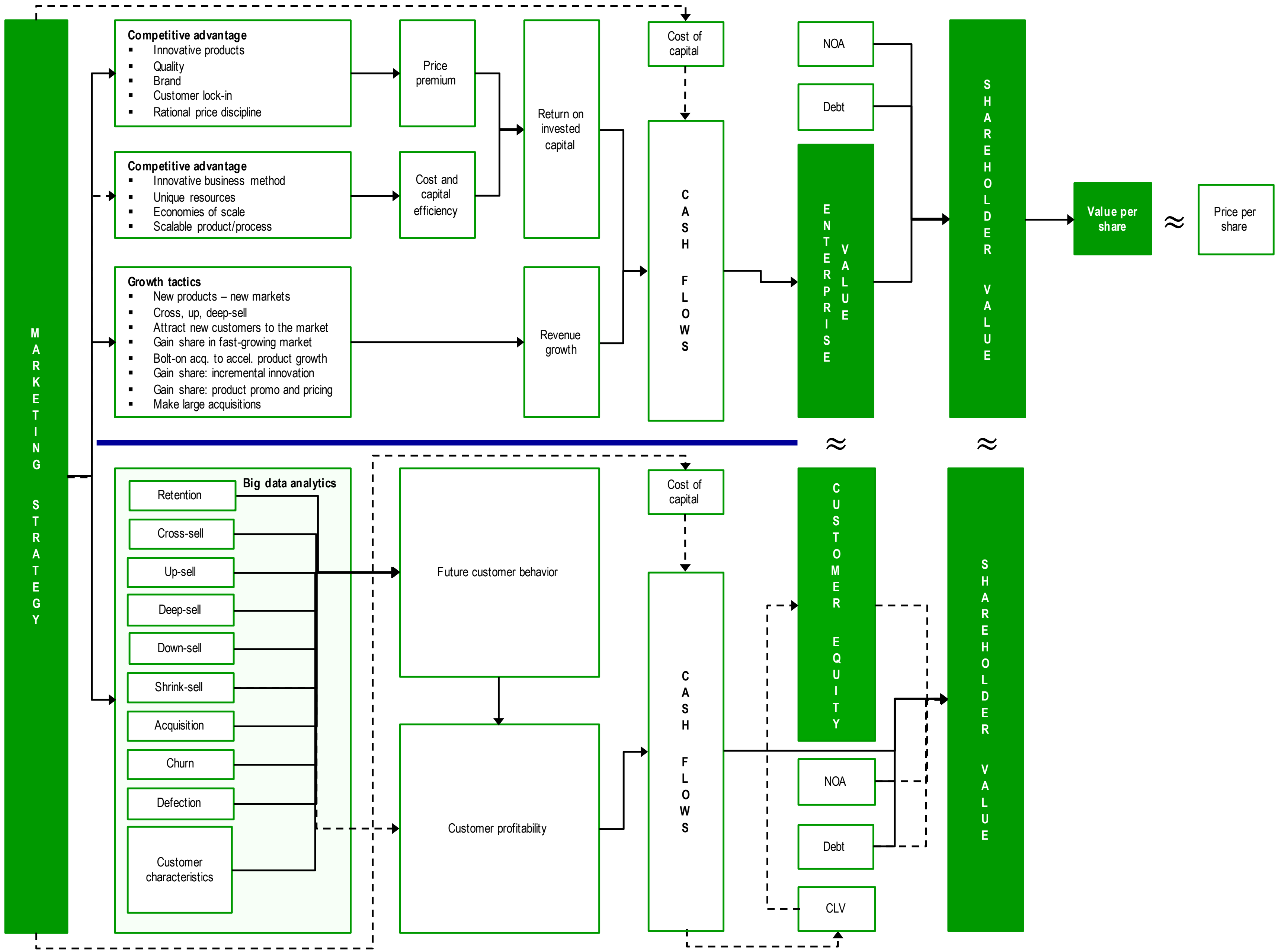
H22: Share of wallet affects customer purchase-behavior.

H23: There is a positive relation between share of wallet and customer profitability.

2.3 Conceptual model

The conceptual model derived from theory is displayed in Figure 3, presenting two value driver concepts in valuation. The concept above the blue line is in essence the value driver model derived from DCF valuation theory. Below the line, is a value driver model based on customer behavior derived from both CBV and DCF theory. Both concepts are two sides of the same coin, having only one value driver in common: the firm's marketing-strategy, resulting from boardroom strategy development. A well-balanced marketing mix execution then drives the chain of value drivers for both concepts, driving the product-market performance of the firm. The conceptual model emphasizes the differences in value driver's origin. For the DCF value driver concept this is more 'product-centric' oriented, where for the customer behavior based value driver concept has a solely 'customer-centric' orientation. Both concepts aim to forecast future CFs based on the changes in value drivers. The systematic risk surrounding future CFs needs to be taken into account by discounting future CFs at the firm's WACC representing the COC. The level of WACC is essentially a consequence of the firm's strategy. Ultimately, after some financial adjustments, both value driver concepts are expected to result similar SHV estimates. In addition, estimated CE (including NOA) is expected to be of a same level as the EV. Finally, there is a feedback loop of SHV to strategy. This line is left out on purpose from the conceptual model, as it is out of the scope of this study. Nevertheless, it is important to underline the continuous process underlying this conceptual model.

Figure 3 Conceptual model



3. Data

"In order to value and manage customers, extensive data and complex modelling is required"

Gupta & Lehmann (2003)

This chapter describes the scope of the two main sources of data underlying this study. The first source is *publicly available firm financial* information, serving as input for the DCF value driver concept. The other source is an *integrated customer-centric dataset*, which is custom-built and derived from big data, serving as input for the customer behavior based value driver concept.

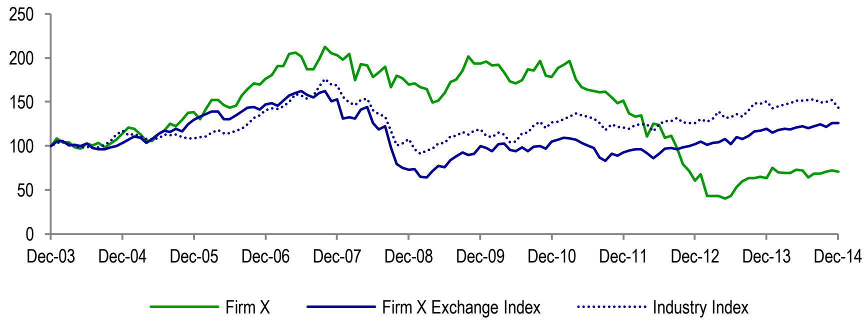
3.1 Financial data

The *financial data* is taken from publicly available sources. Most of the information comes from the firm's annual reports (2003–2014). Additional financial data is taken from financial datastreams (Thomson One Banker, Factset) and high quality equity research reports, provided by a department of the firm. The combination of these sources serve mainly as an input for a DCF valuation. A summary of historical financial statements (P&L, BS and CF statement) is reported in Table 29 of the appendix.

3.1.1 Historical performance

A good understanding of the firm's industry dynamics[9] and its competitive position and strategy[10] is needed before conducting historical analysis (Koller et al. 2010). A summary of the historical performance analysis is reported in Table 30 of the appendix. The analysis summarized in KPIs, clearly shows that the past four years have been challenging. ROIC and revenue growth have been under heavy pressure. However, the firm is now financially stabilizing, despite the difficult times for the BM segment of the firm[11]. The indexed share price performance confirms this view (Figure 4).

Figure 4 Share price index 2003–2014



Source: Thomson One Banker, prices rebased to Firm X share price of EUR 3.71 on December 31, 2003 (=100)

[9] Koller et al. (2010): "e.g. key customers, technological trends, number of competitors and level of fragmentation, consolidation trends and M&A activity, maturity profitability and growth prospects of the industry, entry/exit barriers."

[10] Koller et al. (2010): "e.g. quality and track record of management, strength & weakness, core competences, strategic options/scenario's, strategic focus: diversification vs niche player, low cost vs top line growth and innovation speed."

[11] Source: Firm X annual report 2014.

3.2 Integrated customer-centric dataset

Besides the use of publicly available financials in this study, an *integrated customer-centric dataset* is custom-built for the purpose of analysis. Table 4 reports a brief overview concerning the dimensions of the dataset.

Table 4 Quick overview integrated customer-centric dataset

Overall	
▪ 12 million customers (including potential)	▪ 2 market segments
▪ 4 brands	▪ 29 product categories
Initial dataset dimensions	
▪ 3 years historical RFM data (12 months' interval)	▪ 79 customer characteristic variables (third party)
▪ 230 RFM variables	
Dimensions dataset after preparation	
▪ 36 dummies concerning the customer behavior value driver spectrum	▪ 61 dummies calculated based on from third party customer characteristics
▪ 4 variables concerning EBITDA (profit)	▪ 1,126 dummies concerning customer characteristics
Dimensions dataset after model estimation and solving equations	
▪ 2 billion computed probabilities	▪ >10 different datasets
▪ >150GB of data	

The dataset contains almost 12 million customers and 3 years of behavior data. The time period considered in this dataset begins June 2012 and ends June 2014, with a one-year interval. The firm sells many different types of products, some of them very diffused. For reasons of simplicity and for model estimation (Donkers et al. 2003), the ownership of these diffused products have been grouped in two categories: 'tailored solutions' and 'other solutions.' The firm is successful in targeting their different products on two market segments (business and consumer), using a multi-brand strategy. The almost 12 million customers consist of active and non-active customers (or potential customers). For each active customer, the following information is observed per year: 'purchase and cancellation for each product type for all brands on both market segments', 'revenues for every purchased BSP', 'sub-type' (where this is applicable) and 'the number of subscriptions per BSP combination.' The 'start-date' of the relationship per BSP combination is observed in the last period of the dataset. Information on 'EBITDA-margins' per BSP combination (Table 5) are derived from annual reports. Where several EBITDA-margins are obtained from a BM department of the firm.

Table 5 EBITDA-margins 2014

BY BSP-COMBINATION							
EBITDA margin (%)							
Product 1	Brand 1	CM	[redacted]	**Product 16**	Brand 1	BM	[redacted]
Product 2	Brand 4	CM	[redacted]	**Product 17**	Brand 3	BM	[redacted]
Product 3	Brand 1	BM	[redacted]	**Product 18**	Brand 1	BM	[redacted]
Product 4	Brand 1	CM	[redacted]	**Product 19**	Brand 1	BM	[redacted]
Product 5	Brand 3	CM	[redacted]	**Product 20**	Brand 2	CM	[redacted]
Product 6	Brand 1	BM	[redacted]	**Product 21**	Brand 2	BM	[redacted]
Product 7	Brand 3	BM	[redacted]	**Product 22**	Brand 2	CM	[redacted]
Product 8	Brand 1	CM	[redacted]	**Product 23**	Brand 2	CM	[redacted]
Product 9	Brand 3	CM	[redacted]	**Product 24**	Brand 2	CM	[redacted]
Product 10	Brand 1	BM	[redacted]	**Product 25,**	Brand 1	CM	[redacted]
Product 11	Brand 3	BM	[redacted]	**Product 26**	Brand 1	BM	[redacted]
Product 12	Brand 1	CM	[redacted]	**Product 27**	Brand 1	CM	[redacted]
Product 13	Brand 1	BM	[redacted]	**Product 28**	Brand 1	CM	[redacted]
Product 14	Brand 1	CM	[redacted]	**Product 29**	Brand 1	CM	[redacted]
Product 15	Brand 3	CM	[redacted]				

Source: annual report Firm X and internal department BM

Recency, frequency and monetary value dummies | RFM-variables have been derived from these observations. First, dummies for ownership of each product type during each period (frequency) are derived. Based on the timing of ownership (purchases and cancellations) (Donkers et al. 2003) and the behavioral spectrum (Figure

2) 9 behavioral dummies (recency) have been derived. These behavioral dummies are derived based on the transition during the periods 2012–2013 and 2013–2014. A customer's total EBITDA contribution (monetary value), is derived as the sum of: ownership dummies for each product type times the product specific EBITDA-margin.

Relationship age dummies | The relationship age per product in the customer's portfolio is observed for the last period (2014). The longest relationship among the customer's portfolio is taken for the derivation of 11 dummies indicating the relationship age.

Customer characteristic dummies | Variables on customer characteristics (socio-demographics) complement the dataset. These variables originate from commercial third-party sources,[12] and contain information on an aggregated business and household level. For each individual customer in the dataset (consumer and business; active and potential-customers), these variables are observed in the last period (2014) of the dataset. These variables may be aggregated on the location, household or business level. Customer characteristics have predictive power (Verhoef & Donkers 2001). In addition, these variables bridge the 'data-gap' in between active customers and non-active customers (potential customers). Hence, there is no purchase behavior data available for non-active customers. As a first impression of predictability, Pearson correlation coefficients between the customer characteristics (before being recoded into dummies) and EBITDA (2013 and 2014) are reported in Table 6. These variables have been selected from a broader list of variables by economic reasoning. There are two significant and relatively substantial correlations (≥.10) with regards to the 'number of employees.' Indicating that the size of a firm is positively related to total EBITDA. It is expected that, especially after recoding into dummies, more variables will have substantial predictive power. All customer characteristics have been recoded, resulting in 1,176 dummy variables.

Share of wallet dummies | Combining observed RFM-variables with customer characteristics enables the computation of a customer's SOW. The formula (Eq. 11) for calculating SOW for a CM customer i at time t (June 2014) (Cooil et al. 2007) is:

$$SOW_{CM_{i,t}} = \frac{ARev_{i,t}}{FI_{i,t}} \qquad \text{Eq. 11}$$

Where $ARev_{i,t}$ is customer's i annual revenues with the firm at time t and $FI_{i,t}$ is its aggregated average annual fiscal income. For a BM customer i the SOW concerning Firm X industry's related products and services at time t is defined (Eq. 12) (Gartner IT Key Metrics Data 2012) as:

$$SOW_{BM_{ij,t}} = \frac{ARev_{ij,t}}{E(S_{ij,t})} \qquad \text{Eq. 12}$$

Here j is the type industry where the BM customer is active in, $E(S_{ij,t})$ is its estimated annual industry related spending at time t. Then the estimated annual industry related spending ($E(S_{ij,t})$) is derived as follows (Eq. 13):

$$E(S_{ij,t}) = GP_{ij,t} * RARev_{ij,t} \qquad \text{Eq. 13}$$

[12] SIZO provides business related information (www.sizo.com). Mosaic provides household related information (www.experian.nl/mosaic).

Table 6 Pearson correlations of third party customer characteristics and EBITDA 2013–2014 (r-coefficient)

			EBITDA					EBITDA	
	Customer characteristics		**2013**	**2014**		**Customer characteristics**		**2013**	**2014**
1	Number of SIZO	BM	.01**	.01**	**36**	House type	CM	.01**	.01**
2	Number of ultimate parents	BM	.01**	.01**	**37**	Tenure	CM	.00**	.00**
3	Special location (indicator)	HYB	-.00**	-.00**	**38**	Number of moves	CM	.00	.00
4	Complex for demolition (indicator)	HYB	-.01**	-.01**	**39**	Last move	CM	-.00**	-.00**
5	Competitor 1 available on location (indicator)	HYB	.00*	.00	**40**	Business	HYB	-.01**	-.01**
6	Competitor 2 available on location (indicator)	HYB	.00	.00	**41**	Density surrounding addresses	HYB	.00	.00
7	Competitor 3 available on location (indicator)	HYB	.00	.00	**42**	Degree of urbanity	HYB	.00	.00
8	Competitor 4 available on location (indicator)	HYB	.00	.00	**43**	Number of residents	CM	.00	.00
9	Years since business establishment	BM	-.01**	-.01**	**44**	Number of men	CM	.00	.00
10	Importing business (indicator)	BM	.01**	.01**	**45**	Number of women	CM	.00	.00
11	Exporting business (indicator)	BM	.01**	.01**	**46**	Percentage age 0-5	CM	.00	.00
12	Mother company (indicator)	BM	.02**	.02**	**47**	Percentage age 5-25	CM	.00	.00
13	Number of employees	BM	.15**	.15**	**48**	Percentage age 25-45	CM	.00	.00
14	Number of employees in concern	BM	.02**	.02**	**49**	Percentage age 45-65	CM	.00	.00
15	Number of employees on concern location	BM	.19**	.19**	**50**	Percentage age ≥65	CM	.00	.00
16	Business complex (indicator)	BM	.02**	.02**	**51**	Percentage nonwestern immigrant	CM	-.01**	-.01**
17	Number of parts in concern	BM	.01**	.01**	**52**	Number of total private households	CM	.00	.00
18	Score decision making unit (DMU)	BM	.01**	.01**	**53**	Percentage one person households	CM	.00	.00
19	Score decision making unit location (DMU)	BM	.03**	.03**	**54**	Percentage more persons households without children	CM	.00	.00
20	Months since last annual report	BM	.02**	.02**	**55**	Percentage more persons households with children	CM	.00	.00
21	Consolidated results (category)	BM	.04**	.04**	**56**	Average household size	CM	.00	.00
22	Revenues	BM	.07**	.07**	**57**	Number of housing	CM	.00	.00
23	Consolidated revenues	BM	.06**	.06**	**58**	Average house value EUR000	CM	.00	.00
24	Special location type (category)	BM	-.00*	-.00*	**59**	Average fiscal income EUR/month	CM	.00*	.00
25	Mosaic group description (category)	CM	-.00**	-.00**	**60**	Percentage low income	CM	.00	.00
26	Segment type (category)	CM	.00	.00	**61**	Percentage high income	CM	.01	.00
27	Age household	CM	.00*	.00**	**62**	Percentage benefit recipients	CM	.00	.00
28	Age oldest child in household	CM	.06**	.05**	**63**	Percentage entrepreneur	CM	-.00	.00
29	Household size	CM	.00**	.00**	**64**	SBI segment description	BM	.01**	.01**
30	Marital status	CM	.00**	.00**	**65**	Percentage on industry related spending (Gartner)	BM	-.01	-.00
31	Average income (category)	CM	.01**	.01**	**66**	NACE description	BM	.01**	.01**
32	Level of education	CM	.00**	.00**	**67**	Main or sub (indicator)	BM	.00	.00
33	Work situation	CM	.00	.00	**68**	Legal entity type	BM	-.00**	-.00**
34	Number of cars household	CM	.00**	.00**	**69**	Relationship to concern	BM	.02**	.02**
35	Number of children	CM	.01**	.02**	**70**	Code ZZP type	BM	-.01**	-.01**

**: p<0.01, *: p<0.05

Where $GP_{ij,t}$ is the Gartner industry related percentage spending for customer i in industry j at time t and $RARev_{ij,t}$ is its reported annual revenue taken from the annual report customer i in industry j at time t. Finally, the Gartner Percentage ($GP_{ij,t}$) (Eq. 14) for customer i in industry j at time t is calculated as:

$$GP_{ij,t} = \frac{S_{j,t_{-1}}}{Rev_{j,t_{-1}}} \qquad \text{Eq. 14}$$

Where $S_{j,t_{-1}}$ is the total industry related spending per industry j in the previous period t_{-1} and $Rev_{j,t_{-1}}$ are the total revenues generated by this industry j in the previous period t_{-1}. The Gartner percentage on industry related spending is available for many different industries. Based on industry descriptions in the customer dataset, coming from third party sources, Gartner's industry related percentage is linked to individual business customers.

3.2.1 Data availability

Five major internal and external factors have influenced the eventual shape and content of the integrated customer-centric dataset.

Geographical definition | The first factor of influence is the geographical definition of the customers represented in the dataset. The focus is on the home country activities of the firm,[13] accounting for the vast majority of revenues; about 80%[14] of total revenues in 2014. The major brands positioned on its home market are: Brand 1[15], Brand 2[16], Brand 3[17] and Brand 4[18] accounting for an estimated 75% of total revenues for the home market division. As a result, the Brand 5[19] group (foreign division) and Brand 6[20] customers are out of the scope of the dataset.

Data architecture | The second factor of influence is the architecture of data within the firm. As a consequence, there is no data available for the remaining home market labels: Brand 7[21], Brand 8[22] and Brand 9[23]. Roughly estimated, these labels represent at maximum just a few percent of total revenues in 2014. However, the firm does not disclose any information on these brands. One explanation for the current data-architecture arises from talks with internal data-specialists. Historical agreements at times of mergers and acquisitions left the acquired firm with a certain degree of autonomy, such as data-ownership. This has resulted in situations where information sharing (customer data) is executed on aggregated levels.

Data accessibility | The third factor of influence is the accessibility of customer data. The specialized analyst team is limited to accessing customer data on the level of product ownerships. Analysis on e.g. web related activity of customers is analyzed by another specialized team. Customer-service related activities are analyzed by yet another team. In short, the firm has diffused teams across the brands and market segments that do not cooperate in sharing data or conducting analysis. As a result, there is a limited data accessibility for analysts across the firm. The diffused data-ownership across the firm, has limited the data availability for this study.

Regulation | The fourth factor of influence comes from regulation imposed by the regulation authority. It follows that, the collection of the data is in compliance with these regulations. Two measures with major impact on the data collection are: (1) restricted period of customer data storage, and (2) the use of customer specific data for analysis purposes is forbidden. The last measure directly limits the amount of available variables in the dataset with expected highly predictive capacity, as it was expected to contain detailed information on customer behavior.

Newly developed dataset | This dataset is the outcome of a first-time attempt within the firm, in developing an integrated customer-centric view. Therefore, this dataset is a unique approach in bridging the analysis-gap in multi-dimensional customer purchase-behavior (in a context of multi-segment, multi-brand and multi-product). As a result, learnings from the development-process of this dataset serve as input in developing a dataset with even more integration of data sources in the future.

Consequences | Two consequences emerge from the limitations surrounding the data. In the first place, the almost 12 million active and non-active customers in the dataset are in fact *unique locations*. At the moment of constructing the dataset it was impossible to build a dataset based on solely individual customers. For simplicity reasons it is assumed[24] that every unique location equals one unique customer. On average, in 88% of the cases there is an one-to-one relation between the location and the customer as reported in Table 31 of the appendix. In the second place,

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[13] At the time of constructing the dataset, Firm X was in the process of selling foreign activities.
[14] Source: Firm X annual report 2014.
[15] Is the quality brand, providing their customers with value-added services (source: Firm X annual report 2014).
[16] Is the brand serving the no frills segment (source: Firm X annual report 2014).
[17] Is the high-end brand for the top of the market (source: Firm X annual report 2014).
[18] Is the brand targeting youth (source: Firm X annual report 2014).
[19] Is the brand that pursues a challenger strategy on a foreign market (source: Firm X annual report 2014).
[20] Is the brand that provides national and international wholesale to third parties (source: Firm X annual report 2014).
[21] Is the online brand with specific propositions (source: Firm X annual report 2014).
[22] Is the low-cost brand for internationally oriented customers (source: Firm X annual report 2014).
[23] Is the challenger brand that focusses on the SME segment (source: Firm X annual report 2014).
[24] The assumption may influence the valuation outcome; as customer-behavior is not always observed for the individual, thus affecting the profitability or CF forecast, hence value.

the dataset has an *asymmetric structure*. Table 7 reports this asymmetry during the three periods among all the BSP-combinations. In order to deal with this asymmetry much of the analysis is split up in products 1 to 19 and 1 to 26 between the three periods. The maximum number of months' on data storage (as imposed by the regulation authority), hence data availability, is not even met for all products. This is the case for products 20 and 21 and can potential cause estimation problems. Both products are available with a maximum contract period of 24 months. Not having 25 months on customer purchase data available implies that a repurchase or cancellation after the contract period has ended is not observed. In case of all the remaining products 25 months on purchase data is available. With the exception of products 25 and 26 where contractual periods reach up to a maximum of 12 months only.

Table 7 Data availability by BSP-combination per period

ASYMMETRY IN DATA-AVAILABILITY

Year to					June 2012	June 2013	June 2014
	Brand	Segment	Product	Type			
1	Brand 1	CM	Product 1	-	✓	✓	✓
2	Hi	CM	Product 2	-	✓	✓	✓
3	Brand 1	BM	Product 3	-	✓	✓	✓
4	Brand 1	CM	Product 4	Type 1	✓	✓	✓
5	Brand 3[25]	CM	Product 5	Type 1	✓	✓	✓
6	Brand 1	BM	Product 6	Type 1	✓	✓	✓
7	Brand 3	BM	Product 7	Type 1	✓	✓	✓
8	Brand 1	CM	Product 8	Type 1	✓	✓	✓
9	Brand 3	CM	Product 9	Type 1	✓	✓	✓
10	Brand 1	BM	Product 10	Type 1	✓	✓	✓
11	Brand 3	BM	Product 11	Type 1	✓	✓	✓
12	Brand 1	CM	Product 12	-	✓	✓	✓
13	Brand 1	BM	Product 13	-	✓	✓	✓
14	Brand 1	CM	Product 14	Type 1	✓	✓	✓
15	Brand 3	CM	Product 15	Type 1	✓	✓	✓
16	Brand 1	BM	Product 16	Type 1	✓	✓	✓
17	Brand 3	BM	Product 17	Type 1	✓	✓	✓
18	Brand 1	BM	Product 18	Type 1	✓	✓	✓
19	Brand 1	BM	Product 19	Type 1	✓	✓	✓
20	Brand 2[26]	CM	Product 20	-	-	✓	✓
21	Brand 2	BM	Product 21	-	-	✓	✓
22	Brand 2	CM	Product 22	Type 1	-	✓	✓
23	Brand 2	CM	Product 23	Type 1	-	✓	✓
24	Brand 2	CM	Product 24	Type 1	-	✓	✓
25	Brand 1	CM	Product 25,	Type 1[27]	-	✓	✓
26	Brand 1	BM	Product 26	Type 1	-	✓	✓
27	Brand 1	CM	Product 27	Type 2[28]	-	-	✓
28	Brand 1	CM	Product 28	Type 2	-	-	✓
29	Brand 1	CM	Product 29	Type 2	-	-	✓

✓: data is available, -: data is not available

3.2.2 Descriptive statistics

Descriptive statistics on the integrated customer-centric dataset are reported in Table 8. In line with the historical performance analysis, the 'revenues' and 'EBITDA' index (2012=100) have decreased for CM to 98.5 (2014) and 77.7 (2014), for BM 85.3 (2014) and 78.1 (2014), respectively. Then, the average number of product types in a customer's portfolio increased for CM from 1.59 (2013) to 1.63 (2014) and decreased for BM from 2.09 (2013) to 2.05 (2014).

[25] For Brand 3 there is no data available on revenues; revenues are estimated based on observed ownership combined with historical pricelists.
[26] For Brand 2 there is no data available at June 2012.
[27] Purchase data on the product 25 and 26 are only available at June 2013 and June 2014, this product is offered solely in a contractual setting with a duration of 12 months.
[28] Purchase data on the sub-type 'Type 2' is only available at June 2014.

Table 8 Descriptive statistics

KEY DESCRIPTIVES BY MARKET SEGMENT								
Segment		**CM**				**BM**		
Year to		**2012**	**2013**	**2014**		**2012**	**2013**	**2014**
Indexed revenues	**EURm**				**EURm**			
Product 1-19 (2012=100)	1,693	100.0	96.4	96.0	1,934	100.0	95.5	81.5
Product 1-26 (2013=100)	2,353	-	100.0	98.5	2,646	-	100.0	85.3
Product 1-29	2,603	-	-	100.0	2,274	-	-	100.0
Indexed EBITDA	**EURm**							
Product 1-19 (2012=100)	427	100.0	89.3	68.3	799	100.0	96.9	74.6
Product 1-26 (2013=100)	613	-	100.0	77.7	774	-	100.0	78.1
Product 1-29	518	-	-	100.0	596	-	-	100.0
Average number of product types in portfolio (RGUs)	**N**							
Product 1-19	2,852,069	1.48	1.58	1.41	474,997	1.66	1.68	1.76
Product 1-26	4,040,857	-	1.59	1.63	598,325	-	2.09	2.05
Product 1-29	-	-	-	-	-	-	-	-
Average share of wallet (SOW)	**N**				**N**			
CM based on avg. income	1,805,431	-	-	1.6%	-	-	-	-
CM based on fiscal. income	1,722,746	-	-	3.1%	-	-	-	-
BM based on cons. results	-	-	-	-	7,791	-	-	33.8%
BM based on revenues	-	-	-	-	16,433	-	-	23.6%
BM based on cons. revenues	-	-	-	-	2,956	-	-	9.0%
Average retention rates	**N (2012)**							
Product 1-19	2,852,069	-	86.0%	71.8%	474,997	-	91.4%	82.2%
Product 1-26	4,040,857	-	-	87.9%	598,325	-	-	91.6%
Average max number of relationship years in portfolio	**N (2014)**				**N (2014)**			
Relationship age (years)	3,941,674	-	-	8.4	543,961	-	-	10.8

Then, the average SOW used for model estimation is observed in the last period of the dataset. For CM customers SOW ranges between 1.6–3.1% on average and for BM customers between 9.0–33.8%. The retention rate in the years used for model estimation for CM is 86.0% (2013) and 87.9% (2014). For BM this is 91.4% (2013) and 91.6% (2014). The average maximum relationship age among the customer's portfolio used for model estimation for CM and BM is 8.4 and 10.8 years respectively, observed in 2014.

Dependencies across customer-behavior | The existence of dependencies across customer behavior value drivers (Figure 2), concerning the development of the model, are reported for CM in Table 9 and BM in Table 10. The customer behavior value drivers are derived from product ownership transitions between the periods 2012–2013 and 2013–2014. The reported Pearson correlation coefficients represent these dependencies. In addition, it shows that the firm is successful in retaining customers, but also in deep- and cross-selling to them. Unfortunately, there are relatively high correlation for shrink-sell among other types of customer behavior. In addition, there are relatively high correlations on the diagonal, indicating that customer behavior during 2012–2013 is correlated with similar behavior during 2013–2014. More important, there are also substantial correlations across different customer behavior-events.

Table 9 Pearson correlation matrix customer-behavior in 2013 and 2014 CM

CONSUMER MARKET										
		2014								
	2013	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**Retention**	**.331****	.084**	.050**	**.224****	**.164****	**.286****	**-.245****	**.163****	-.004**
2	**Cross-sell**	**.118****	.025**	.034**	**.166****	**.145****	**.243****	-.062**	**.149****	-.049**
3	**Up-sell**	.059**	.012**	.022**	.053**	**.106****	.079**	-.027**	.034**	-.032**
4	**Deep-sell**	**.191****	.031**	.061**	**.189****	**.142****	**.296****	**-.130****	**.132****	-.022**
5	**Down-sell**	.032**	.040**	.009**	.003**	.017**	.038**	-.041**	.018**	.031**
6	**Shrink-sell**	**.169****	.052**	.045**	**.160****	**.105****	**.129****	**-.109****	**.102****	-.032**
7	**Acquisition**	.056**	.037**	-.002**	.082**	.027**	.027**	-.056**	.027**	.027**
8	**Churn**	.032**	.041**	.006**	.001*	.011**	.024**	-.035**	.012**	.020**
9	**Defection**	**-.395****	-.054**	-.024**	**-.239****	-.074**	**-.139****	.042**	-.069**	-.071**

**: p<0.01, *: p<0.05

Table 10 Pearson correlation matrix customer-behavior in 2013 and 2014 BM

BUSINESS MARKET

		2014								
	2013	1	2	3	4	5	6	7	8	9
1	Retention	**.329****	.033**	.052**	**.136****	**.198****	**.311****	**-.279****	**.192****	-.073**
2	Cross-sell	**.106****	.012**	.037**	**.135****	**.139****	**.171****	-.057**	**.137****	-.065**
3	Up-sell	.054**	.008**	.043**	.061**	.092**	.085**	-.027**	.039**	-.036**
4	Deep-sell	**.184****	.027**	.061**	**.206****	**.169****	**.294****	**-.118****	**.153****	-.090**
5	Down-sell	.042**	.023**	.019**	-.003*	.039**	.050**	-.048**	.032**	.007**
6	Shrink-sell	**.157****	.011**	.048**	.059**	**.131****	**.128****	**-.136****	**.120****	-.033**
7	Acquisition	.028**	.004**	-.010**	-.046**	-.012**	-.014**	-.044**	-.005**	.020**
8	Churn	.033**	.023**	.011**	-.011**	.024**	.031**	-.043**	.020**	.013**
9	Defection	**-.368****	-.037**	-.021**	**-.179****	-.091**	**-.160****	.066**	-.089**	0.002

**: p<0.01, *: p<0.05

Purchase rates | Descriptive statistics on purchase rates across product ownerships are reported in Table 32 of the appendix. Customer defection in relation to purchase rates of the products is expected to decrease over time for the retained customers. However, for 10 out of 26 products (2013–2014) these rates increase, indicating that the firm is relatively successful at cross-selling. This is expected, since customers who purchase more products are more likely to stay with the firm (Donkers et al. 2007).

Ownership correlations | An ownership correlations matrix of these products is reported in Table 33 of the appendix. There are high correlations on the diagonal, so having a certain product type in 2013 is highly correlated with having that same product in 2014. More important, there are also substantial correlations across different product types. Both findings are in in accordance with Donkers et al. (2007).

4. Methodology

"Forecasting is very difficult, especially if it's about the future"

Niels Bohr (1885–1962), Nobel Prize in Physics

This chapter describes the different methods used for valuation. Both main methods, DCF and CBB valuation aim to determine the level of SHV, but have a total different approach in forecasting key value drivers in determining future CFs. As described in the previous chapter, the DCF valuation method leverages publicly available firm financials. Most of the input data is aggregated on firm, brand, segment, product and customer-cohort level. Then, a forecast on the traditional value driver framework drives the forecast on future CFs. In contrast, the CBB valuation method leverages and integrates big data analytics on individual customer-behavior. Then, algorithm-driven models analyze and forecast individual customer purchase-behavior, driving the forecast of future CFs. Once the value of operations has been determined for both methods, the method of accounting for the effect of NOA and debt on EV is in accordance with valuation theory and is therefore identical for both models. In theory both models should produce approximately similar SHV results, despite that the value drivers and forecast methodology are entirely different.

4.1 Discounted cash flow valuation model

DCF valuation uses expected future FCFs and discounts them to arrive at a PV estimate, ultimately in order to determine SHV, which is a widely used method in the field of finance (Berk & DeMarzo 2007; Koller et al. 2010).

Present value | Much of financial valuation theory builds on the PV-rule (Berk & DeMarzo 2007), where the value of any asset is the PV (Eq. 15) of expected future CFs, denoted as (Koller et al. 2010):

$$PV = \sum_{t=1}^{t=n} \frac{CF_t}{(1+d)^t} \quad \text{Eq. 15}$$

Where n is the life of the asset, CF_t is the cash flow in period t and d is the discount rate reflecting the riskiness surrounding the future CFs (Koller et al. 2010). An extension of the PV-rule is the DCF valuation method, that estimates the intrinsic value of an asset based on its fundamentals (Koller et al. 2010). The intrinsic value is obtained by discounting future expected CFs at the WACC during the PP (Koller et al. 2010).

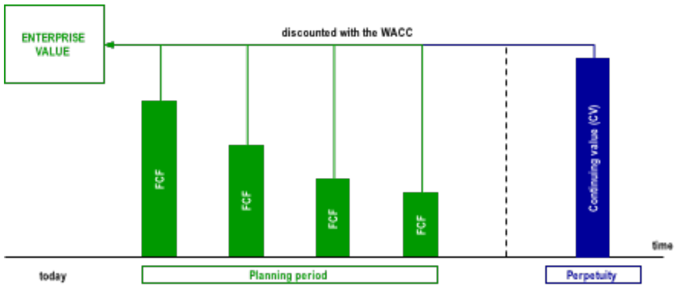
Firm value | Koller et al. (2010) rewrite the PV-rule (Berk & DeMarzo 2007) (Eq. 16) and show that the value of a firm is denoted as:

$$Value\ of\ firm = \sum_{t=1}^{t=n} \frac{FCF\ to\ firm_t}{(1+WACC)^{(t-0.5)}} \quad \text{Eq. 16}$$

Where $FCF\ to\ firm_t$ is the FCF available to the firm at time t. As CFs are equally spread out over the year, the discount rate needs to be corrected (Koller et al. 2010). The end of a year in which the CFs are expected, is represented by t. In order to reflect the equal spread-out of receiving CFs throughout a year, a correction of minus a half is required, hence $t - 0.5$ (Koller et al. 2010).

DCF valuation methodology | The DCF valuation methodology is basically an expansion of Eq. 16 and consists of the following steps: (1) identifying key value drivers (2) forecasting expected FCFs (3) selecting an appropriate CV methodology (4) estimating the proper WACC (Koller et al. 2010). The associated framework is presented in Figure 5.

Figure 5 DCF framework



Source: Berk & DeMarzo (2007); Damodaran (2006) and Koller et al. (2010)

Industry dynamics, competitive position and strategy | However, before the firm can be valued an understanding of the industry dynamics, competitive position and strategy is required (Koller et al. 2010). While conducting historical performance analysis (see previous chapter) a deep understanding and view on these three items is developed. It is critically important to understand the future development of revenue growth and the underlying drivers per revenue line (Koller et al. 2010). After a breakdown in volume and price components, these key business drivers can be forecasted, as reported in Table 34 of the appendix. Then, the valuation process can start.

Key value drivers | First, is the identification of key value drivers derived from the forecasted profit and loss statement and balance sheet as reported in Table 35 of the appendix (Koller et al. 2010). The key value drivers for the firm are: revenue growth displayed in Figure 6 and Figure 7, EBITDA displayed in Figure 8 and EBITDA-margin displayed Figure 9, CAPEX to depreciation displayed in Figure 10, net working capital (NWC) displayed in Figure 11, tax rate displayed in Figure 12 and the FCF displayed in Figure 13. The view on the development of the business going forward is fundamental to the development of the key value drivers (Koller et al. 2010). The forecast on the firm's key value drivers, especially the development of revenues, are quite in line with analysts' consensus.

Forecasting FCFs during planning period | Then, the expected future FCFs are forecasted. FCF is defined as the CFs (generated by the operating assets of the firm) available to both equity and debt holders (Koller et al. 2010). The overview of how FCFs are obtained during the PP is presented in Table 11 (Berk & DeMarzo 2007; Damodaran 2006 and Koller et al. 2010).

Table 11 Free cash flow definition

	Revenues
(-)	COGS
	Gross margin
(-)	G&A
(-)	Personnel cost
	EBITDA
(-)	Depreciation and amortization
	EBIT
(-)	Taxes over operating profit
	NOPLAT
(+)	Depreciation and amortization
(+)	Increase in operating provisions
(-)	Investments in operating NWC
(-)	Investments in fixed assets and intangibles
	FCF

Source: Berk & DeMarzo (2007); Damodaran (2006) and Koller et al. (2010)

Figure 6 Revenues (EURm)

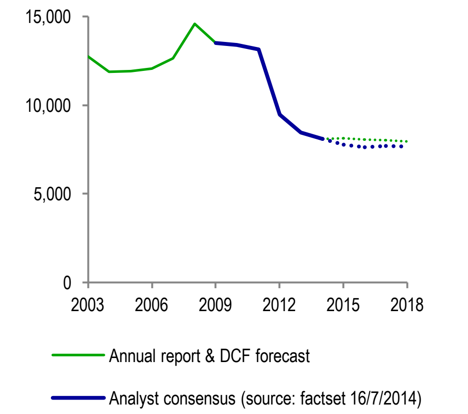


Figure 7 Revenue growth (YoY%)

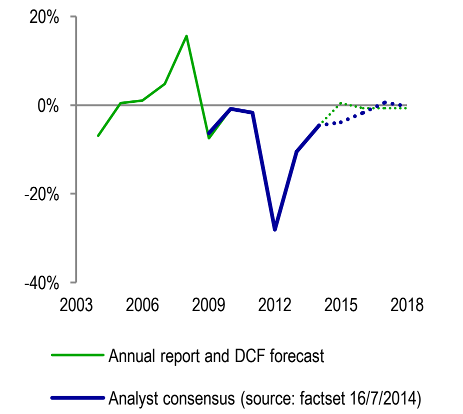


Figure 8 EBITDA (EURm)

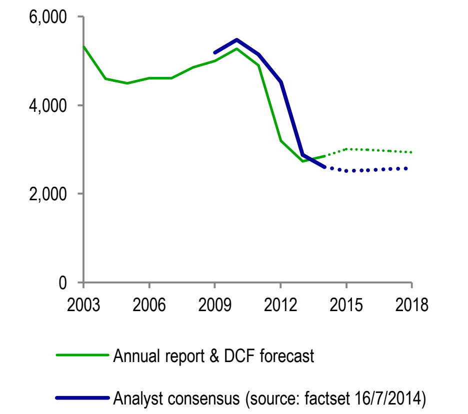


Figure 9 EBITDA-margin (%)

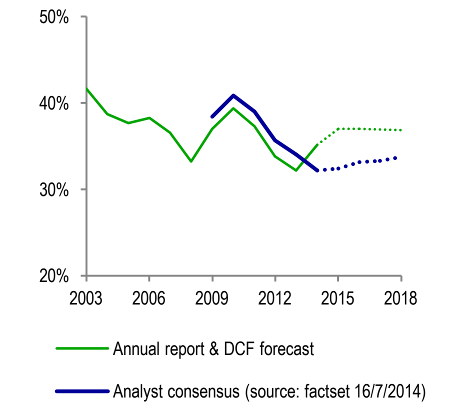


Figure 10 CAPEX to depreciation ratio (x)

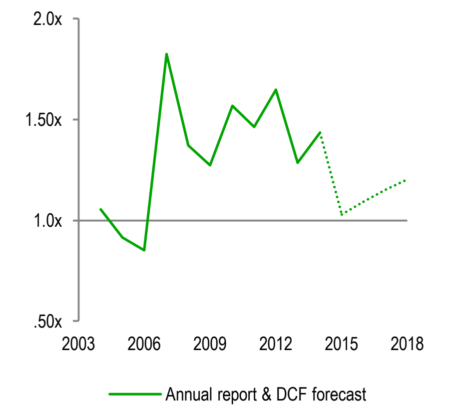


Figure 11 Net working capital (EURm)

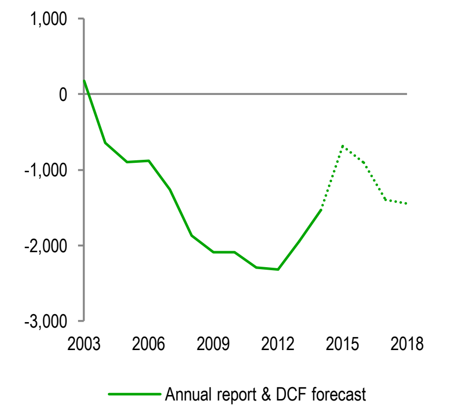


Figure 12 Tax rate (%)

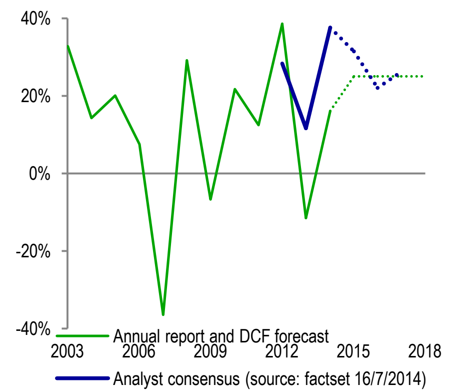
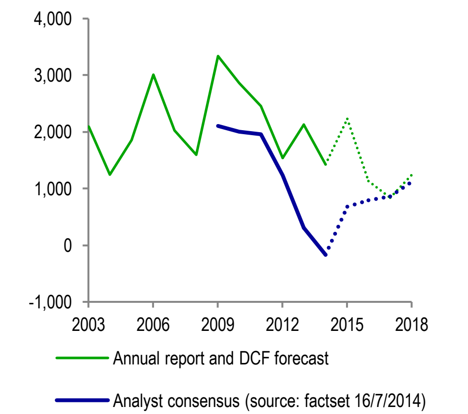


Figure 13 FCF (EURm)



These CFs are obtained assuming the firm is all equity financed; the financing effects will be incorporated in the valuation through the WACC (Koller et al. 2010).

Continuing value | Next, is the CV[29] to be derived, which is the value of the business going forward, after the PP (Koller et al. 2010). The value during and after the PP added together results in the EV (Koller et al. 2010). The value-driver model for deriving the CV by Koller et al. (2010) assumes that the firm generates a RONIC higher than the WACC. This implies that the firm maintains a competitive advantage in the near future (Koller et al. 2010). An alternative model for estimating the CV, the 'aggressive growth formula,' is expected to overestimate the CV, as it assumes that the firm will generate a RONIC which is approaching infinity (Koller et al. 2010). In contrast, the 'converge model' is expected to underestimate the CV of the firm, as it assumes that the firm will generate a RONIC equal to the WACC (Koller et al. 2010). So, the formula for deriving the CV_{t+1} (Eq. 17), which equals the key value driver formula (Eq. 1), is (Koller et al. 2010):

$$CV_{t+1} = \frac{\left[NOPLAT_{t+1}\left(1 - \frac{E(g_t)}{ROIC_t}\right) / \left(WACC - E(g_t)\right)\right]}{(1 + WACC)^{(t-0.5)}} \quad \text{Eq. 17}$$

Where $NOPLAT_{t+1}$ (Eq. 18) is the after-tax operating profit for all investors, which on its turn is defined as (Koller et al. 2010):

$$NOPLAT_{t+1} = EBIT_{t+1} - Operating\ taxes_{t+1} \quad \text{Eq. 18}$$

$E(g_t)$ (Eq. 19) is the estimated growth rate after the planning period and is defined as (Koller et al. 2010):

$$E(g_t) = ROIC_t * RR_t \quad \text{Eq. 19}$$

$ROIC_t$ (Eq. 20) is the return on invested capital and is defined as (Koller et al. 2010):

$$ROIC_t = \frac{NOPLAT_t}{Operating\ capital_t} \quad \text{Eq. 20}$$

RR_t (Eq. 21) is the reinvestment ratio and is defined as (Koller et al. 2010):

$$RR_t = \frac{Net\ investment_t}{NOPLAT_t} \quad \text{Eq. 21}$$

$Net\ investment_t$ (Eq. 22) is defined as (Koller et al. 2010):

$$Net\ investment_t = Investment\ in\ NWC_t + Total\ Capex_t - Depreciation_t \quad \text{Eq. 22}$$

Summing the value during and after the PP (CV), results in the EV (Eq. 23) (Koller et al. 2010):

$$EV = PV(FCF) + PV(CV) \quad \text{Eq. 23}$$

---

[29] The estimation of this value is critical as it significantly affects firm value (>50% of value) (Koller et al. 2010).

Adjustments to get to value of common equity is needed, because the CF implications of these assets and liabilities are not reflected in the expected FCF (Koller et al. 2010). The final step to be taken is to derive the equity value from the EV, this results in the value available to shareholders. The adjustments to the EV (Eq. 24) are as follows (Koller et al. 2010):

$$Equity\ value = EV + NOA - Nonequity\ claims \qquad \text{Eq. 24}$$

Where nonequity claims are: short-term debt, long-term debt, unfunded retirement liabilities, capitalized operating leases, and outstanding employee options (Koller et al. 2010).

Estimating WACC | The final step in the DCF valuation process, is to estimate the WACC (Eq. 25) (Koller et al. 2010). The WACC is the "composite forward looking after tax cost of capital of the firm and forms the discount factor for discounting the future expected CFs and CV, accounting for future CF risk" (Koller et al. 2010), and is defined as:

$$WACC = k_e \left[\frac{E}{(E + D)}\right] + k_d(1 - \tau_c)\left[\frac{D}{(D + E)}\right] \qquad \text{Eq. 25}$$

Where E and D are the proportion of equity and debt used to fund the business, k_e is the cost of equity, k_d is the pretax cost of debt and τ_c is the tax rate. The cost of equity (k_e) is estimated via the CAPM (Eq. 26) (Fama 1965):

$$k_e = E(R_i) = r_f + \beta_{e,i}[MRP + SFP_i] \qquad \text{Eq. 26}$$

Where $E(R_i)$ is the expected return for security i, r_f the risk free rate, MRP the market risk premium. The systematic market risk of the firm i's ($\beta_{e,i}$), reflects the correlation of returns with the returns of the market portfolio (Koller et al. 2010). The CAPM (Fama 1965) does not take into account the size of the firm, that may come with limited liquidity, higher default risk and limited trading volumes (Koller et al. 2010). In order not to underestimate the cost of equity (k_e) of small caps, a small firm premium (SFP_i) is added (Koller et al. 2010). The SFP depends on the firm's market capitalization (Koller et al. 2010), and is set in this case to 3.6%. The r_f is set to 1.5%; it is assumed that the very low current yield on a ten year German government bond (0.34% at 31/12/2014) will overestimate the CV of the firm. The MRP is given by an internal department of the firm and is set to 6%, which is in line with the market risk premium for well-developed capital markets (Koller et al. 2010). The equity beta ($\beta_{e,i}$) is derived by the relevering the unlevered beta using the Hamada (1972) (Eq. 27) formula:

$$\beta_{e,i} = \beta_u\left(1 + (1 - \tau_c)\frac{D}{E}\right) \qquad \text{Eq. 27}$$

Where β_u is the unlevered beta, implying that the firm is all equity financed (Hamada 1972), and reflects the risk of the operating assets (Koller et al. 2010). The unlevered beta for the firm equals 0.54[30]. Further, τ_c is the tax rate and D/E the target ratio debt to equity. The cost of debt (k_d) (Eq. 28) is estimated through the CAPM (Fama 1965) as well, denoted as:

[30] Source: Thomson Banker One (31/12/2014).

$$k_d = r_f + \beta_d * MRP + DRP \qquad \text{Eq. 28}$$

Where β_d is the beta of debt and DRP is the default risk premium (3.5%). The cost of debt (k_d) equals the promised yield to maturity (Koller et al. 2010). This is given the duration and rating set to investment grade bond (rating >BBB) (Koller et al. 2010). This is similar for high yield bonds (rating <BBB), with the exception that the default probability is taken into account (Koller et al. 2010). This is approximated by the yield on a BBB bond (Copeland 1979). The rating of Firm X is BBB-, which implies medium risk, resulting in a post-tax cost of debt (k_d) of 3.8% at a marginal tax rate of 25%.

Forecasting CE | Finally, the forecast on CE is estimated based on the CFOs resulting from the EBITDA forecast. These values are inserted into the CE formula (Eq. 29) in combination with assumptions on the forward looking retention rate ($r_{t_{1\ to\ 4}}$), discount rate ($d_{t_{1\ to\ 4}}$) and growth rate ($g_{t_{1\ to\ 4}}$).

4.2 Customer-based valuation models

The forecast of individual customer behavior, hence individual customer CFs, is rather complex. The firm is active in a multi-product industry, executing a multi-brand strategy, targeting multi-segments. This results in multidimensional customer purchase behavior. Due to this complexity, two 'basic' methods are introduced first in determining customer based benchmark values. First, a replication of the approach of Gupta et al. (2004) for calculating historical CE from publicly available information. The historical development of CE is linked to the historical share price of the firm, hence SHV. Then, in line with Donkers et al. (2003) a status quo model is developed. This model assumes a constant forecast on the total of individual customer EBITDA contributions during the PP. Finally, based on a combination of methods presented by Bolton et al. (2000), Donkers et al. (2003), Malthouse & Blattberg (2005) and Verhoef & Donkers (2001) an advanced forecast model is developed. This CBB valuation model combines various *profit regression models* in forecasting a customer's EBITDA contribution, hence SHV. Nine predictors of the profit models are 'updated' through various *behavior logit* models, forecasting individual customer behavior. The core of the CBB valuation model is the customer behavior value driver spectrum as presented in Figure 2.

4.2.1 Customer equity valuation model

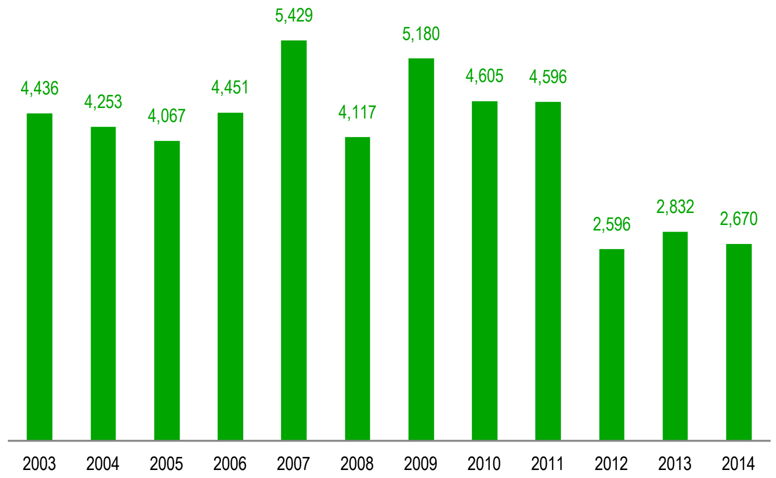
The method used for modelling historical CE based on publicly available data is to a large extent in accordance with Gupta & Lehmann (2003) and Gupta et al. (2004) method. With the only remark that, in order to obtain more accurate results, publicly available data is replaced by the firm's internal data when available. The CE model used, relies on the concept of CLV (Eq. 29), denoted as:

$$CE_t = \sum CLV_{i,t} = m_{i,t}\left(\frac{r_{i,t}}{1 + d_t - r_{i,t}}\right) * (1 + g_{i,t}) \qquad \text{Eq. 29}$$

Where CE_t at time t is the sum of all individual customer i lifetime values, $m_{i,t}$ is the margin, $r_{i,t}$ the retention rate, d_t the discount rate and $g_{i,t}$ is the growth rate incorporating acquisition.

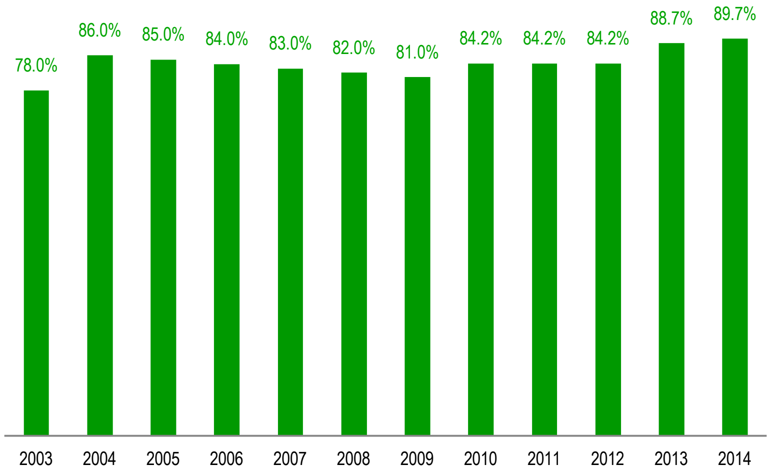
Model input | As a first input, the calculated annual CFOs (2003–2014) as displayed in Figure 14, serve as a proxy for margin ($m_{i,t}$).

Figure 14 Cash flow from operations 2003–2014 (EURm) ($\boldsymbol{m}$)



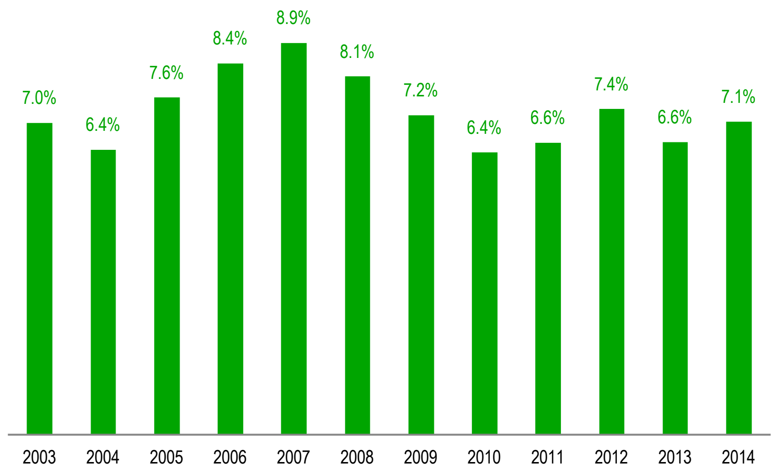
Source: Firm X annual reports and own calculations

Figure 15 Average annual retention rate 2003–2014 ($\boldsymbol{r}$)



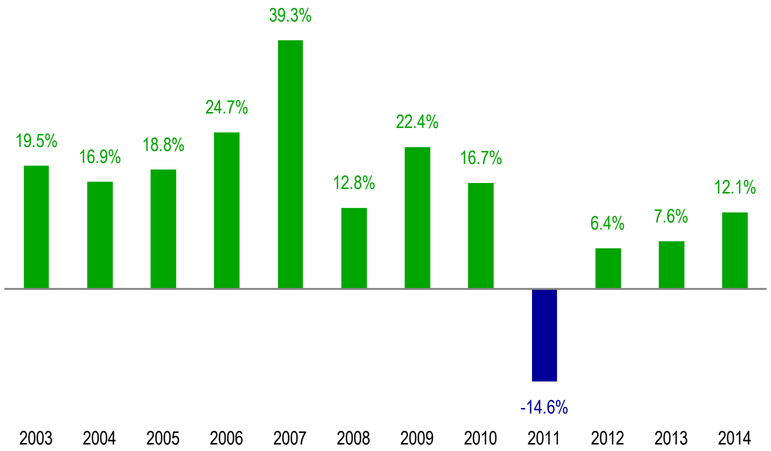
Source: Firm X annual reports, Integrated customer-centric dataset

Figure 16 Average post tax WACC 2003–2014 ($\boldsymbol{d}$)



Source: Firm X internal department

Figure 17 Growth rate after customer defection 2003–2014 ($\boldsymbol{g}$)



Source: Firm X annual reports and own calculations

To obtain the margin in EUR per customer, total CFO is divided by the average number of customers during that period. The next input is the retention rate ($r_{i,t}$) as displayed in Figure 15, which is one of the most difficult metrics to empirically estimate. For the years 2003–2009 the retention rates are derived from the annual report, for 2010–2012 the retention rate is set equal to the firm average computed over the years 2003–2009, 2013 and 2014. Finally, for 2013–2014 the retention rates are the calculated averages from the customer dataset for CM and BM as reported in Table 8. The retention rates are quite in line with Blattberg et al. (2001), who set the retention rate at 80% for the estimation period. The third input for the model is the firm level historical post-tax WACC representing the discount rate (d_t) as displayed in Figure 16. These rates are obtained from an internal department of the firm, which are roughly in line with the 8–12% that is normally used according to Gupta & Lehmann (2003). The final input for the model is the historical growth rate ($g_{i,t}$) (Eq. 30), which is derived from YOY growth of total net sales after the effect of retention ($r_{i,t}$) (hence defection) and acquisition, and is calculated as follows:

$$g_{i,t} = \left(\frac{total\ net\ sales_{t+1}}{total\ net\ sales_t * r_{i,t}}\right) - 1 \qquad \text{Eq. 30}$$

The growth rates presented in Figure 17 are actual growth rates (corrected for the effect of customer defection) and serve as a proxy for the historical forecasted next year's growth rate. The outcome of the model; the historical CE for every year during the period 2003-2014, is correlated with the historical share price[31] during that same period.

CE to SHV | CE is a proxy for firm value (Gupta & Lehmann 2003; Gupta et al. 2004), such that CE equals EV (Eq. 31):

$$EV_t = CE_t \qquad \text{Eq. 31}$$

In order to obtain SHV from CE a few financial adjustments are needed equal to the adjustments on EV to SHV (Eq. 24), such that SHV is (Eq. 32):

$$SHV_t = CE_t + NOA_t - Nonequity\ claims_t \qquad \text{Eq. 32}$$

4.2.2 Customer behavior based status quo valuation model

Donkers et al. (2003) introduce a status quo model, which serves as a benchmark model for the subsequent CBB valuation model. The mathematical model (Eq. 33) is:

$$EBITDA_{i,t_{+1}} = EBITDA_{i,t} \qquad \text{Eq. 33}$$

It assumes that the monthly EBITDA realized at time t (2014) simply remains constant during the planning period (2015–2018).

Composition EBITDA forecast | In the behavior based status quo valuation model total EBITDA consists of three components: (1) CM, (2) BM and (3) 'EBITDA not included in the dataset.' The formula (Eq. 34) for deriving the total annual EBITDA for CM and BM customers is straightforward:

[31] Source: Thomson One Banker (historical monthly share price 2003–2014).

$$Y_{i,t} = \sum_{i} (Own_{ij,t} * Rev_{ij,t} * EBITDAM_{j,t} * 12) \quad \text{Eq. 34}$$

Where $Y_{i,t}$ is the sum of EBITDA contribution per individual customer i, $Own_{ij,t}$ is a dummy for ownership for a particular BSP-combination (j) at time t, $Rev_{ij,t}$ and $EBITDAM_{j,t}$ are the corresponding revenues and EBITDA-margins aggregated on the BSP-level j, as reported in Table 5. The EBITDA that is not included in the dataset ($EBITDA_{NINCL,t}$), as a consequence of data availability (see chapter 3), is an average-based estimate (2013–2014; t_{-1}, t). The estimated amount is added as a fixed amount to every single year of the forecast and is calculated as follows (Eq. 35 through Eq. 37):

$$EBITDA_{NINCL,t} = EBITDA_{TOT,t} - E(EBITDA_{INCL,t}) \quad \text{Eq. 35}$$

Where, $EBITDA_{TOT,t}$ is total EBITDA reported in the annual report, $E(EBITDA_{INCL,t})$ is the 'normally' expected amount of EBITDA included in the dataset as a percentage of included revenues in the dataset, at time t. Then, $E(EBITDA_{INCL,t})$ (Eq. 36) is calculated as follows:

$$E(EBITDA_{INCL,t}) = EBITDAM_{TOT,t} * \sum Rev_{INCL,i,t} \quad \text{Eq. 36}$$

Where $EBITDAM_{TOT,t}$ is the total EBITDA-margin and $\sum Rev_{INCL,i,t}$ is the sum of the revenues for all individual customer i's included in the dataset, at time t. The total EBITDA-margin ($EBITDAM_{TOT,t}$) (Eq. 37) is calculated as follows:

$$EBITDAM_{TOT,t} = \frac{EBITDA_{TOT,t}}{Rev_{TOT,t}} \quad \text{Eq. 37}$$

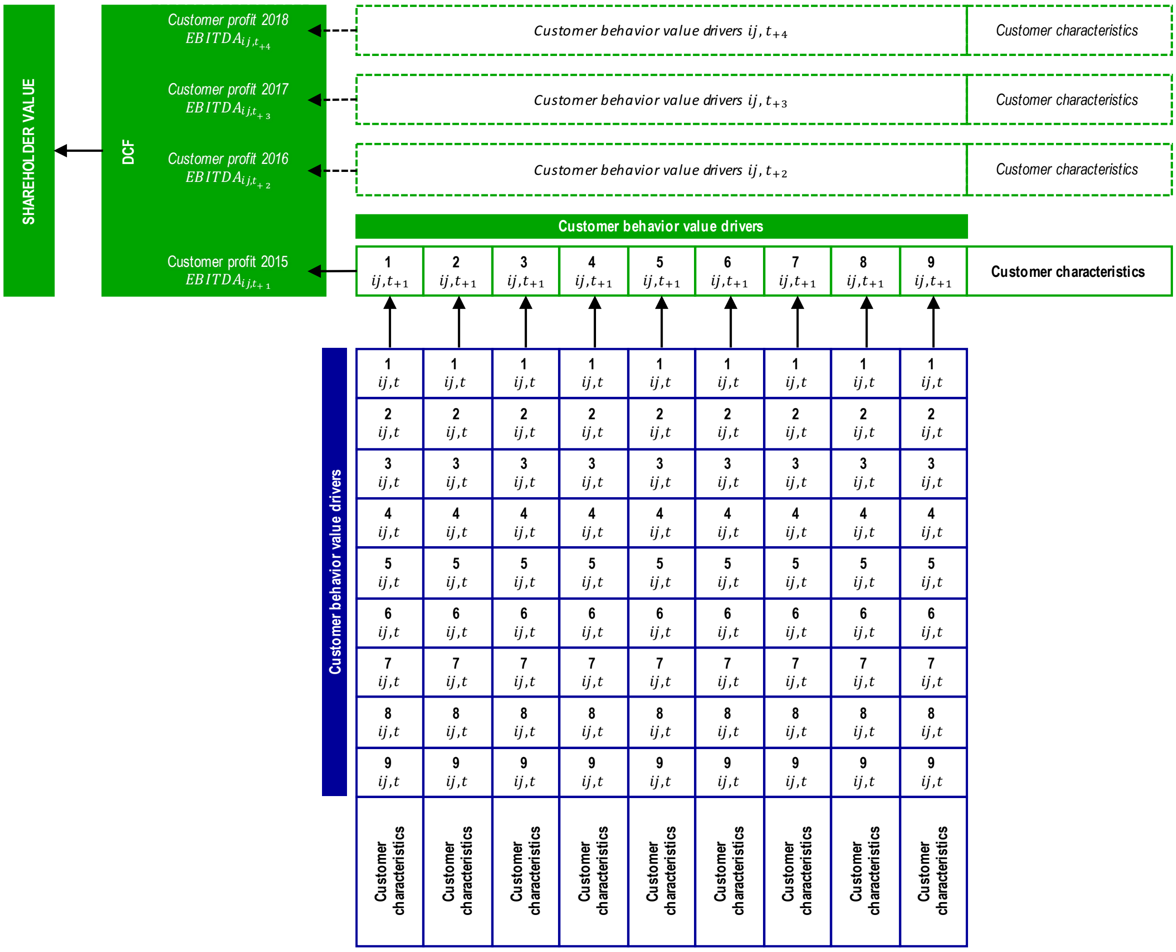
Where, $EBITDA_{TOT,t}$ is the total EBITDA and $Rev_{TOT,t}$ are total revenues at time t, taken from the annual report of the firm.

Merging forecast output | In order to obtain the amount of SHV from the customer behavior based status quo valuation model forecast, the obtained EBITDA during the planning period is inserted into the DCF valuation model. Both models merge on the level of 'EBITDA' as presented in Table 11. From here the last part of the model continues until the end with DCF valuation methodology.

4.2.3 Customer behavior based valuation model

The CBB valuation model originates from a combination of methods presented by Bolton et al. (2000), Donkers et al. (2003), Malthouse & Blattberg (2005) and Verhoef & Donkers (2001). The derived framework is displayed in Figure 18, revealing that the model forecast is entirely algorithm driven. For each year of the PP (2015–2018) 4 horizontal 'main-algorithms,' forecast an individual customer's EBITDA contribution. Then, 9 vertical sub-algorithms 'update' the predictor values, the customer behavior value driver probability, based on Figure 2, in each of the 4 'main-algorithms.' The 'main-algorithms' consists of a multiple linear regression model, called the 'profit regression models.' And the 'sub-algorithms' consists of a binary logistic regression model, called the 'behavior logit models.'

Figure 18 CBB valuation framework



Source: Framework derived from Bolton et al. (2000), Donkers et al. (2003), Malthouse & Blattberg (2005) and Verhoef & Donkers (2001)

Both models use the customer characteristics as reported in Table 6, recoded into dummy variables, serving as predictors. The models customer behavior value driver predictors are derived from observed customer behavior transitions between periods 2012–2013 and 2013–2014. The customer characteristic predictors are assumed to remain stable over time and are observed in 2014. Profit regression estimation is based on a long-body dataset with the DV consisting of EBITDA observed in 2013 and 2014, with the corresponding IVs derived from transition periods.

Additional data preparation | Introducing the custom behavior value driver concept, in analogy with DCF valuation methodology, creates a 'new layer' in the dataset based on the traditional derived RFM variables (Donkers et al. 2003). This resolves the shortcoming in the dataset based on data asymmetry[32] (see chapter 3), and prevents biased model estimates.

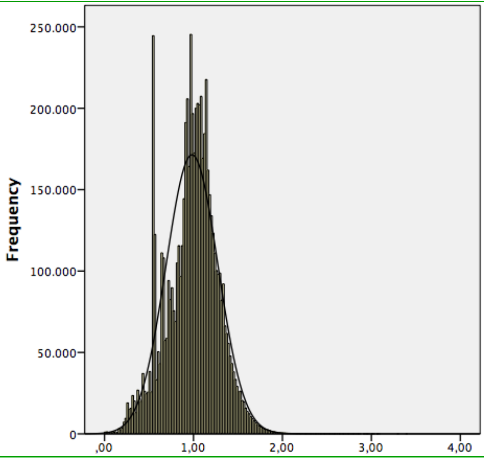
Dependent variable | The distribution of the DV for the CM model is displayed in Figure 19 and for BM in Figure 20. Both approximate a normal distribution after a 'first-aid' *logarithm transformation*[33] (Eq. 38) is performed, in order to deal with positive skewness:

$$Logarithm\ transformed\ EBITDA = \log_{10}(EBITDA + 1) \qquad \text{Eq. 38}$$

[32] "Asymmetrical data causes that variables can't be used for the forecast of individual customer profitability" (Verhoef & Donkers 2001).

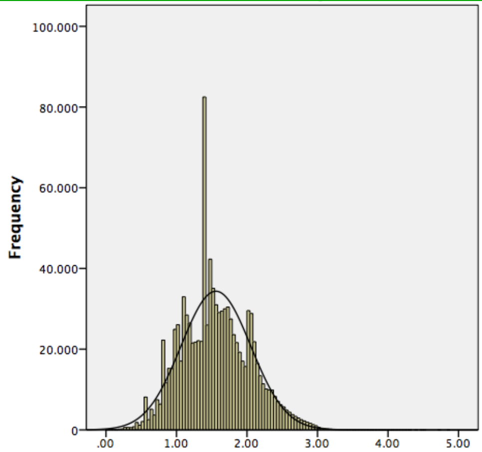
[33] When obtaining the results from the profit regression model, the output requires an inverse logarithm transformation in order to obtain the EBITDA values.

Figure 19 DV distribution log transformed EBITDA - CM



Source: Firm X integrated customer-centric dataset

Figure 20 DV distribution log transformed EBITDA - BM (excl. outliers)



Source: Firm X integrated customer-centric dataset

In addition, for BM model *outliers* have been removed by trimming[34] the data, in accordance with Mosteller & Tukey (1977). The lower threshold is determined as follows (Eq. 39):

$$Lower\ threshold = Q_1 - factor * (Q_3 - Q_1) \qquad \text{Eq. 39}$$

And the upper threshold is determined as follows (Eq. 40):

$$Upper\ threshold = Q_3 + factor * (Q_3 - Q_1) \qquad \text{Eq. 40}$$

The quartiles Q_1 and Q_3 are determined by analysis in SPSS, resulting in 4.775 and 14.433 respectively, the 'factor' value is 2.2 (Mosteller & Tukey 1977). This results in a lower bound of -16.473 (set equal to 0, as there are no log values lower than 0), and an upper bound of 35.681.

Predictor variables | The 'main' predictors in both profit regression and behavior logit models are the customer behavior value drivers (dummies / probabilities). Then, the customer characteristics recoded into dummy variables, complement the main predictors. The last predictor is 'EBITDA in the previous period'. The distribution of this last predictor variable for the CM model is displayed in Figure 21 and for BM in Figure 22. Both approximate a normal distribution after a 'first-aid' logarithm transformation as well. The predictors account for a 'non-linear effect' (Mosteller & Tukey 1977), based on the combined nature of dummy and log transformed variables. Hence, the assumption of linearity is not violated.

Restructuring dataset | Before the models can be estimated, extensive restructuring of the dataset from 'wide to long' is needed. A 'wide-body' format is needed when deriving the customer behavior value driver dummies and total EBITDA. However, a 'long-body' format is needed for model estimation.

Composition EBITDA forecast | The CBB valuation model, compared to the customer behavior based status quo valuation model, consists of three additional EBITDA components. For the customer behavior based status quo valuation model these were: (1) customer base CM, (2) customer base BM, (3) 'non-included in the dataset.' The additional components are: (4) potential CM, (5) potential BM and (6) 'outlier EBITDA' not included in the model.

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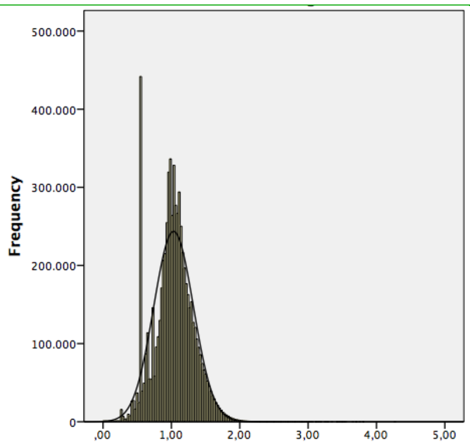
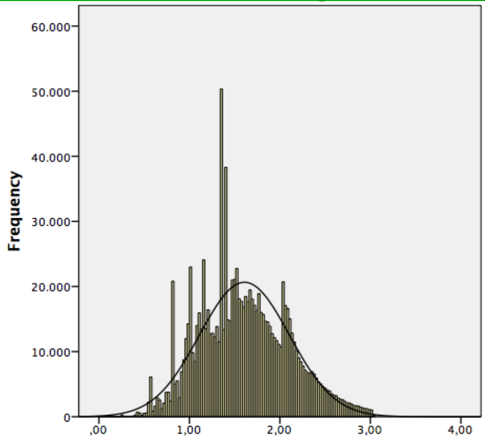
[34] The effect of 1% Winsorizing (Hasings et al. 1947; Tukey 1962) on the DV has been examined as well. Values greater than the 99th percentile are set equal to the 99th percentile, resulting in an extreme observation at the end of the distribution tail. Concluding that the Winsorization procedure is not appropriate for data preparation in this case.

Figure 21 Predictor distribution log transformed EBITDA - CM



Source: Firm X integrated customer-centric dataset

Figure 22 Predictor distribution log transformed EBITDA - BM (excl. outliers)



Source: Firm X integrated customer-centric dataset

The derivation of the new components will be explained next. First, EBITDA from potential customers (CM and BM) results from the customer characteristic variables. As potential customer's equal non-customers, there is no observation for these customers on the customer behavior value drivers. In addition, both market segments (CM and BM) have their own unique characteristic predictors, avoiding 'the allocation' of CM value at BM and vice versa. Then, the amount of total outlier EBITDA ($EBITDA_{out,t}$) arises from the sum of customers that are excluded from the analysis because of data trimming (Eq. 41):

$$Total\ EBITDA_{out,t} = \sum_{i} EBITDA_{i,out,t} \qquad \text{Eq. 41}$$

In the results chapter it will become clear how relevant these 'outlier-customers' are in terms of EBITDA contribution. Total outlier EBITDA for the next period ($EBITDA_{out,t_{+1}}$) is estimated as follow (Eq. 42):

$$Total\ EBITDA_{out,t_{+1}} = Total\ EBITDA_{out,t} * \left(1 + i_{r,t}\right) \qquad \text{Eq. 42}$$

It is assumed that for each year of the PP this fixed amount of outlier EBITDA grows by the forward looking inflation rate ($i_{r,t}$), fixed at 1.5%. In addition, it is assumed that the customers behind the outlier EBITDA remain with the firm during the PP, so that incorporating the retention rate (r) is not needed[35]. Now, the six components can be added together for deriving total EBITDA (Eq. 43):

$$Total\ EBITDA_t = Base_{CM,t} + Pot._{CM,t} + Base_{BM,t} + Pot._{BM,t} + Out._{BM,t} + Nonincl_t \qquad \text{Eq. 43}$$

Merging forecast output | In order to obtain the amount of SHV from the customer behavior based valuation model forecast, the obtained EBITDA during the planning period is inserted into the DCF-model. Both models merge

[35] "Outlier customers are exceptionally large customers in terms of EBITDA, as they represent 56% (2014) of total BM EBITDA (EUR 764m). However, in terms of numbers of customers they only account for 1.8% (2014) of total BM customers. The average EBITDA for an 'outlier' (or large) customer is EUR 65,000 (2014), compared to an average of EUR 955 (2014) for all other business customers. It is likely that the exceptional large size of these customers directly affects each customer's retention probability. Or in other words, because of their large size it is not likely for these customers to leave Firm X.

on the level of 'EBITDA' as presented in Table 11. From here the last part of the model continues with DCF valuation methodology.

SHV range (95% CI) | EBITDA is calculated for three different scenarios: the base case, low and high. For the low- and high-scenarios, parameter estimates for the lower and upper bound of the 95% CI are used. Then, for each scenario the 4 profit equations and 9 behavior logit[36] equations are solved, resulting in three EBITDA values per customer. These values then again merge into the DCF valuation model. The behavior logit models report exponential betas on the CI estimates. In order to prepare these parameters for equation solving, the inverse needs to be obtained (Eq. 44):

$$\beta = \ln\left(e^{\beta}\right) \qquad \text{Eq. 44}$$

SHV contribution per customer behavior value driver | Next, now that scenario analysis has set the lower and upper bound of the SHV range, is to determine the SHV contribution range per customer behavior value driver. In order to obtain the range of SHV contribution per driver, the value is estimated for the low and high scenarios. The exact same procedure for estimating the SHV range is applied here as well. However, there is one difference. In order to estimate the isolated SHV contribution of one customer behavior value driver, the SHV is estimated by eliminating[37] the concerning driver. In other words, all corresponding values are set to '0' for the concerning value driver. Now SHV can be estimated without the concerning customer behavior value driver. Then, this SHV outcome is subtracted from the 'full-model' (including all value drivers) outcome, resulting in the SHV contribution for the corresponding customer behavior value driver.

Incremental SHV at customer behavior value driver improvement | Almost a similar method will be applied in determining the impact of an improvement of a particular customer behavior value driver. However, an improvement in value driver means in practice an improvement of the customer probability for the corresponding value driver. This implies that for all customers in the customer base their probability on a value driver is improved by a certain fixed percentage. Then again, the difference in outcome is the estimated incremental SHV when improving the customer probabilities for the concerning value driver.

Forecasting CE | Finally, the forecast on CE is estimated based on the CFOs resulting from the EBITDA forecast. These values are inserted into the CE formula (Eq. 29) in combination with assumptions on the forward looking retention rate ($r_{t_1\, to\, 4}$), discount rate ($d_{t_1\, to\, 4}$) and growth rate ($g_{t_1\, to\, 4}$).

4.2.3.1 Profit regression model

The profit regression model is a multiple linear regression model, aiming to forecast a customer's EBITDA contribution (Malthouse & Blattberg 2005) for each year of the planning period (2015–2018). The general idea behind the profit regression model is as follows (Eq. 45):

$$\sum_{i} EBITDA_{ij,t_{+1}} = f\left\{P\left(X_{nij,t_{+1}}\right), E_{nij,t}, C_{nij}\right\} \qquad \text{Eq. 45}$$

[36] For the logit equations, for each year the same scenario-type output is used as input for the same scenario-type in the next year. Or in other words, the output for the low-scenario is used as input for the low-scenario of the next period.

[37] Given that all else remains the same.

Where the next periods total EBITDA ($\sum_i EBITDA_{ij,t_{+1}}$) is a function of the probability forecast on the 9 customer behavior value drivers ($X_{nij,t_{+1}}$), the EBITDA observed in this period ($E_{nij,t}$) and the customer characteristics (C_{nij}) for customer i in market segment j. The mathematical model for parameter estimation is (Eq. 46):

$$Y_{ij,t} = \alpha + \beta_{1j}X_{1ij,t} + \cdots \beta_{9j}X_{9ij,t} + \beta_{10j}E_{10ij,t_{-1}} + \cdots \beta_{nj}C_{nij} + \varepsilon_j \qquad \text{Eq. 46}$$

Where $Y_{ij,t}$ is the computed total log EBITDA contribution from Eq. 34 of customer i, in market segment j (CM or BM), in period t. For model estimation the dataset is restructured into a long-body format, so that $Y_{ij,t}$ consists of EBITDA in 2013 (t_{-1}) and 2014 (t). The model intercept is α, $X_{1-9ij,t}$ are the observed customer behavior value drivers modelled into dummies based on customer purchase behavior. The variables are observed from transitions in purchase behavior between 2012–2013 and 2013–2014. Then, $E_{10ij,t_{-1}}$ is the observed EBITDA contribution from the previous period, observed in 2012 (t_{-2}) and 2013 (t_{-1}). And C_{nij} are the various customer characteristic predictors (dummy variables) for customer i in market segment j during period t. Then, β_{nj} are the corresponding estimated parameters and ε_j is the error term of the model. The model parameters are estimated separately for both the CM and BM segment j.

Forecasting four periods ahead | In line with the other models (DCF valuation and customer behavior based status quo valuation) the CBB valuation model forecast as well four periods ahead (2015–2018). The customer behavior value driver predictor variables ($X_{1-9ij,t_{+1-4}}$) are forecasted each by the 9 behavior logit models. Or in other words the various logit models 'forecast the forecasters.' The logit model is presented in more detail in the next paragraph. Then, the log EBITDA variable ($E_{10ij,t}$) from the previous period is simply entered into the forecast equation. Finally, for reasons of simplicity it is assumed that the customer characteristic (C_{nij}) variables remain stable over time. This results in the first forecast equation (2015; t_{+1}) on the individual customer EBITDA contribution, which is denoted as follows (Eq. 47):

$$Y_{ij,t_{+1}} = \alpha + \beta_{1j}X_{1ij,t_{+1}} + \cdots \beta_{9j}X_{9ij,t_{+1}} + \cdots \beta_{10j}E_{10ij,t} + \cdots \beta_{nj}C_{nij} \qquad \text{Eq. 47}$$

The equation for 2016 (t_{+2}) is as follows (Eq. 48):

$$Y_{ij,t_{+2}} = \alpha + \beta_{1j}X_{1ij,t_{+2}} + \cdots \beta_{9j}X_{9ij,t_{+2}} + \cdots \beta_{10j}E_{10ij,t_{+1}} + \cdots \beta_{nj}C_{nij} \qquad \text{Eq. 48}$$

The same methodology applies for the last two years of the PP; 2017 (t_{+3}) and 2018 (t_{+4}).

4.2.3.2 Behavior logit model

The behavior logit model is a binary logistic regression model, aiming to forecast the probabilities for each of the 9 individual customer behavior value drivers. The forecast on these probabilities are calculated for each year of the PP (2015–2018) and serve as the input values ($X_{1-9ij,t_{+1-4}}$) in the 4 profit regression models. In addition, the forecasted probabilities serve again in the next periods behavior logit model as input in forecasting the next period's probability for each customer behavior value driver. In other words, the next period's customer behavior is depending on this period's behavior. The transition of probabilities from on to the other period is based on a Markov chain model. Pfeifer & Carraway (2000) have used Markov chains to model customer relationship developments. The general idea behind the behavior logit model is as follows (Eq. 49):

$$P\left(X_{nij,t_{+1}}\right) = f\left\{P\left(X_{nij,t}\right), C_{nij}\right\} \quad \text{Eq. 49}$$

Where the next period's forecasted probability ($P\left(X_{nij,t_{+1}}\right)$) for customer i's behavior value drivers (n_{1-9}) in market segment j, is a function of the observed probabilities in the previous period and the observed customer characteristics (C_{nij}). The mathematical model (Eq. 50) for parameter estimation is:

$$P\left(X_{nij,t}\right) = \frac{1}{1 + e^{-(\alpha+\beta_{1j}X_{1i,t_{-1}}+\cdots\beta_{9j}X_{9ij,t_{-1}}+\cdots\beta_{nj}C_{nij}+\varepsilon_j)}} \quad \text{Eq. 50}$$

Where $P\left(X_{nij,t}\right)$ are the observed 'probabilities,' which are dummy variables with a 'probability' of either '0' or '1,' concerning the various customer behavior value drivers (n_{1-9}) for customer i, in market segment j and in period t. Further, α is the model intercept, $X_{1-9i,t_{-1}}$ are the observed 'probabilities,' which are also dummy variables with a 'probability' of either '0' or '1,' concerning the various customer behavior value drivers (n_{1-9}) for customer i, in market segment j, but then from the previous period (t_{-1}). Then, C_{nij} are the observed customer characteristic dummy variables. Finally, β_{nj} are the corresponding estimated parameters and ε_j is the error term.

Forecasting four periods ahead | The forecast on the probabilities for the customer behavior value driver variables ($X_{1-9ij,t_{+1-4}}$) is performed by a unique behavior logit model for each of the variables. This results in the first forecast equation for 2015 (t_{+1}) on the individual customer EBITDA contribution, which is denoted as follows (Eq. 51):

$$P\left(X_{nij,t_{+1}}\right) = \frac{1}{1 + e^{-(\alpha+\beta_{1j}X_{1i,t}+\cdots\beta_{9j}X_{9ij,t}+\cdots\beta_{nj}C_{nij})}} \quad \text{Eq. 51}$$

Where $P\left(X_{nij,t_{+1}}\right)$ is the estimated customer behavior value driver probability between 0 and 1 in the next period 2015 (t_{+1}). Only the first year of the forecast period uses the originally observed dummy variables ($X_{ni,t}$) from 2014 (t) as input for this estimation. Then, the equation for 2016 (t_{+2}) is as follows (Eq. 52):

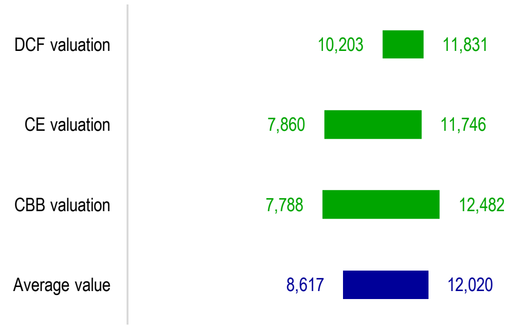
$$P\left(X_{nij,t_{+2}}\right) = \frac{1}{1 + e^{-(\alpha+\beta_{1j}X_{1i,t_{+1}}+\cdots\beta_{9j}X_{9ij,t_{+1}}+\cdots\beta_{nj}C_{nij})}} \quad \text{Eq. 52}$$

Where $X_{1i,t_{+1}}$ is the forecasted probability value input (between 0–1), resulting from the previous period behavior logit equation (Eq. 51). Finally, the same methodology applies for the last two years of the PP, 2017 (t_{+3}) and 2018 (t_{+4}), for all the 9 predictor variables.

5. Results

The main results from the DCF valuation model, the CE valuation model and the CBB valuation model are presented in Figure 23. The scenario analysis results for these three models in a SHV range of EUR 10.2–11.8b, 7.9–11.7b and 7.8–12.5b (2014) respectively. In terms of price per share this is EUR 2.39–2.77, 1.84–2.75 and 1.82–2.92 (2014) respectively. The following paragraphs will discuss in more detail the obtained SHV results. Overall, DCF, CE and CBB valuation models yield fairly similar results in terms of SHV, yet deliver very different but complementary insights.

Figure 23 Shareholder value ranges per valuation model (EURm)



Source: Firm X integrated customer-centric dataset

5.1 Discounted cash flow value

The DCF valuation model results a SHV of EUR 10.9b [10.2–11.8] (2014) for the base case scenario, as reported in Table 12. This equals a value per share of EUR 2.56 [2.39–2.77] (2014). The actual share price is EUR 2.63[38] (31/12/2014), indicating a quite well calibrated DCF valuation model. Table 36 in the appendix reports the DCF valuation scenario analysis.

Table 12 DCF valuation

BASE CASE SCENARIO		
Value during planning period		4,860
Value after planning period (CV)	(+)	12,968
Enterprise value		**17,828**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**10,922**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR) (per 31/12/2014)		**2.56**
Long term growth rate		1.5%

[38] Source: Thomson One Banker.

The discounted cash flow statement is reported in Table 13. The forecast on EBITDA remains fairly stable. NOPLAT increases steadily as a result from decreasing depreciation and amortization charges. The obtained $NOPLAT_{t+4}$ (2018), the last period of the PP is the fundamental value on which the CV (Eq. 17) is based. Any fluctuations in the forecast of $NOPLAT_{t+4}$has a large impact on the total value of the firm, hence SHV. The forecast on the FCF fluctuates considerably, as a result from changes in CFI driven by changes in the NWC of the firm.

Table 13 Discounted cash flow statement

Year to	12/2014a	12/2015f	12/2016f	12/2017f	12/2018f
EBITDA	**2,843**	**3,007**	**2,988**	**2,962**	**2,935**
Depreciation and amortization	(1,769)	(1,880)	(1,761)	(1,663)	(1,581)
EBIT	**1,074**	**1,127**	**1,228**	**1,300**	**1,354**
Taxes over operating profit	(173)	(282)	(307)	(325)	(338)
NOPLAT	**901**	**845**	**921**	**975**	**1,015**
Depreciation and amortization	1,769	1,880	1,761	1,663	1,581
Cash flow from operations (CFO)	**2,670**	**2,725**	**2,681**	**2,637**	**2,597**
Net CAPEX PPE	(986)	(958)	(943)	(929)	(914)
Net CAPEX Intangibles	(711)	(379)	(381)	(383)	(384)
Increase(decrease) in operating NWC	412	841	(219)	(487)	(55)
Increase(decrease) in deferred tax liabilities	(43)	(1)	(1)	(1)	(1)
Increase(decrease) in provisions	79	(2)	(2)	(2)	(2)
Cash flow from investment (CFI)	**(1,249)**	**(498)**	**(1,546)**	**(1,801)**	**(1,356)**
Free cash flow (FCF)	**1,421**	**2,227**	**1,136**	**836**	**1,241**
Discount rate		0.97	0.90	0.84	0.79
PV of FCF		**2,152**	**1.025**	**705**	**977**

The obtained FCFs are discounted at the WACC, estimated at 7.1% as reported in Table 14, resulting in the PV of the FCF. The PV of FCFs added together results in the value during the PP.

Table 14 Weighted average cost of capital

BASE CASE SCENARIO	
Risk-free rate	1,5%
Default risk premium	3,5%
Cost of debt	**5,0%**
Marginal tax rate	25,0%
Cost of debt after taxes	**3,8%**
Risk-free rate	1,5%
Market risk premium (MRP)	6,0%
Unlevered beta[39]	0,54
Target D/E	**66,7%**
Relevered beta	**0,81**
Additional risk premia (SFP)	3,6%
Cost of common equity	**9,3%**
Cost of preferred equity	0%
Target interest-bearing debt	40%
Target preferred equity	0%
Target common equity	**60%**
WACC	**7,1%**

The DCF valuation methodology forms the foundation of translating forecasted EBITDA into SHV for all the models presented. Therefore, a well calibrated DCF valuation model is vital for obtaining 'real-world' results. In addition, the obtained SHV through the DCF valuation model serves as a benchmark value for the SHV obtained through the CBB valuation model, for later comparison of both models.

[39] Source: Thomson One Banker.

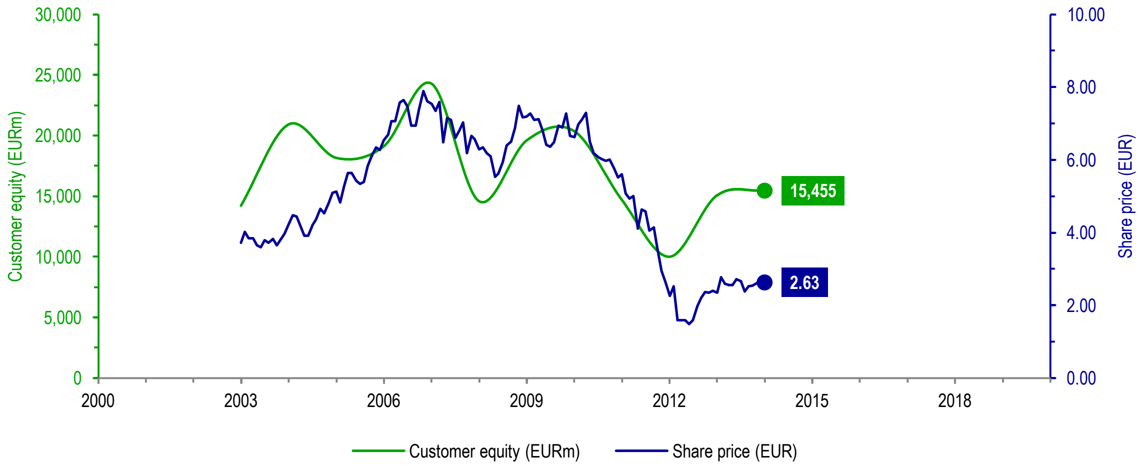
5.2 Customer-based values

The customer-based SHV ranges are estimated by the following models: (1) the CE valuation model, (2) the customer behavior based status quo valuation model and (3) the customer behavior based valuation model. The estimation results are all quite in line in comparison to the estimated SHV range produced by the DCF valuation model. The first customer based value insights are obtained from the CE valuation model. The model finds a positive correlation between the historical CE and the historical share price (2003–2014) of the firm. In addition to this it's found that improvements in the customer retention rate yields substantial improvements in CE, hence SHV. The next customer based insights are obtained from the customer behavior based status quo valuation model. This model merely sets a benchmark value for the CBB valuation model. The model assumes a 'status quo' in total EBITDA for each year of the PP, so that total EBITDA (in 2015–2018) is set equal to the observed total EBITDA in 2014. The final customer based insights are obtained from the CBB valuation model. The model successfully and accurately analysis, forecasts and values individual customer behavior, providing highly valuable new insights.

5.2.1 Customer equity value

The derived historical movements in CE[40] and the observed historical movements in share price are positively correlated ($R = 0.695$) as displayed in Figure 24. Where in 2014 (t) CE is EUR 15.5b at a share price of EUR 2.63 (31-12-2014). This result indicates that, in line with Gupta & Lehmann (2003) and Gupta et al. (2004), that CE (or the sum of CLVs) is potentially a relevant and good proxy for SHV. However, deeper going insights on the link between CE and SHV are required.

Figure 24 Customer equity and share price 2003–2014



Source: Firm X annual reports 2003-2014; Thomson One Banker

CE impact at variable improvement | In addition, it is found that for 2014 an improvement of 100 basis points in the *retention rate* (r) (up to 90.7%) all else being equal, results in an increase of CE by 7.3% (+EUR 1,127m). A similar improvement of 100 basis points in the *discount rate* (d) (down to 6.1%) all else being equal, results in an increase of CE by 6.1% (+EUR 944m). An improvement of 100 basis points in the overall *growth rate* (g) (up to 13.1%)

[40] The input for the CE derivation is displayed in Figure 14, Figure 15, Figure 16 and Figure 17.

all else being equal, results in an increase of CE by 0.9% (+EUR 138m). These results, consistent with the findings of Gupta & Lehmann (2003) and Gupta et al. (2004), indicate that improvements in the customer retention rate (r) yields the highest increase in CE. A range of corresponding CE values, based on a fixed discount rate but simulating various retention and growth rate scenarios is reported in Table 15.

Table 15 Customer equity (EURb)

CUSTOMER EQUITY BY DIFFERENT RETENTION AND GROWTH RATES											
Year to	2014										
	Growth rate (g)										
Retention rate (r)	7.1%	8.1%	9.1%	10.1%	11.1%	12.1%	13.1%	14.1%	15.1%	16.1%	17.1%
84.7%	10.83	10.93	11.03	11.13	11.23	11.33	11.43	11.53	11.64	11.74	11.84
85.7%	11.47	11.57	11.68	11.79	11.89	12.00	12.11	12.22	12.32	12.43	12.54
86.7%	12.17	12.28	12.40	12.51	12.62	12.74	12.85	12.97	13.08	13.19	13.31
87.7%	12.95	13.07	13.19	13.31	13.43	13.55	13.67	13.79	13.91	14.03	14.15
88.7%	13.81	13.93	14.06	14.19	14.32	14.45	14.58	14.71	14.84	14.97	15.10
89.7%	14.77	14.90	15.04	15.18	15.32	15.45	15.59	15.73	15.87	16.01	16.14
90.7%	15.84	15.99	16.14	16.29	16.43	16.58	16.73	16.88	17.03	17.17	17.32
91.7%	17.06	17.22	17.38	17.54	17.70	17.86	18.01	18.17	18.33	18.49	18.65
92.7%	18.44	18.62	18.79	18.96	19.13	19.31	19.48	19.65	19.82	19.99	20.17
93.7%	20.04	20.22	20.41	20.60	20.79	20.97	21.16	21.35	21.53	21.72	21.91
94.7%	21.89	22.09	22.30	22.50	22.71	22.91	23.12	23.32	23.52	23.73	23.93
Post-tax WACC (d)						7.1%					

Source: Firm X integrated customer-centric dataset (based on Gupta et al. (2004))

CE into SHV | The estimated CE of EUR 15.5b (2014) (given the values of the other variables retention rate, discount rate and growth rate in 'green' in Table 15) is translated into SHV through (Eq. 32). In addition, a low and a high scenario are simulated based on the retention and growth values marked in 'blue' and the fixed discount rate as reported in Table 15. The CE based scenario valuation is reported in (Table 17) and yields a quite similar SHV range EUR 8.5b [7.9–11.7] (2014), compared to the DCF valuation model EUR 10.9b [10.2–11.8] (2014).

5.2.2 Customer behavior based status quo value

The SHV estimated by the customer behavior based status quo model is EUR 12.5b (2014) equaling a value per share of EUR 2.93 (2014) as reported in Table 16.

Table 16 Customer behavior based status quo valuation

ONE SCENARIO		
Value during planning period		5,120
Value after planning period (CV)	(+)	14,301
Enterprise value		**19,421**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**12,515**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**2.93**
Long term growth rate		1.5%

Table 17 Customer equity valuation (EURm)

Base case scenario
- Growth 12.1%
- Retention 89.7%

Customer equity		**15,455**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value		**8,549**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**2.00**

Low case scenario
- Growth -500 basis points with respect to base case scenario

Customer equity		**14,765**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value		**7,860**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**1.84**

High case scenario
- Growth +500 basis points with respect to base case scenario
- Retention improvement +200 basis points with respect to base case scenario

Customer equity		**18,652**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value		**11,746**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**2.75**

Source: Firm X annual report, own calculations

The model assumes that the realized total EBITDA contribution from all individual customers in 2014 simply remains constant during the forecast period as reported in Table 18.

Table 18 Customer behavior based status quo cash flow statement

Year to	12/2014a	12/2015f	12/2016f	12/2017f	12/2018f
Free cash flow (EURm)					
EBITDA	**3,074**	**3,074**	**3,074**	**3,074**	**3,074**
Depreciation and amortization	(1,769)	(1,880)	(1,761)	(1,663)	(1,581)
EBIT	**1,305**	**1,194**	**1,314**	**1,412**	**1,493**
Taxes over operating profit	(326)	(299)	(328)	(353)	(373)
NOPLAT	**979**	**896**	**985**	**1,059**	**1,120**
Depreciation and amortization	1,769	1,880	1,761	1,663	1,581
Cash flow from operations (CFO)	**2,748**	**2,776**	**2,746**	**2,722**	**2,701**
Net Capex PPE	(986)	(958)	(943)	(929)	(914)
Net Capex Intangibles	(711)	(379)	(381)	(383)	(384)
Increase(decrease) in operating NWC	412	841	(219)	(487)	(55)
Increase(decrease) in deferred tax liabilities	(43)	(1)	(1)	(1)	(1)
Increase(decrease) in provisions	79	(2)	(2)	(2)	(2)
Cash flow from investment (CFI)	**(1,249)**	**(498)**	**(1,546)**	**(1,801)**	**(1,356)**
Free cash flow (FCF)	**1,499**	**2,278**	**1,200**	**921**	**1,345**
Discount rate		0.97	0.90	0.84	0.79
PV FCF		**2,201**	**1,083**	**776**	**1,059**

The obtained SHV merely serves as a benchmark value for the outcome in the base case scenario of the CBB valuation model.

5.2.3 Customer behavior based value

The CBB valuation model estimates SHV at EUR 9.4b [7.8–12.5] (2014), equaling a value per share of EUR 2.20 [1.82–2.92] as reported in Table 20. The value range is based on the estimated 95% CI from the profit regression models and behavior logit models. The value obtained during the PP is derived in the CF statement (Table 21). The first value in the CF statement is the output of the algorithm driven forecast models: EBITDA.

Forecasted EBITDA composition | The forecast on total EBITDA for each year of the PP is reported in Table 19 and consists of various sub-EBTIDA components. The derivation of these components is described in the methodology chapter. The outlier EBITDA arises from the sum of all BM customers that have been eliminated before model estimation. These customers account for only 1.8% (2014) of total BM customers. However, they account 56% (2014) of the total BM EBITDA. Therefore, the observed BM outlier EBITDA is added to the EBITDA composition and grows annually during the PP at a growth rate (g) of 1.5%.

Table 19 CBB forecasted EBITDA composition

EBITDA COMPONENTS FOR THE BASE CASE SCENARIO				
Year to	**2015**	**2016**	**2017**	**2018**
EBITDA (EURm)				
Total EBITDA	**2,947**	**2,789**	**2,776**	**2,815**
Not included in dataset (and thus not in forecast)	1,174	1,174	1.174	1,174
Outliers not in BM model	775	787	799	811
Customer base CM	398	403	431	463
Potential customers CM	14	14	14	15
Customer base BM	559	381	328	323
Potential customers BM	27	29	29	29

Source: Firm X integrated customer-centric dataset

Table 20 Customer behavior based valuation (EURm)

Base case scenario
- Profit regression model parameter estimates
- Behavior logit model parameter estimates

Value during planning period		4,493
Value after planning period (PV continuing value)	(+)	11,816
Enterprise value		**16,308**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**9,402**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**2.20**
Long term growth rate		1.5%

Low case scenario
- Profit regression model lower bound 95% CI estimates
- Behavior logit model lower bound 95% CI estimates

Value during planning period		4,252
Value after planning period (PV continuing value)	(+)	10,441
Enterprise value		**14,694**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**7,788**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**1.82**
Long term growth rate		1.5%

High case scenario
- Profit regression model upper bound 95% CI estimates
- Behavior logit model upper bound 95% CI estimates

Value during planning period		4,908
Value after planning period (PV continuing value)	(+)	14,480
Enterprise value		**19,388**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**12,482**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR)		**2.92**
Long term growth rate		1,5%

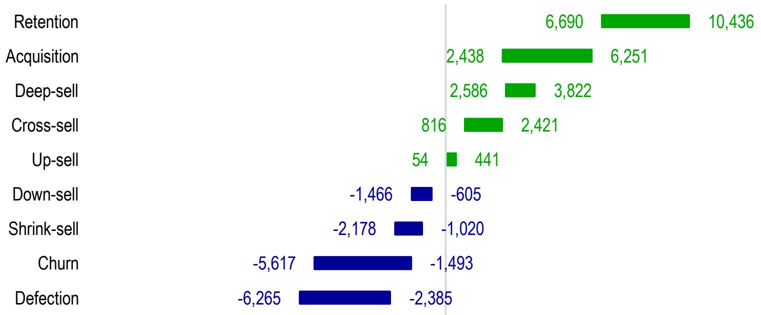
Table 21 Customer behavior based cash flow statement (EURm)

	Base case scenario ▪ Profit regression model parameter estimates ▪ Behavior logit model parameter estimates					**Low case scenario** ▪ Profit regression model lower bound 95% CI estimates ▪ Behavior logit model lower bound 95% CI estimates				**High case scenario** ▪ Profit regression model upper bound 95% CI estimates ▪ Behavior logit model upper bound 95% CI estimates			
Year to	**12/2014a**	**12/2015f**	**12/2016f**	**12/2017f**	**12/2018f**	**12/2015f**	**12/2016f**	**12/2017f**	**12/2018f**	**12/2015f**	**12/2016f**	**12/2017f**	**12/2018f**
Free cash flow (EURm)													
EBITDA	**3.074**	**2.947**	**2.789**	**2.776**	**2.815**	**2.898**	**2.712**	**2.668**	**2.672**	**3.018**	**2.909**	**2.963**	**3.093**
Depreciation and amortization	(1.769)	(1.880)	(1.761)	(1.663)	(1.581)	(1.880)	(1.761)	(1.663)	(1.581)	(1.880)	(1.761)	(1.663)	(1.581)
EBIT	**1.305**	**1.067**	**1.028**	**1.113**	**1.234**	**1.018**	**951**	**1.005**	**1.090**	**1.138**	**1.148**	**1.301**	**1.512**
Taxes over operating profit	(326)	(267)	(257)	(278)	(308)	(254)	(238)	(251)	(273)	(284)	(287)	(325)	(378)
NOPLAT	**979**	**800**	**771**	**835**	**925**	**763**	**713**	**754**	**818**	**853**	**861**	**976**	**1.134**
Depreciation and amortization	1.769	1.880	1.761	1.663	1.581	1.880	1.761	1.663	1.581	1.880	1.761	1.663	1.581
Cash flow from operations (CFO)	**2.748**	**2.680**	**2.532**	**2.498**	**2.507**	**2.644**	**2.474**	**2.417**	**2.399**	**2.734**	**2.622**	**2.638**	**2.715**
Net Capex PPE	(986)	(958)	(943)	(929)	(914)	(958)	(943)	(929)	(914)	(958)	(943)	(929)	(914)
Net Capex Intangibles	(711)	(379)	(381)	(383)	(384)	(379)	(381)	(383)	(384)	(379)	(381)	(383)	(384)
Increase(decrease) in operating NWC	412	841	(219)	(487)	(55)	841	(219)	(487)	(55)	841	(219)	(487)	(55)
Increase(decrease) in deferred tax liabilities	(43)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Increase(decrease) in provisions	79	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)
Cash flow from investment (CFI)	**(1.249)**	**(498)**	**(1.546)**	**(1.801)**	**(1.356)**	**(498)**	**(1.546)**	**(1.801)**	**(1.356)**	**(498)**	**(1.546)**	**(1.801)**	**(1.356)**
Free cash flow (FCF)	**1.499**	**2.182**	**986**	**697**	**1.151**	**2.145**	**929**	**616**	**1.043**	**2.235**	**1.076**	**837**	**1.360**
Discount rate		0,97	0,90	0,84	0,79	0,97	0,90	0,84	0,79	0,97	0,90	0,84	0,79
PV FCF		**2.109**	**890**	**587**	**906**	**2.073**	**838**	**519**	**822**	**2.160**	**971**	**706**	**1.071**

Source: Firm X annual report and integrated customer-centric dataset

Customer behavior value driver contribution | The customer behavior value drivers vary considerably in their contribution to SHV as displayed in Figure 25[41]. As expected, the customer behavior value driver 'retention' is the largest 'pillar' of SHV, accounting for EUR 6.7–10.4b. This is assuming no interaction among the model estimated parameters, or in other words: 'all else remains the same.' Also expected is 'defection' as the largest negative 'pillar' to SHV, accounting for a decrease of total SHV between EUR 2.4–6.3b. In other words, the forecasted customer defection during the period 2015–2018 is expected to cost shareholders between the 2.4 and 6.2 billion euros (assuming all else remains the same).

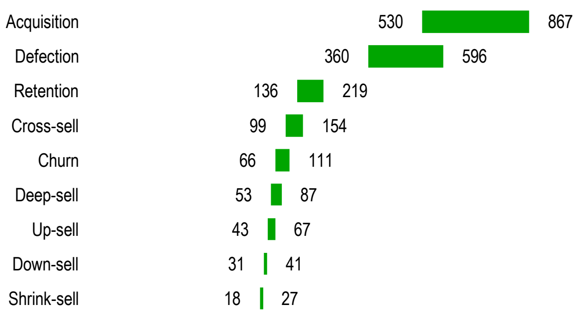
Figure 25 Shareholder value contribution range per customer behavior value driver (95% CI – EURm)



Source: Firm X integrated customer-centric dataset

Customer behavior value driver improvement | Each customer behavior value driver has a different contribution to SHV when the underlying probabilities for each customer are improved, e.g. by marketing investments in the customer base as displayed in Figure 26. For instance, a 100 basis points improvement in the customers' retention probability, results in an increase of SHV of EUR 136–219m. As customer retention and loyalty are strongly related (Reichheld & Sasser 1990; Zeithaml 2000), it is expected that externalities of marketing investments in order to increase the customers' retention probability will positively contribute to the probabilities for cross-sell, churn, deep-sell, up-sell, down-sell and shrink-sell. Ultimately, yielding even higher SHV improvements through externalities on the other customer behavior value drivers.

Figure 26 Shareholder value impact by 1% improvement per customer behavior value driver (95% CI – EURm)



Source: Firm X integrated customer-centric dataset

Interpretation of results on acquisition and defection | The results on the customer behavior value drivers acquisition and defection from both contribution and improvement results should be carefully interpreted. Customer

[41] A summation of these values does not add up exactly to the total SHV as obtained from the CBB valuation model. This is due to interaction among the customer behavior value drivers and the other predictors in the model.

acquisition and defection are not 'continuous' processes and therefore cannot produce value throughout the years of the PP. Once a customer is acquired it cannot be reacquired in the subsequent years, such that the probability value after acquisition should go down to zero for these years. However, the probability of acquisition for potential customers is very relevant. The inverse interpretation holds for defection.

5.2.3.1 Estimation results profit regression models

The parameter estimation results for the profit regression model is reported in Table 22 for CM and Table 23 for BM.

Sign | All of the *customer behavior value drivers* (betas: 1–9) have the expected signs for both CM and BM models. Retention, cross-sell, up-sell, deep-sell and acquisition have a positive sign. Therefore, a 'unit' increase in one of these predictors increases a customer's EBITDA contribution, hence profitability. Down-sell, shrink-sell, churn and defection have a negative sign. Therefore, a 'unit' increase in one of these predictors decreases a customer's EBITDA contribution, hence profitability. Then, *log EBITDA in the previous period* (beta 10) has the expected sign for both CM and BM models. Next, the *customer relationship ages* (betas: 11–21) reveal an interesting pattern. For CM year 1–7 and 10 have a negative sign, where year 8,9 and more than 10 have a positive sign. For BM year 1–8 have a negative sign, where year 8, 9, 10 and more than 10 have a positive sign. Overall, having a relationship age above 8 years is positively related to a customer's EBITDA contribution. Finally, there is a large variety in signs among the *customer characteristics* (betas: 22 and further).

Size | The logarithm transformation of the DV must be considered when interpreting the size of the estimated parameters. The size interpretation for all the *customer behavior value drivers* are identical for both CM and BM model. For instance, the CM model forecasts that a 1% increase in the customer's retention probability, leads to an increase of log EBITDA by 0.269% (beta 1). Where, in line with the findings of Schulze et al. (2012), for the CM and BM model the size of 'acquisition' is the largest. Where for the CM model 'shrink-sell' and for the BM model 'down-sell' has the least impact. The size interpretation for the *log EBITDA in the previous period* differs again as both DV and predictor have a logarithm transformation. In this case the CM model forecasts that a 1% increase in the *log EBITDA in the previous period*, leads to an increase of log EBITDA by 0.634% (beta 10). A possible explanation for this phenomenon is the ongoing price pressure effect in the market[42], which results in a customer repurchase with lower EBITDA contribution compared to the previous contract. The same reasoning for interpretation applies to the BM model. The size interpretation for the *customer relationship ages* are identical for both CM and BM model. For instance, the CM model forecasts that a customer in its first year of the relationship with the firm, leads to a decrease in log EBITDA by 4.8% (beta 11). The exact same holds for customers in their second year. In addition, these both effects are the largest among the relationship age predictors. The size effect decreases from the third year onwards. A possible explanation is that common contract periods in the industry last 1 or 2 years. The effect of relationship age decreases from the third year onwards. Where the effect from 10 years of more is relatively large again (3.3%; beta 21). The same trend applies to the BM results, but were the size in the first and second year are considerably larger, a decrease of 10.3% (beta 11) and 6.3% (beta 12) respectively. Finally, overall the sizes for the *customer characteristics* are relatively small for both the CM and BM model.

[42] Source: Firm X annual report 2014.

Table 22 Estimation results profit regression model (CM)

CONSUMER MARKET											
Adjusted R^2		**0.901**									
Coefficient estimates		**B (Std. Error)**	**Lower 95% C.I.**	**Upper 95% C.I.**	**Stdzd. Beta**			**B (Std. Error)**	**Lower 95% C.I.**	**Upper 95% C.I.**	**Stdzd. Beta**
Intercept		-0.007** (0.000)	-0.007	-0.007		**36**	Income: 1.5x modal	-0.004** (0.000)	-0.005	-0.004	-0.003
1	Retention	0.269** (0.000)	0.269	0.270	0.251	**37**	Income: 2x modal	-0.004** (0.000)	-0.004	-0.003	-0.002
2	Cross-sell	0.228** (0.000)	0.228	0.229	0.109	**38**	Work situation: part-time	-0.001** (0.000)	-0.001	-0.001	-0.001
3	Up-sell	0.116** (0.000)	0.115	0.117	0.028	**39**	Work situation: fulltime	-0.003** (0.000)	-0.003	-0.003	-0.003
4	Deep-sell	0.105** (0.000)	0.105	0.105	0.099	**40**	Highest level of education: higher education	-0.001** (0.000)	-0.002	-0.001	-0.001
5	Down-sell	-0.091** (0.001)	-0.092	-0.090	-0.040	**41**	Number of cars (household): 1	-0.003** (0.000)	-0.003	-0.003	-0.003
6	Shrink-sell	-0.033** (0.000)	-0.034	-0.033	-0.027	**42**	Number of cars (household): ≥2	-0.005** (0.000)	-0.005	-0.004	-0.003
7	Acquisition	0.938** (0.000)	0.937	0.939	0.409	**43**	Segment (Mosaic): contemporary agrarians	0.026** (0.001)	0.024	0.028	0.003
8	Churn	-0.082** (0.001)	-0.083	-0.081	-0.032	**44**	Segment (Mosaic): countryside freedom	0.025** (0.001)	0.024	0.026	0.005
9	Defection	-0.577** (0.000)	-0.577	-0.576	-0.330	**45**	Segment (Mosaic): satisfied outdoors	0.002** (0.000)	0.001	0.002	0.001
10	Log $EBITDA_{t_{-1},t_{-2}}$ (EUR/month)	0.634** (0.000)	0.634	0.635	0.639	**46**	Segment (Mosaic): freedom and space	-0.003** (0.000)	-0.003	-0.002	-0.001
11	Relationship age: year 1	-0.048** (0.000)	-0.049	-0.047	-0.024	**47**	Segment (Mosaic): teen rural families	0.020** (0.000)	0.019	0.021	0.005
12	Relationship age: year 2	-0.048** (0.000)	-0.048	-0.047	-0.025	**48**	Segment (Mosaic): wealthy back to back	0.010** (0.000)	0.009	0.011	0.003
13	Relationship age: year 3	-0.018** (0.000)	-0.018	-0.017	-0.008	**49**	Segment (Mosaic): enjoy deserved	0.001** (0.000)	0,000	0.001	0,000
14	Relationship age: year 4	-0.012** (0.000)	-0.013	-0.012	-0.005	**50**	Segment (Mosaic): advanced wealthy	0.016** (0.000)	0.015	0.017	0.004
15	Relationship age: year 5	-0.015** (0.000)	-0.016	-0.015	-0.007	**51**	Segment (Mosaic): flourishing families	0.020** (0.001)	0.019	0.021	0.004
16	Relationship age: year 6	-0.005** (0.000)	-0.005	-0.004	-0.002	**52**	Segment (Mosaic): stately exclusivity	0.033** (0.001)	0.031	0.035	0.004
17	Relationship age: year 7	0.015** (0.000)	0.014	0.016	0.007	**53**	Household size: 1p	-0.005** (0.000)	-0.005	-0.004	-0.004
18	Relationship age: year 8	0.016** (0.000)	0.016	0.017	0.007	**54**	Household size: 2p	-0.004** (0.000)	-0.004	-0.003	-0.003
19	Relationship age: year 9	0.002** (0.000)	0.001	0.003	0.001	**55**	Household size: 4p	-0.003** (0.000)	-0.003	-0.002	-0.002
20	Relationship age: year 10	-0.009** (0.000)	-0.010	-0.008	-0.002	**56**	Household age: 35-45	-0.001** (0.000)	-0.001	0,000	0,000
21	Relationship age: year >10	0.033** (0.000)	0.032	0.033	0.021	**57**	Household age: 45-55	0.002** (0.000)	0.002	0.003	0.002
22	Location: building for demolition	-0.059** (0.001)	-0.060	-0.057	-0.008	**58**	Household age: 55-65	-0.004** (0.000)	-0.005	-0.004	-0.003
23	Location: business	0.015** (0.001)	0.013	0.016	0.002	**59**	Household age: >65	-0.005** (0.000)	-0.005	-0.004	-0.004
24	Location: mixed	0.006** (0.000)	0.005	0.006	0.003	**60**	Household children: 2	0.001** (0.000)	0.001	0.002	0.001
25	Location: other non-residential	0.004** (0.001)	0.002	0.005	0.001	**61**	Household age oldest child: 19-24	0.003** (0.000)	0.002	0.003	0.001
26	Location: 5% non-western immigrants	0.000** (0.000)	-0.001	0,000	0,000	**62**	Tenure: rent house	0.002** (0.000)	0.002	0.003	0.002
27	SOW: 0-10% (average income based)	0.043** (0.000)	0.043	0.044	0.041	**63**	House type: row house in between	-0.003** (0.000)	-0.003	-0.002	-0.002
28	SOW: 10-20% (average income based)	0.131** (0.002)	0.127	0.134	0.008	**64**	House type: row house corner	-0.004** (0.000)	-0.004	-0.003	-0.002
29	SOW: 0-10% (fiscal income based)	0.006** (0.000)	0.006	0.006	0.005	**65**	House type: semidetached	-0.006** (0.000)	-0.007	-0.006	-0.004
30	SOW: 10-20% (fiscal income based)	0.084** (0.001)	0.082	0.087	0.008	**66**	House type: detached	-0.006** (0.000)	-0.006	-0.005	-0.004
31	SOW: 20-30% (fiscal income based)	0.115** (0.003)	0.110	0.120	0.005	**67**	Degree of urbanity: non-urban (<500 area addresses per km2)	0.003** (0.000)	0.003	0.003	0.002
32	SOW: 30-40% (fiscal income based)	0.140** (0.005)	0.131	0.149	0.003	**68**	Degree of urbanity: high urbanity (>2,500 area addresses per km2)	0.004** (0.000)	0.004	0.005	0.004
33	SOW: 40-50% (fiscal income based)	0.152** (0.007)	0.139	0.165	0.002	**69**	Number of moves: no moves	-0.006** (0.000)	-0.006	-0.005	-0.005
34	Income: below modal	-0.006** (0.000)	-0.007	-0.006	-0.005	**70**	Number of moves: ≥2	-0.004** (0.000)	-0.004	-0.003	-0.003
35	Income: modal	-0.004** (0.000)	-0.005	-0.004	-0.003	**71**	Last move: before 2006	0.000** (0.000)	0,000	0.001	0,000

Dependent variable: log transformed $EBITDA_{t_0,t_{-1}}$; **: p<0.01; *: p<0.05; standard error between parentheses

Table 23 Estimation results profit regression model (BM)

BUSINESS MARKET

Adjusted R^2 **0.902**

	Coefficient estimates	**B (Std. Error)**	**Lower 95% C.I.**	**Upper 95% C.I.**	**Stdzd. Beta**			**B (Std. Error)**	**Lower 95% C.I.**	**Upper 95% C.I.**	**Stdzd. Beta**
	Intercept	0.007** (0.001)	0.006	0.009		**31**	Gartner industry related spending: ≤2%	0.008** (0.001)	0.006	0.010	0.002
1	Retention	0.335** (0.001)	0.333	0.337	0.180	**32**	Number of employees: 1	-0.019** (0.001)	-0.021	-0.018	-0.012
2	Cross-sell	0.199** (0.001)	0.197	0.200	0.070	**33**	Number of employees: 2	-0.012** (0.001)	-0.013	-0.010	-0.005
3	Up-sell	0.067** (0.002)	0.064	0.070	0.012	**34**	Number of employees: 11-20	0.009** (0.001)	0.007	0.011	0.003
4	Deep-sell	0.135** (0.001)	0.134	0.137	0.085	**35**	Number of employees: 21-50	0.026** (0.001)	0.024	0.028	0.007
5	Down-sell	-0.027** (0.002)	-0.031	-0.024	-0.011	**36**	Number of employees: 51-100	0.039** (0.002)	0.036	0.042	0.007
6	Shrink-sell	-0.045** (0.001)	-0.046	-0.044	-0.027	**37**	Years since establishment: 2-5	0.009** (0.001)	0.007	0.010	0.003
7	Acquisition	1.401** (0.001)	1.398	1.404	0.360	**38**	Years since establishment: 10-20	-0.007** (0.001)	-0.009	-0.006	-0.004
8	Churn	-0.231** (0.002)	-0.235	-0.227	-0.086	**39**	Years since establishment: 20-50	-0.013** (0.001)	-0.015	-0.012	-0.007
9	Defection	-1.052** (0.001)	-1.055	-1.050	-0.343	**40**	Years since establishment: 50-100	-0.009** (0.001)	-0.011	-0.006	-0.002
10	Log $EBITDA_{t_{-1},t_{-2}}$ (EUR/month)	0.733** (0.001)	0.732	0.734	0.728	**41**	Legal entity: foundation	0.029** (0.001)	0.027	0.032	0.007
11	Relationship age: year 1	-0.103** (0.001)	-0.106	-0.101	-0.028	**42**	Legal entity: partnership	0.006** (0.002)	0.003	0.009	0.001
12	Relationship age: year 2	-0.063** (0.001)	-0.066	-0.061	-0.018	**43**	Legal entity: association partnership	0.003** (0.001)	0.001	0.004	0.001
13	Relationship age: year 3	-0.047** (0.001)	-0.049	-0.044	-0.012	**44**	Legal entity: private company	0.018** (0.001)	0.017	0.020	0.010
14	Relationship age: year 4	-0.033** (0.001)	-0.036	-0.031	-0.009	**45**	Parts in concern: 3-5	0.004** (0.001)	0.002	0.006	0.001
15	Relationship age: year 5	-0.028** (0.001)	-0.030	-0.026	-0.008	**46**	Parts in concern: 6-10	0.011** (0.002)	0.007	0.014	0.002
16	Relationship age: year 6	-0.022** (0.001)	-0.025	-0.020	-0.007	**47**	Mother company	0.037** (0.001)	0.035	0.038	0.013
17	Relationship age: year 7	-0.018** (0.001)	-0.020	-0.015	-0.005	**48**	Import	0.009** (0.001)	0.006	0.011	0.002
18	Relationship age: year 8	-0.008** (0.001)	-0.010	-0.005	-0.002	**49**	Export	0.017** (0.001)	0.015	0.020	0.005
19	Relationship age: year 9	0.007** (0.001)	0.004	0.010	0.002	**50**	Segment: other services	0.003* (0.001)	0.001	0.005	0.001
20	Relationship age: year 10	0.026** (0.002)	0.023	0.029	0.005	**51**	Segment: sbi description 20	0.012** (0.001)	0.009	0.014	0.002
21	Relationship age: year >10	0.058** (0.001)	0.056	0.060	0.032	**52**	Segment: construction industry	0.008** (0.001)	0.006	0.010	0.002
22	Location: business	0.004** (0.001)	0.002	0.006	0.002	**53**	Segment: industry	0.005** (0.001)	0.003	0.008	0.001
23	Location: mixed	-0.035** (0.001)	-0.036	-0.033	-0.020	**54**	Segment: health and welfare	0.005** (0.001)	0.003	0.007	0.001
24	Location: other non-residential	0.006** (0.001)	0.004	0.008	0.002	**55**	Segment: agriculture, forestry and fisheries	-0.003* (0.001)	-0.006	0.000	-0.001
25	Location: private owned	-0.032** (0.001)	-0.034	-0.031	-0.018	**56**	Segment: advanced research and other special business services	0.012** (0.001)	0.010	0.013	0.004
26	Location: business complex	0.020** (0.001)	0.019	0.021	0.011	**57**	Segment: accommodation and meals and drinks	-0.005** (0.001)	-0.007	-0.002	-0.001
27	SOW: 0-10% (revenues based)	0.009** (0.002)	0.004	0.014	0.001	**58**	Self-employed without employees: science	-0.004** (0.001)	-0.006	-0.002	-0.002
28	Revenues: EUR ≤100,000	-0.008** (0.001)	-0.011	-0.006	-0.002	**59**	Self-employed without employees: location bound	0.008** (0.001)	0.006	0.010	0.002
29	Consolidated results: loss	0.008** (0.001)	0.005	0.010	0.002	**60**	Nace: description 9	-0.008** (0.001)	-0.011	-0.006	-0.002
30	Consolidated results: profit	0.035** (0.001)	0.033	0.037	0.011	**61**	Mailbox	-0.052** (0.011)	-0.074	-0.030	-0.001

Dependent variable: log transformed $EBITDA_{t_0,t_{-1}}$; **: p<0.01; *: p<0.05; standard error between parentheses

Significance | For the CM model all 71 predictors have a p-value of 0.01 or lower. Where for the BM model 2 out of 61 predictors have a p-value between 0.01–0.05, all others have a value of 0.01 or lower.

Model fit | The fit of the model is indicated by the adjusted R^2 which is for the CM model 0.901 and 0.902 for the BM model. A hypothetical model with just the customer behavior value drivers as predictors for CM and BM results in an adjusted R^2 of 0.819 and 0.701. This means that customer behavior value drivers explain to a large extent the variance in customer profitability. Donkers et al. (2007) suggest that the model might be somewhat over-parameterized, which can potentially be an obstacle.

Multiple linear regression assumptions | *Multiple linear regression analysis* makes several key assumptions. The first assumption is the *linear relation between IVs and DV* (Field 2013). Normally matrix scatterplots inform on this assumption. However, due to the number of predictors in the models and cases in the dataset these plots cannot be produced as the software runs into memory problems. But, all independent variables in the model are either recoded into dummy variables or logarithm transformed. Therefore, the non-linear effects of the predictors are captured. The second assumption is *normality* (Field 2013). The DV is log transformed and checked on normality and the IVs recoded into dummy variables and also log transformed and checked on normality. The third assumption is the *homoscedasticity/homogeneity of variance* (Field 2013). Again due to shortcomings in hardware and software the scatterplots of the residuals cannot be produced. Therefore, this assumption cannot be tested. The fourth assumption is that the *values of the residuals are independent*, validating whether there is collinearity within the data. When selecting the predictor variables, the VIF level is checked on values above 10 (Bowerman and 'O'Connell, 1990; Myers, 1990) and if so removed from the model.

5.2.3.2 Estimation results behavior logit models

The estimation results on the 9 behavior logit models are reported in Table 24 for CM and in Table 25 for BM. Because of efficiency reasons a combination of the CM retention and defection model will be discussed, producing some interesting insights. There are many more interesting insights obtainable from the model estimates. However, this requires extensive elaborating. The applied model interpretation holds in essence for the remaining 17 non-interpreted behavior logit models.

Sign | The customer behavior value drivers (betas 1–9) with a positive sign are: retention, cross-sell, deep-sell, shrink-sell, acquisition and churn. The only negative sign is for down-sell. Up-sell and defection are not significant in this model. All the relationship age predictors have a positive sign. The customer characteristics 19 out of 47 have a negative sign.

Size | The interpretation of the size of the coefficients is based on the odds ratio; the exponential of the beta value. A customer is about 21 times ($e^{3.040}$) more likely to retain in the next period if it is retained in the current period, controlling for the other variables in the model. If a customer is acquired in the current period, it is about 39 times more likely to retain in the next period, controlling for the other variables in the model. However, when a customer has purchased a less expensive version of the same service or product (down-sell) in the current period, it is less likely to retain in the next period (0.24 times), controlling for the other variables in the model. When the relationship age is >10 years the customer is almost 81,000 times more likely to retain in the next period, controlling for the other variables in the model. In addition, a customer is less likely to defect in the next period:

- when it purchased a more expensive version of the same service or product (up-sell; 0.20 times);
- when it used less of the same service or product (shrink-sell; 0.42 times);

- when it purchased a product from another category (cross-sell; 0.45 times);
- when it used more of the same service or product (deep-sell; 0.47 times) in the current period, controlling for the other variables in the model.

However, a customer is more likely to defect in the next period:

- when it purchased a less expensive version of the same service or product (down-sell; 2.4 times);
- when it simply purchased the exact same (retention; 1.74 times);
- when it just joined the firm as a new customer (acquisition; 1.36 times);
- when it cancelled one of its product categories in its portfolio (churn; 1.16 times) in the current period, controlling for the other variables in the model.

Overall, the pattern shows that once a CM customer decreases its relationship intensity with the firm in terms of number of products and/or usage, then it becomes more likely to completely end its relationship (defect) with the firm. However, the opposite holds as well, once a CM customer increases its relationship intensity with the firm it becomes less likely to end its relationship with the firm. In addition, some 'rationalizing' behavior (shrink-sell) of the customer among his portfolio seems to make it less likely to defect in the next period.

Significance | Not all of the predictors are significant for each of the models, these are represented by a blank cell in the tables. All the other variables are significant at the 0.01 or 0.05 level.

Model fit | The model fit is based on the full-model overall percentage from the classification table in the SPSS output. In addition, the Nagelkerke r-squared is used for interpretation of the model fit. However, this is a pseudo r-squared. Both of the model fit criteria are reported in Table 24 for CM and in Table 25 for BM. In general, the retention model performs particularly well, so do acquisition and deep-sell.

Binary logistic regression assumptions | The binary logistic regression model *assumes a linear relationship between any continuous predictor variable and the logit of the outcome variable* (Field 2013). As all predictors are recoded into dummy variables their possible non-linear effects are already captured. In addition, the model assumes *independence of errors*, a violation of this assumption produces over-dispersion (Field 2013). This occurs when the model's observed variance is larger than the expected (Field 2013). Which can be due to either correlated observations (so no independence of errors) or variability in success probabilities (Field 2013). Some *unique problems* arise from the iterative procedure (Field 2013). If the software (IBM SPSS 22) can't find a correct solution, incorrect results are revealed by implausibly large standard errors (Field 2013). All of the reported standard errors, within the parentheses, in Table 24 for CM and in Table 25 for BM are small. Large standard errors arise from two situations, both are related to the ratio of cases to variables: incomplete information and complete separation (Field 2013). Solving the problem of incomplete information is done by the recoding of the predictors into dummy variables, such that there is no incomplete information (Field 2013). Not in one of the models, the dependent variable can be perfectly predicted by one predictor or a combination of predictors, cancelling out the problem of complete separation (Field 2013).

Table 24 Estimation results behavior logit models CM

CONSUMER MARKET

		1	2	3	4	5	6	7	8	9
Model performance		**Retention**	**Cross-sell**	**Up-sell**	**Deep-sell**	**Down-sell**	**Shrink-sell**	**Acquisition**	**Churn**	**Defection**
Intercept-model overall percentage		76,2%	93,7%	98,3%	51,9%	92,1%	75,1%	94,9%	93,6%	89.5%
Full-model overall percentage		**95.9%**	**93.7%**	**98.3%**	**77.9%**	**92.2%**	**79.0%**	**95.6%**	**93.6%**	**89.5%**
Percentage 'No' (0)		94.2%	100.0%	100.0%	62.7%	99.9%	93.0%	98.6%	99.9%	100.0%
Percentage 'Yes' (1)		96.5%	0.0%	0.0%	91.9%	1.7%	36.9%	40.4%	1.5%	0.0%
Nagelkerke R2		**0.890**	**0.120**	**0.135**	**0.490**	**0.183**	**0.339**	**0.539**	**0.190**	**0.145**
Coefficients estimates										
Intercept		-7.057** (0.019)	-7.373** (0.031)	-11.847** (0.317)	-5.664** (0.014)	-7.124** (0.022)	-6.383** (0.015)	-4.821** (0.015)	-7.626** (0.023)	-1.490** (0.007)
1	Retention (2012-2013)	3.040** (0.014)	0.861** (0.007)	-	-0.106** (0.004)	1.498** (0.007)	1.159** (0.005)	-	2.026** (0.009)	0.553** (0.004)
2	Cross-sell (2012-2013)	0.353** (0.023)	-0.026** (0.007)	0.321** (0.011)	1.185** (0.006)	0.736** (0.005)	1.365** (0.004)	-	0.815** (0.005)	-0.797** (0.009)
3	Up-sell (I2012-2013)	-	-	-	-0.164** (0.010)	1.026** (0.009)	0.137** (0.009)	-	0.040** (0.012)	-1.591** (0.028)
4	Deep-sell (2012-2013)	0.142** (0.015)	-0.377** (0.005)	0.419** (0.008)	0.575** (0.003)	0.562** (0.005)	0.970** (0.003)	-	0.613** (0.005)	-0.748** (0.005)
5	Down-sell (2012-2013)	-1.409** (0.046)	0.096** (0.019)	0.162** (0.032)	-0.194** (0.013)	0.178** (0.016)	0.584** (0.012)	-	0.136** (0.018)	0.874** (0.014)
6	Shrink-sell (2012-2013)	1.810** (0.016)	-0.140** (0.006)	0.347** (0.009)	0.646** (0.004)	0.359** (0.005)	0.142** (0.003)	-	0.365** (0.005)	-0.876** (0.006)
7	Acquisition (2012-2013)	3.668** (0.022)	0.941** (0.009)	-	1.045** (0.006)	1.081** (0.009)	1.212** (0.006)	-	1.500** (0.010)	0.306** (0.006)
8	Churn (2012-2013)	0.134* (0.055)	0.579** (0.021)	-0.246** (0.038)	-0.384** (0.015)	-0.552** (0.019)	-0.654** (0.014)	-	-0.559** (0.021)	0.145** (0.016)
9	Defection (2012-2013)	-	-	-	-	-	-	1.341** (0.010)	-	-
10	Relationship age: year 1	6.198** (0.015)	4.560** (0.029)	7.406** (0.316)	3.959** (0.014)	3.776** (0.020)	5.135** (0.014)	5.342** (0.011)	3.753** (0.021)	-
11	Relationship age: year 2	9.994** (0.018)	4.127** (0.029)	7.974** (0.316)	6.061** (0.014)	3.974** (0.020)	4.413** (0.014)	1.190** (0.015)	3.773** (0.020)	-
12	Relationship age: year 3	9.331** (0.021)	4.103** (0.030)	7.523** (0.317)	5.740** (0.014)	2.874** (0.020)	3.939** (0.014)	1.142** (0.019)	2.574** (0.020)	-
13	Relationship age: year 4	9.317** (0.023)	4.034** (0.030)	7.441** (0.317)	5.975** (0.014)	2.825** (0.020)	3.752** (0.014)	0.935** (0.021)	2.545** (0.020)	-
14	Relationship age: year 5	9.463** (0.024)	4.059** (0.030)	7.515** (0.317)	5.756** (0.014)	2.853** (0.020)	3.857** (0.014)	0.839** (0.022)	2.553** (0.020)	-
15	Relationship age: year 6	9.458** (0.024)	4.105** (0.029)	7.523** (0.317)	5.590** (0.014)	2.825** (0.020)	3.867** (0.014)	0.762** (0.022)	2.528** (0.020)	-
16	Relationship age: year 7	9.368** (0.024)	4.172** (0.029)	7.537** (0.317)	5.476** (0.014)	2.777** (0.020)	3.994** (0.014)	0.787** (0.022)	2.459** (0.020)	-
17	Relationship age: year 8	9.056** (0.023)	4.220** (0.029)	7.524** (0.316)	6.163** (0.014)	2.555** (0.020)	3.930** (0.014)	0.662** (0.022)	2.215** (0.020)	-
18	Relationship age: year 9	9.448** (0.034)	4.109** (0.030)	7.607** (0.317)	5.318** (0.015)	2.776** (0.021)	3.974** (0.015)	0.840** (0.032)	2.472** (0.022)	-
19	Relationship age: year 10	9.472** (0.038)	3.987** (0.031)	7.588** (0.317)	5.523** (0.015)	2.728** (0.022)	3.855** (0.015)	0.831** (0.036)	2.427** (0.022)	-
20	Relationship age: year >10	11.302** (0.022)	3.756** (0.029)	7.539** (0.316)	6.086** (0.013)	2.658** (0.019)	3.599** (0.014)	-	2.389** (0.020)	-
21	SOW 0-10% (based on average income)	-0.110** (0.010)	-0.685** (0.008)	-1.275** (0.020)	-0.466** (0.004)	0.137** (0.007)	-0.218** (0.005)	0.331** (0.010)	0.299** (0.008)	-1.451** (0.007)
22	SOW 10-20% (based on average income)	-0.458** (0.071)	0.247** (0.043)	0.495** (0.052)	-0.152** (0.037)	-	0.081* (0.035)	0.438** (0.066)	-	-2.885** (0.210)
23	SOW 0-10% (based on fiscal income)	-0.109** (0.010)	-0.216** (0.008)	-0.673** (0.022)	-0.112** (0.004)	0.029** (0.007)	-0.088** (0.005)	0.199** (0.010)	0.041** (0.008)	-1.152** (0.008)
24	SOW 10-20% (based on fiscal income)	-	0.754** (0.031)	2.358** (0.035)	0.697** (0.024)	-0.205** (0.033)	0.138** (0.023)	-	-0.223** (0.036)	-1.840** (0.101)
25	SOW 20-30% (based on fiscal income)	-	0.551** (0.074)	2.396** (0.065)	0.832** (0.061)	-0.168* (0.077)	0.132* (0.053)	-	-0.235** (0.089)	-3.303** (0.449)
26	SOW 30-40% (based on fiscal income)	-	0.341* (0.134)	2.465** (0.104)	0.882** (0.109)	-	0.190* (0.092)	-	-	-
27	SOW 40-50% (based on fiscal income)	-	0.573** (0.180)	2.605** (0.143)	0.810** (0.154)	-	-	-	-0.621* (0.265)	-
28	Income: below modal	-0.166** (0.014)	-	-0.084** (0.014)	-0.040** (0.005)	-	-0.011* (0.004)	0.076** (0.010)	-	0.082** (0.006)
29	Income: modal	-0.093** (0.012)	-	-	-0.024** (0.004)	-	-	-	-	-
30	Income: 1.5x modal	-0.133** (0.013)	-	-	-0.030** (0.005)	-0.023** (0.006)	-	0.044** (0.010)	-0.018** (0.006)	-0.033** (0.006)
31	Income: 2x modal	-0.056** (0.011)	-	-	-	-	-	-	-	-0.063** (0.006)
32	Income: >2x modal	-	-	-	-	-	0.010** (0.004)	-	-	-0.046** (0.006)
33	Work situation: part time	0.078** (0.011)	-	-0.034* (0.017)	0.076** (0.005)	-0.059** (0.008)	-0.049** (0.005)	-	-0.061** (0.008)	-
34	Work situation: full time	0.101** (0.011)	-0.022** (0.006)	-0.054** (0.017)	0.095** (0.005)	-0.033** (0.008)	-0.039** (0.005)	-	-0.047** (0.008)	0.027** (0.005)
35	Work situation: retirement	0.177** (0.016)	-0.062** (0.010)	-0.210** (0.020)	0.093** (0.007)	-0.120** (0.010)	-0.108** (0.007)	0.072** (0.013)	-0.125** (0.011)	0.141** (0.005)
36	Highest level of education: low	0.080** (0.013)	0.028** (0.009)	-0.077** (0.013)	0.106** (0.004)	-0.079** (0.009)	-0.039** (0.004)	-0.036** (0.012)	-0.074** (0.010)	-
37	Highest level of education: high school	-0.059** (0.009)	0.062** (0.007)	-	-	-0.037** (0.007)	-	0.051** (0.008)	-0.035** (0.008)	-

**: p ≤ 0.01; *: p ≤ 0.05; standard error within parentheses; -: insignificant result

	Coefficients estimates	Retention	Cross-sell	Up-sell	Deep-sell	Down-sell	Shrink-sell	Acquisition	Churn	Defection
38	Highest level of education: university of applied sciences	-	0.015* (0.008)	-	-0.023** (0.003)	-0.034** (0.007)	-	-	-0.033** (0.007)	-
39	Housing: rental	0.473** (0.012)	-	-	0.164** (0.005)	0.027** (0.009)	0.037** (0.006)	-0.366** (0.012)	0.020* (0.009)	-0.059** (0.007)
40	Housing: own property	0.617** (0.013)	-0.193** (0.007)	-0.109** (0.013)	0.211** (0.005)	-0.131** (0.009)	-0.034** (0.006)	-0.493** (0.012)	-0.127** (0.009)	-0.144** (0.008)
41	House type: back to back	0.066** (0.008)	-0.040** (0.006)	0.235** (0.012)	-	0.065** (0.005)	0.011** (0.003)	-0.055** (0.007)	0.032** (0.006)	-
42	House type: back to back on the corner	0.058** (0.010)	-0.041** (0.008)	0.229** (0.014)	0.018** (0.004)	0.066** (0.007)	-	-0.054** (0.010)	0.038** (0.007)	-
43	House type: semidetached	-	-0.116** (0.009)	0.210** (0.016)	0.031** (0.004)	0.027** (0.007)	-0.034** (0.005)	-	0.019** (0.007)	0.090** (0.006)
44	House type: detached	-0.052** (0.014)	-0.104** (0.011)	0.174** (0.019)	0.056** (0.006)	-	-0.045** (0.007)	-	-	0.029** (0.008)
45	Number of cars: 1	0.033** (0.007)	-0.011* (0.005)	0.089** (0.011)	-	0.031** (0.005)	0.028** (0.003)	-0.075** (0.007)	0.032** (0.006)	-0.119** (0.004)
46	Number of cars: ≥2	0.028** (0.010)	-0.035** (0.007)	0.179** (0.013)	-0.037** (0.003)	0.139** (0.006)	0.086** (0.004)	-0.132** (0.010)	0.122** (0.007)	-0.183** (0.006)
47	Segment (Mosaic): contemporary agrarians	-	-0.077** (0.030)	0.176** (0.053)	0.104** (0.022)	-0.135** (0.030)	-0.042* (0.020)	-	-0.062* (0.031)	-
48	Segment (Mosaic): countryside freedom	-	-0.091** (0.021)	-	0.064** (0.015)	-0.055** (0.021)	-	-	-	-
49	Segment (Mosaic): rural life	0.331** (0.025)	0.372** (0.016)	0.048* (0.023)	0.172** (0.010)	0.083** (0.014)	0.166** (0.009)	-0.443** (0.023)	-	-
50	Segment (Mosaic): satisfied outdoors	-0.278** (0.029)	-0.311** (0.018)	-	-0.144** (0.011)	0.045** (0.017)	-0.102** (0.010)	0.323** (0.029)	0.147** (0.013)	0.163** (0.011)
51	Segment (Mosaic): freedom and space	-0.068** (0.013)	0.043** (0.010)	0.039* (0.016)	-	0.055** (0.008)	0.024** (0.006)	-	0.040** (0.009)	0.045** (0.007)
52	Segment (Mosaic): teen rural families	-	-	0.061* (0.029)	-	-	-	-	-	-0.400** (0.016)
53	Segment (Mosaic): wealthy back to back	0.166** (0.024)	-	-	0.058** (0.012)	-0.076** (0.016)	-0.046** (0.012)	-	-0.039* (0.017)	-0.035** (0.013)
54	Segment (Mosaic): enjoy deserved	0.053** (0.013)	0.032** (0.009)	-	0.054** (0.005)	0.027** (0.008)	-	-0.082** (0.013)	0.055** (0.009)	0.053** (0.007)
55	Segment (Mosaic): advanced wealthy	0.237** (0.029)	0.221** (0.018)	0.114** (0.028)	0.028** (0.010)	0.187** (0.014)	0.214** (0.021)	-0.387** (0.050)	0.256** (0.033)	-0.088** (0.021)
56	Segment (Mosaic): flourishing families	0.267** (0.033)	0.232** (0.020)	0.075* (0.031)	-	0.150** (0.017)	0.188** (0.022)	-0.323** (0.054)	0.259** (0.034)	-
57	Segment (Mosaic): stately exclusivity	0.407** (0.061)	0.115** (0.033)	-	0.097** (0.020)	0.323** (0.026)	0.262** (0.027)	-0.405** (0.076)	0.388** (0.040)	-0.161** (0.035)
58	Segment (Mosaic): gold rim	-	0.094** (0.011)	0.043** (0.016)	-0.036** (0.007)	0.146** (0.011)	0.097** (0.008)	-	0.142** (0.012)	-
59	Segment (Mosaic): elitist class	-	-	-	-	-	-0.052** (0.018)	0.175** (0.042)	-0.070* (0.030)	-0.148** (0.015)
60	Household size: 1p	-	-0.068** (0.010)	-0.096** (0.028)	-	-0.084** (0.005)	-0.098** (0.008)	-	-0.075** (0.006)	-
61	Household size: 2p	-	-0.039** (0.010)	-0.027* (0.011)	-0.017** (0.003)	-	-	-0.054** (0.008)	-	-0.058** (0.004)
62	Household size: 3p	0.065** (0.010)	-0.035** (0.010)	-	-	-	0.026** (0.004)	-0.069** (0.012)	-	-
63	Household size: 4p	-	-0.027* (0.011)	-	-	0.027** (0.007)	-	-	0.029** (0.007)	-
64	Household size: ≥5p	-	-	-	-	-	-	-	-	-0.017* (0.008)
65	Household age: 35-45	0.094** (0.009)	-	0.080** (0.013)	0.109** (0.004)	-0.048** (0.007)	-0.100** (0.004)	-	-0.043** (0.007)	0.053** (0.005)
66	Household age: 45-55	0.083** (0.010)	0.040** (0.006)	0.272** (0.012)	0.136** (0.004)	0.037** (0.007)	-0.075** (0.004)	-0.040** (0.008)	0.021** (0.007)	-
67	Household age: 55-65	0.190** (0.010)	-0.023** (0.006)	0.116** (0.012)	0.198** (0.004)	0.037** (0.007)	-0.088** (0.005)	-0.120** (0.009)	0.023** (0.008)	-0.048** (0.005)
68	Household age: >65	0.383** (0.014)	-0.086** (0.009)	-	0.251** (0.006)	-0.030** (0.009)	-0.150** (0.006)	-0.263** (0.014)	-0.027** (0.010)	-
69	Household children: 1	-	-	-0.100** (0.012)	0.013** (0.004)	-	-	-	-	-
70	Household children: 2	-0.051** (0.016)	0.033** (0.011)	-	0.044** (0.006)	-0.058** (0.010)	-0.029** (0.006)	0.039* (0.016)	-0.039** (0.012)	-
71	Household age oldest child: 6-12	-0.077** (0.012)	0.100** (0.008)	0.291** (0.014)	-	-0.024** (0.007)	-0.051** (0.005)	0.053** (0.012)	-0.023** (0.008)	-
72	Household age oldest child: 13-18	-0.172** (0.015)	0.079** (0.010)	0.386** (0.016)	-0.048** (0.006)	0.077** (0.008)	-	0.063** (0.015)	0.067** (0.009)	-0.018* (0.008)
73	Household age oldest child: 19-24	-0.133** (0.024)	-0.051** (0.014)	0.280** (0.022)	-0.143** (0.009)	0.225** (0.011)	0.143** (0.008)	-0.100** (0.025)	0.178** (0.012)	-0.164** (0.012)
74	Household marital status: living together or married	-	-	0.087** (0.023)	-	-	-0.035** (0.008)	-	-	-0.019** (0.005)
75	Household marital status: other	-	-	-	-	-	-	0.043** (0.009)	-	-
76	Location: building for demolition	0.982** (0.025)	-2.683** (0.115)	-0.331** (0.076)	0.679** (0.018)	-0.999** (0.060)	-0.382** (0.023)	-0.747** (0.026)	-1.592** (0.099)	0.134** (0.018)
77	Location: private owned	-0.165** (0.022)	0.805** (0.017)	0.363** (0.038)	-	0.462** (0.016)	0.571** (0.012)	-0.358** (0.019)	0.459** (0.018)	0.073** (0.010)
78	Location: business	0.294** (0.037)	-0.120** (0.033)	-	0.253** (0.016)	0.277** (0.027)	0.127** (0.018)	-0.342** (0.036)	0.302** (0.030)	-0.164** (0.020)
79	Location: mixed	-0.127** (0.024)	0.788** (0.018)	0.510** (0.039)	-0.085** (0.005)	0.572** (0.017)	0.680** (0.013)	-0.421** (0.021)	0.536** (0.019)	-0.042** (0.012)
80	Location: other non-residential	-0.283** (0.027)	0.054* (0.024)	-	0.164** (0.013)	0.075** (0.023)	-0.068** (0.014)	0.066** (0.024)	0.106** (0.026)	-0.223** (0.016)
81	Location: 5% non-western immigrants	0.019** (0.006)	-0.031** (0.004)	-0.101** (0.008)	0.047** (0.003)	-0.035** (0.004)	-0.029** (0.003)	-	-0.034** (0.004)	0.030** (0.004)
82	Degree of urbanity: non-urban	-0.120** (0.009)	0.120** (0.006)	-	0.081** (0.004)	-0.068** (0.006)	-0.010** (0.004)	-0.033** (0.009)	-0.049** (0.006)	-0.127** (0.005)
83	Degree of urbanity: high urbanity	0.197** (0.007)	0.103** (0.005)	-	-0.033** (0.003)	0.039** (0.005)	0.064** (0.003)	-0.126** (0.007)	0.043** (0.006)	-0.078** (0.004)
84	Number of moves: no moves	0.175** (0.009)	-0.101** (0.006)	-0.031** (0.008)	0.132** (0.004)	-0.105** (0.006)	-0.085** (0.004)	-0.059** (0.009)	-0.072** (0.006)	-
85	Number of moves: 1	0.025** (0.009)	-0.027** (0.006)	-	0.037** (0.004)	-0.037** (0.006)	-0.027** (0.004)	0.023** (0.009)	-0.029** (0.006)	-
86	Last move before 2006	0.032** (0.007)	0.036** (0.005)	0.021* (0.009)	0.020** (0.003)	0.013** (0.004)	0.010** (0.003)	-0.044** (0.007)	-	0.016** (0.004)

**: $p \leq 0.01$; *: $p \leq 0.05$; standard error within parentheses; -: insignificant result

Table 25 Estimation results behavior logit models BM

BUSINESS MARKET	1	2	3	4	5	6	7	8	9
Model performance	**Retention**	**Cross-sell**	**Up-sell**	**Deep-sell**	**Down-sell**	**Shrink-sell**	**Acquisition**	**Churn**	**Defection**
Intercept-model overall percentage	85.5%	91.1%	97.7%	59.7%	83.7%	59.5%	96.4%	85.9%	92.1%
Full-model overall percentage	**95.3%**	**91.1%**	**97.7%**	**79.5%**	**83.7%**	**71.0%**	**96.8%**	**85.9%**	**92.1%**
Percentage 'No' (0)	79.5%	100.0%	100.0%	55.5%	99.5%	76.5%	99.4%	99.9%	100.0%
Percentage 'Yes' (1)	98.0%	0.0%	0.0%	95.6%	2.9%	62.8%	26.2%	1.0%	0.0%
Nagelkerke R2	**0.801**	**0.085**	**0.083**	**0.479**	**0.165**	**0.315**	**0.390**	**0.159**	**0.061**
Coefficients estimates									
Intercept	-4.312** (0.03)	-6.832** (0.074)	-6.790** (0.068)	-4.017** (0.025)	-4.764** (0.024)	-4.385** (0.019)	-2.527** (0.022)	-5.116** (0.026)	-1.597** (0.011)
1 Retention (2012-2013)	2.458** (0.028)	0.123** (0.014)	0.201** (0.032)	-0.718** (0.010)	1.335** (0.015)	1.392** (0.010)	-	1.654** (0.017)	-0.125** (0.013)
2 Cross-sell (2012-2013)	-	-0.108** (0.016)	0.334** (0.025)	0.861** (0.014)	0.541** (0.011)	0.678** (0.011)	-	0.549** (0.011)	-
3 Up-sell (I2012-2013)	2.759** (0.126)	-	0.472** (0.039)	0.126** (0.026)	0.628** (0.020)	0.284** (0.021)	-	-	-1.662** (0.101)
4 Deep-sell (2012-2013)	-0.331** (0.029)	-0.061** (0.011)	0.429** (0.020)	0.594** (0.008)	0.509** (0.008)	0.789** (0.007)	-	0.503** (0.008)	-0.660** (0.015)
5 Down-sell (2012-2013)	-0.599** (0.090)	-	0.428** (0.056)	-	0.436** (0.028)	0.610** (0.029)	-	0.353** (0.030)	-0.228** (0.060)
6 Shrink-sell (2012-2013)	2.132** (0.026)	-0.023* (0.012)	0.421** (0.020)	0.361** (0.009)	0.381** (0.008)	0.162** (0.007)	-	0.347** (0.009)	-0.186** (0.014)
7 Acquisition (2012-2013)	4.331** (0.035)	0.264** (0.023)	0.163** (0.053)	-0.272** (0.017)	1.032** (0.022)	1.276** (0.016)	-	1.335** (0.024)	-0.066** (0.020)
8 Churn (2012-2013)	-0.831** (0.097)	0.243** (0.020)	-0.493** (0.065)	-0.313** (0.015)	-0.638** (0.031)	-0.758** (0.031)	-	-0.594** (0.033)	0.759** (0.062)
9 Defection (2012-2013)	-	-	-	-	-	-	0.447** (0.023)	-	-
10 Relationship age: 1st year	4.035** (0.028)	4.421** (0.074)	1.586** (0.078)	1.944** (0.028)	2.048** (0.025)	3.572** (0.020)	2.935** (0.021)	2.119** (0.026)	-
11 Relationship age: 2nd year	7.023** (0.046)	3.877** (0.074)	2.288** (0.069)	4.487** (0.026)	2.261** (0.023)	2.790** (0.020)	-0.571** (0.041)	2.211** (0.024)	-
12 Relationship age: 3rd year	6.437** (0.046)	3.912** (0.075)	1.609** (0.076)	4.134** (0.026)	1.686** (0.024)	2.773** (0.020)	-0.401** (0.042)	1.629** (0.025)	-
13 Relationship age: 4th year	7.059** (0.059)	3.931** (0.075)	1.656** (0.076)	4.416** (0.026)	1.637** (0.024)	2.524** (0.020)	-0.998** (0.056)	1.588** (0.025)	-
14 Relationship age: 5th year	7.145** (0.062)	3.951** (0.075)	1.729** (0.073)	4.440** (0.026)	1.545** (0.023)	2.463** (0.020)	-1.228** (0.060)	1.488** (0.024)	-
15 Relationship age: 6th year	7.067** (0.062)	3.949** (0.074)	1.760** (0.071)	4.413** (0.026)	1.525** (0.023)	2.256** (0.019)	-1.281** (0.060)	1.455** (0.024)	-
16 Relationship age: 7th year	7.269** (0.064)	4.013** (0.074)	1.815** (0.070)	4.483** (0.026)	1.498** (0.023)	2.316** (0.019)	-1.413** (0.062)	1.413** (0.024)	-
17 Relationship age: 8th year	7.151** (0.064)	4.078** (0.074)	1.871** (0.069)	4.842** (0.026)	1.387** (0.023)	2.314** (0.019)	-1.386** (0.062)	1.294** (0.024)	-
18 Relationship age: 9th year	7.371** (0.073)	3.977** (0.075)	1.782** (0.072)	4.753** (0.027)	1.370** (0.024)	2.230** (0.020)	-1.522** (0.071)	1.287** (0.025)	-
19 Relationship age: 10th year	7.538** (0.081)	3.946** (0.076)	1.878** (0.074)	4.990** (0.028)	1.380** (0.026)	2.352** (0.021)	-1.374** (0.079)	1.276** (0.027)	-
20 Relationship age: >10th year	8.107** (0.037)	3.828** (0.072)	1.916** (0.062)	5.402** (0.024)	1.225** (0.019)	2.287** (0.016)	-1.739** (0.033)	1.079** (0.020)	-
21 Location: demolition building	-0.829** (0.062)	-2.314** (0.303)	1.538** (0.126)	0.356** (0.062)	-0.805** (0.125)	-0.724** (0.074)	-0.514** (0.075)	-2.103** (0.269)	0.949** (0.046)
22 Location: business	0.135** (0.026)	0.225** (0.021)	0.085** (0.031)	0.118** (0.013)	0.357** (0.016)	0.312** (0.012)	-0.834** (0.029)	0.353** (0.016)	-
23 Location: mixed	0.379** (0.026)	0.621** (0.021)	0.332** (0.031)	0.306** (0.013)	0.329** (0.016)	0.294** (0.012)	-1.416** (0.031)	0.375** (0.016)	-0.356** (0.015)
24 Location: private owned	0.248** (0.021)	0.741** (0.020)	0.229** (0.032)	0.215** (0.012)	0.277** (0.015)	0.207** (0.011)	-0.865** (0.024)	0.352** (0.016)	-0.418** (0.012)
25 Location: other non-residential	-0.066** (0.024)	0.192** (0.025)	-	0.031* (0.015)	0.069** (0.019)	0.066** (0.014)	-0.156** (0.026)	0.079** (0.020)	-
26 SOW 0-10% (based on consolidated results)	1.882** (0.129)	-0.213* (0.107)	-0.435* (0.171)	-0.711** (0.062)	0.440** (0.061)	-	0.688** (0.126)	0.582** (0.062)	-2.636** (0.449)
27 SOW 10-20% (based on consolidated results)	0.606** (0.205)	-0.579** (0.175)	-0.758** (0.285)	-0.690** (0.089)	0.324** (0.095)	-	0.855** (0.198)	0.419** (0.098)	-2.669** (0.709)
28 SOW 20-30% (based on consolidated results)	1.128** (0.351)	-0.494** (0.185)	-0.676* (0.309)	-0.751** (0.097)	0.250* (0.105)	-	-	0.441** (0.107)	-2.429** (0.710)
29 SOW 30-40% (based on consolidated results)	-	-0.465* (0.195)	-0.804* (0.361)	-0.678** (0.104)	0.373** (0.112)	-	-	0.474** (0.116)	-1.883** (0.581)
30 SOW 40-50% (based on consolidated results)	0.847* (0.402)	-1.333** (0.307)	-0.827* (0.385)	-0.423** (0.110)	0.357** (0.116)	-	-	0.516** (0.119)	-
31 SOW 50-60% (based on consolidated results)	-	-0.69** (0.232)	-	-0.595** (0.113)	0.374** (0.122)	-	-	0.461** (0.127)	-
32 SOW 60-70% (based on consolidated results)	-	-1.079** (0.309)	-	-0.668** (0.125)	0.457** (0.134)	-	-	0.637** (0.136)	-
33 SOW 70-80% (based on consolidated results)	-	-1.145** (0.308)	-	-0.534** (0.124)	0.338** (0.131)	-	-	0.472** (0.135)	-
34 SOW 80-90% (based on consolidated results)	-	-0.628* (0.259)	-	-0.354** (0.133)	-	-	-	-	-
35 SOW 90-100% (based on consolidated results)	-	-0.688* (0.288)	-	-0.529** (0.147)	0.414** (0.158)	-	0.970** (0.364)	0.480** (0.166)	-
36 SOW 0-10% (based on revenues)	0.799** (0.096)	-0.355** (0.066)	-0.555** (0.101)	-0.554** (0.036)	0.246** (0.038)	0.085** (0.031)	0.254** (0.094)	0.348** (0.040)	-3.790** (0.409)
37 Consolidated results: loss	-0.144** (0.046)	0.059* (0.025)	-	-	0.141** (0.018)	0.118** (0.016)	-	0.124** (0.019)	-

**: p ≤ 0.01; *: p ≤ 0.05; standard error within parentheses; -: insignificant result

Coefficients estimates		Retention	Cross-sell	Up-sell	Deep-sell	Down-sell	Shrink-sell	Acquisition	Churn	Defection
38	Consolidated results: profit	-0.426** (0.040)	0.139** (0.020)	0.173** (0.029)	0.135** (0.015)	0.042** (0.015)	0.074** (0.013)	-0.285** (0.047)	-	-
39	Number of employees: 1	-0.097** (0.021)	0.051** (0.012)	-0.498** (0.027)	-0.065** (0.011)	-0.152** (0.012)	-0.141** (0.011)	0.143** (0.032)	-0.063** (0.011)	-
40	Number of employees: 2	-0.110** (0.026)	0.049** (0.014)	-0.370** (0.029)	-0.031** (0.011)	-0.100** (0.012)	-0.076** (0.012)	0.178** (0.034)	-	-
41	Number of employees: 3-5	-	-	-0.392** (0.028)	-	-0.066** (0.012)	-0.063** (0.012)	0.099** (0.035)	-	-
42	Number of employees: 6-10	-	-	-0.228** (0.03)	-0.029* (0.013)	-	-0.032* (0.013)	0.143** (0.039)	-	-
43	Number of employees: 11-20	-	-	-	-	-	-0.055** (0.015)	0.129** (0.046)	-	-
44	Number of employees: 51-100	-	-	0.110* (0.044)	-	-	-0.052* (0.023)	-	-	-
45	Number of employees: 101-150	-	-	0.174* (0.072)	-	-	-	-	-	-
46	Number of employees: 151-200	-	-	-	-	-	-0.118* (0.050)	-	-	-
47	Number of employees: 201-250	-	-	-	-	-	-	0.432** (0.158)	-	-
48	Number of employees: 501-1,000	-	-	-	-	-	-	0.228* (0.116)	-	-
49	Number of employees: 1,001-2,000	-	0.160* (0.075)	-	-	-	-	1.021** (0.097)	-0.182** (0.059)	-
50	Number of employees: >2,001	-	-	0.290** (0.096)	-	-	-	0.936** (0.096)	-0.261** (0.042)	-
51	Parts in concern: 1	0.153** (0.027)	-	0.824** (0.040)	-	0.237** (0.018)	0.393** (0.028)	-1.272** (0.085)	-	-0.658** (0.018)
52	Parts in concern: 2	0.113** (0.038)	-	0.916** (0.052)	-	0.252** (0.020)	0.378** (0.029)	-1.170** (0.091)	-	-0.569** (0.028)
53	Parts in concern: 3-5	0.218** (0.040)	-	1.061** (0.052)	-	0.298** (0.021)	0.403** (0.030)	-1.251** (0.092)	-	-0.584** (0.030)
54	Parts in concern: 6-10	0.375** (0.058)	-	1.163** (0.064)	-	0.332** (0.028)	0.390** (0.034)	-1.151** (0.102)	-	-0.487** (0.042)
55	Parts in concern: 11-20	0.205** (0.064)	-	1.129** (0.076)	-	0.312** (0.036)	0.268** (0.039)	-1.274** (0.107)	-	-0.183** (0.045)
56	Parts in concern: 21-50	0.218** (0.064)	-	1.138** (0.083)	-0.235** (0.036)	0.253** (0.040)	0.155** (0.042)	-1.201** (0.100)	-	-
57	Parts in concern: 51-100	0.448** (0.087)	-	0.704** (0.134)	-	0.257** (0.058)	-	-1.060** (0.112)	-	-
58	Parts in concern: 101-150	-	-0.264* (0.119)	0.765** (0.170)	-0.485** (0.068)	-	-0.415** (0.072)	-	-	-
59	Parts in concern: 151-200	-	-	-	-0.571** (0.103)	0.355** (0.113)	-	-	-	-
60	Parts in concern: 201-250	0.715** (0.190)	-	-	-0.539** (0.123)	-	-	-0.922** (0.197)	-	-
61	Parts in concern: 251-500	1.380** (0.101)	-	0.940** (0.170)	-0.317** (0.071)	-	-	-1.499** (0.141)	-	-
62	Parts in concern: 501-1.000	0.756** (0.159)	-	1.043** (0.229)	-	-	-	0.378** (0.131)	-	-
63	Parts in concern: >1,000	1.534** (0.152)	-	0.798** (0.233)	-0.382** (0.109)	-	-0.389** (0.106)	-1.101** (0.174)	-	-0.416** (0.143)
64	Years since establishment: 1	-0.961** (0.056)	0.406** (0.038)	-	-	-	-	0.855** (0.053)	-	0.506** (0.042)
65	Years since establishment: 1-2	-1.071** (0.035)	-	-	-	-	-	0.929** (0.033)	-	0.375** (0.028)
66	Years since establishment: 2-5	-0.441** (0.025)	-	-	0.374** (0.018)	-0.066** (0.014)	-	-	-0.089** (0.015)	0.281** (0.018)
67	Years since establishment: 5-10	-	-0.126** (0.016)	-	0.396** (0.016)	-0.044** (0.011)	-	-	-0.057** (0.011)	-
68	Years since establishment: 10-20	-	-0.130** (0.015)	-	0.337** (0.016)	-	-	-	-	-
69	Years since establishment: 20-50	-	-0.152** (0.016)	-0.147** (0.021)	0.364** (0.016)	-0.025** (0.010)	-	-	-	-
70	Years since establishment: 50-100	-	-0.176** (0.025)	-	0.452** (0.021)	-	-	-	-	-0.275** (0.030)
71	Years since establishment: >100	-	-0.214** (0.052)	-0.188* (0.082)	0.414** (0.039)	-	-	-0.403** (0.124)	-	-
72	Import	-	-	-	-	0.064** (0.016)	0.033* (0.013)	-	-	-
73	Export	-	-	-	0.032* (0.016)	-	-	-	-	-
74	Legal entity: sole proprietorship	-	0.109** (0.014)	-	-0.080** (0.011)	-0.031** (0.012)	0.064** (0.015)	-	-0.039** (0.012)	0.213** (0.017)
75	Legal entity: foundation	0.171** (0.041)	-	0.159** (0.046)	-	0.212** (0.022)	0.136** (0.021)	-0.288** (0.052)	0.165** (0.023)	-
76	Legal entity: partnership	0.461** (0.075)	-	0.221** (0.048)	-	-	-	-	-0.110** (0.028)	-
77	Legal entity: association partnership	-	0.105** (0.017)	-	-	-	0.079** (0.016)	-	-	-
78	Legal entity: private company	-	-	0.064* (0.027)	-	-	0.094** (0.016)	-	-	-0.122** (0.018)
79	Legal entity: limited company	0.732** (0.144)	0.359** (0.101)	-	-	-	-	-1.028** (0.175)	-	-0.449** (0.110)
80	Segment: special business services	-	-	-	0.098** (0.021)	-	-	-0.100* (0.042)	-	-
81	Segment: other services	-	-	-0.189** (0.046)	0.184** (0.024)	-0.157** (0.021)	-0.125** (0.017)	-	0.045* (0.019)	-
82	Segment: description 20	-	0.162** (0.027)	-	0.105** (0.027)	-0.061** (0.023)	-	0.191** (0.056)	-	-
83	Segment: accommodation meal and drink supply	-	-	-	-0.142** (0.021)	-	-	-	-	-
84	Segment: health and welfare	-	-	-	-	-0.080** (0.02)	-0.255** (0.033)	0.701** (0.096)	-	-
85	Segment: wholesale and retail trade repair of cars	-	-0.174** (0.016)	-	-0.149** (0.014)	-	-	-	-	-

**: p ≤ 0.01; *: p ≤ 0.05; standard error within parentheses; -: insignificant result

	Coefficients estimates	Retention	Cross-sell	Up-sell	Deep-sell	Down-sell	Shrink-sell	Acquisition	Churn	Defection
85	Segment: wholesale and retail trade repair of cars	-	-0.174** (0.016)	-	-0.149** (0.014)	-	-	-	-	-
86	Segment: financial institution	-	-	-0.170** (0.037)	-	-	-0.181** (0.037)	0.876** (0.119)	-	-
87	Segment: education	-	-	-	0.136** (0.031)	-	0.074** (0.025)	-0.408** (0.075)	0.139** (0.029)	0.113** (0.039)
88	Segment: transport and storage	-	-	0.239** (0.048)	-	0.105** (0.033)	0.088** (0.028)	-	-	-
89	Location: business complex	-0.070** (0.018)	0.234** (0.010)	0.419** (0.019)	-	0.134** (0.008)	0.147** (0.007)	-	0.082** (0.009)	-
90	Self-employed without employees: science	-	-	-	0.070** (0.016)	-0.064** (0.014)	-0.036** (0.011)	-0.233** (0.034)	-0.098** (0.013)	-0.269** (0.020)
91	Self-employed without employees: location bound	-	-	-0.259** (0.053)	0.092** (0.020)	-	-	-	-	-
92	Self-employed without employees: trading	-	-	-	-	-	-	-0.122* (0.049)	-	-
93	Self-employed without employees: administrative	-0.245** (0.042)	-	-	-	-0.096** (0.024)	-0.102** (0.021)	-	-	0.09* (0.038)
94	Self-employed without employees: creation	0.154** (0.041)	-	-0.315** (0.057)	-0.082** (0.022)	-0.144** (0.024)	-0.161** (0.020)	-	-	0.124** (0.030)
95	Self-employed without employees: knowledge	-	-	-0.264** (0.040)	-	-0.141** (0.019)	-0.123** (0.016)	-	-	-
96	Self-employed without employees: not	-	0.071** (0.013)	-	-0.038** (0.012)	-	-	-	-	-0.136** (0.017)
97	Mother company	-0.190** (0.035)	0.110** (0.018)	0.232** (0.032)	-	-	0.150** (0.014)	-0.219** (0.040)	-	-0.215** (0.025)
98	Location: special	1.146** (0.081)	-	-	-0.365** (0.092)	-1.035** (0.206)	-0.476** (0.125)	0.986** (0.079)	-1.054** (0.214)	-0.476** (0.069)
99	Special location: mailbox	1.139** (0.285)	-	-	-	2.565** (0.287)	1.137** (0.216)	-3.438** (0.474)	-	0.622** (0.164)
100	Special location: pumping station	-1.304** (0.266)	-	-	-	-	-0.804* (0.341)	-	-	1.015** (0.200)
101	Special location: elevator	-	-2.724** (0.579)	-	1.517** (0.136)	-1.390** (0.542)	-1.105** (0.221)	-1.088** (0.187)	-1.779* (0.740)	-
102	Nace: description 9	-	-	-	-	-0.084** (0.020)	-0.080** (0.023)	0.226* (0.089)	-0.077** (0.028)	-
103	Nace: description 38	-	-	-	-0.073** (0.023)	-	-	-	-	-
104	Nace: description 355	-	-	-0.649* (0.304)	-0.799** (0.104)	-0.623** (0.119)	-	-	-0.432** (0.129)	-
105	Nace: description 395	0.424** (0.065)	-0.573** (0.095)	-0.383** (0.125)	0.351** (0.054)	-	-0.268** (0.049)	-0.687** (0.144)	0.182** (0.058)	0.348** (0.059)
106	Nace: description 412	1.274** (0.132)	0.276** (0.031)	-	-	-0.356** (0.035)	-0.200** (0.025)	-1.217** (0.162)	-0.368** (0.038)	-
107	Nace: description 543	-	-	-	-	-	-	-0.266* (0.132)	-	-
108	Gartner industry related spending: 1%	-	0.249** (0.014)	-	0.099** (0.016)	-0.235** (0.013)	-0.278** (0.031)	0.975** (0.089)	-	-
109	Gartner industry related spending: 1-2%	-	0.167** (0.021)	-	-	-0.172** (0.023)	-0.300** (0.035)	0.850** (0.097)	-	-
110	Gartner industry related spending: 2-3%	0.246** (0.035)	0.045* (0.022)	-	0.100** (0.020)	-	-	-	0.095** (0.019)	-
111	Gartner industry related spending: 3-4%	-	-	-	-0.149** (0.021)	-	-0.158** (0.032)	0.991** (0.093)	-	-
112	Gartner industry related spending: ≥5%	-	-	-	-0.084** (0.018)	-	-	-	0.082** (0.024)	0.312** (0.027)
113	Relationship to concern: non	-	-	-	-	-	-	-0.066** (0.023)	-	-

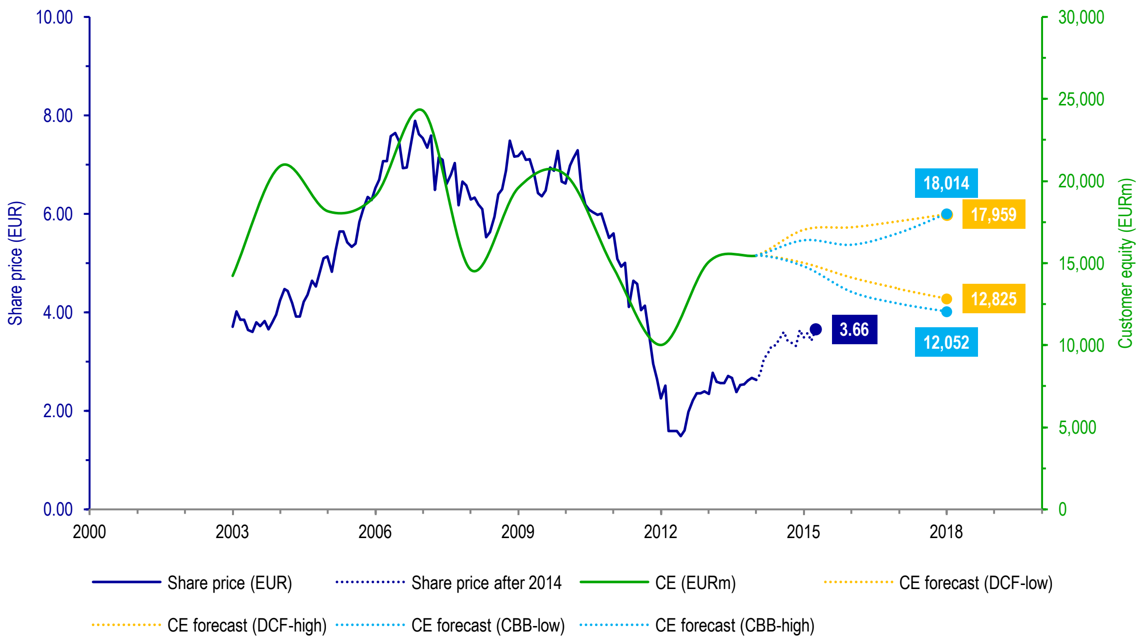
**: p ≤ 0.01; *: p ≤ 0.05; standard error within parentheses; -: insignificant result

6. Conclusions

The new developed CBB valuation model, integrating big data analytics, reveals that indeed customers and their associated behavior form the 'pulse' of the firm, as they provide the CFs driving SHV; the vital sign of life. The CBB valuation model is successful, accurate and insightful in determining these CFs. The model analyses, forecasts and values individual customer behavior, ultimately linking individual customer relationships to SHV.

Successful in driving SHV from forecasted customer behavior | In general, the model is successful in integrating big data analytics in a valuation context, by analyzing, forecasting and valuing individual customer behavior, ultimately driving SHV. It has shown the substantial and positive correlation between the total value from customers known as CE and the share price, hence SHV. The direction of causality can be inferred from economic reasoning. Investors value future CFs to the firm discounted at the WACC, where CFs come from paying customers. This concludes that there is a causal relation between CE and share price. Therefore, the scenario-based-forecast on CE (Figure 27) is a strong indication for the direction of the share price. This CE forecast is driven by the scenario forecast from both DCF and CBB valuation model. The input for deriving the CE forecast using (Eq. 29) is reported in Table 37 of the appendix.

Figure 27 Customer equity scenario forecast by **DCF** and **CBB** valuation 2015–2018



Source: own computations on integrated customer-centric dataset, Firm X annual reports 2003-2014 and Thomson One Banker

High accuracy | The CBB valuation model accuracy stems from the results on the SHV range and the CE forecast in comparison to the results from the DCF valuation model. In other words, the DCF and CBB valuation models have a quite similar performance in terms of SHV forecast.

New and highly detailed managerial insights | The CBB valuation model is essentially a managerial model, providing insights that are relevant for the entire firm, from top to bottom. These insights are available on the most detailed level thinkable: the individual customer, as analysis and forecasts are performed on this level. An example of such a detailed obtained insight is: a CM customer is less likely to defect in the next period when in the current period it is observed that it purchased a more expensive version of the same service or product (up-sell), and/or it purchased a product from another category (cross-sell), and/or it used more of the same service or product (deep-sell).[43] However, a CM customer is more likely to defect in the next period when in the current period it is observed that it purchased a less expensive version of the same service or product, and/or it simply purchased the exact same (retention; 1.74 times more like to defect), and/or it just joined the firm as a new customer (acquisition; 1.36 times more likely), and/ or it cancelled one of its product categories in its portfolio. Yet another detailed insight that can be obtained from the CBB valuation model is the ranking of individual customer values or e.g. ranked cross-sell probabilities; the likeliness a customer is going to cross-buy from the firm. However, this is out of the scope of this study, and is merely an example to illustrate its performance on new and detailed insights. This highly detailed level of information enables managers to estimate ROIC and growth on the individual customer level. Ultimately, the model provides insights that support budget allocation on the individual customer level. This provides managers with the ability to manage customer relationships based on their estimated future value contribution. Or in other words, the model supports managers to seek for the upside potential on the individual customer level.

6.1 Hypotheses testing

A summary on the results of the tested hypotheses is reported in Table 26. Different models have been used in testing these hypotheses. The results on the hypotheses related to the customer behavior value drivers from the CBB valuation model, is in accordance with the empirical findings.

Table 26 Summary of hypotheses-testing results

Hypotheses		Significant (CM; BM)	Sign (CM; BM)	Result (CM; BM)
1	The value per share estimated by DCF valuation, approximates the price per share.	n/a	n/a	EUR 2.56 versus 2.63
2	CE and share price are positively correlated.	*	(+)	R^2= 0.695
3	Improvements in the retention rate affects CE.	**	(+)	accepted
4	The EV estimated by DCF valuation, approximates CE estimated by CE valuation.	n/a	n/a	EUR 17.8b versus 15.5b
5	Customer purchase behavior explains the variance in customer profitability.	n/a	n/a	R^2= 0.819; R^2= 0.701
6	There is a positive relation between retention and customer profitability.	**; **	(+; +)	accepted; accepted
7	There is a positive relation between cross-sell and customer profitability.	**; **	(+; +)	accepted; accepted
8	There is a positive relation between up-sell and customer profitability.	**; **	(+; +)	accepted; accepted
9	There is a positive relation between deep-sell and customer profitability.	**; **	(+; +)	accepted; accepted
10	There is a negative relation between down-sell and customer profitability.	**; **	(–; –)	accepted; accepted
11	There is a negative relation between shrink-sell and customer profitability.	**; **	(–; –)	accepted; accepted
12	There is a positive relation between acquisition and customer profitability.	**; **	(+; +)	accepted; accepted
13	There is a negative relation between churn and customer profitability.	**; **	(–; –)	accepted; accepted
14	There is a negative relation between defection and customer profitability.	**; **	(–; –)	accepted; accepted
15	Observed customer behavior affects future customer behavior.	~	(±; ±)	accepted; accepted
16	Customer brand choice affects customer behavior.	n/a	n/a	n/a
17	Customer brand choice affects customer profitability.	n/a	n/a	n/a
18	Customer characteristics affect customer behavior.	~	(±; ±)	accepted; accepted
19	Customer characteristics affect customer profitability.	~	(±; ±)	accepted; accepted
20	Relationship age affects customer purchase behavior.	**; **	(±; ±)	accepted; accepted
21	There is a positive relation between relationship age and customer profitability.	**; **	(±; ±)	accepted; accepted
22	Share of wallet affects customer purchase-behavior.	~	(±; ±)	accepted; accepted
23	There is a positive relation between share of wallet and customer profitability.	~	(±; ±)	accepted; accepted

**: p ≤ 0.01; *: p ≤ 0.05; n/a: not applicable; ~: various variables significant but on different levels; ±: both signs are applicable; /: ambiguous results

In an attempt to bridge the gap between quantitative marketing and finance, this study leveraged big data analytics as the connective tissue in a firm valuation context. An accurate CF forecast is vital to a proper valuation. Big data analytics, applied in a such a context, has the potential to increase the forecast accuracy. The new insights and

[43] Controlling for other variables in the model.

forthcoming applications from this valuation model has the potential to create significant SHV. The model enables senior executives to conduct value relevant data driven decision making. Resulting in better strategies that provide the firm with competitive advantages that drives price premiums and efficient capital use, thus increasing ROIC and growth, hence SHV.

SHV is driven by a chain of value drivers, where incremental CFs discounted at the firm's WACC is the most primary source of SHV creation. The right balance between ROIC and revenue growth is critical for the increase in CFs. Improvements in ROIC and growth are driven by the firm's competitive advantage resulting from its strategy. The DCF valuation methodology is the most common used methodology in determining SHV, relying solely on CFs in and out of the firm. The forecast on the breakdown into price and volume components of key value drivers is based on the analyst's personal view. The DCF valuation model estimated value per share is EUR 2.56 and approximates the price per share EUR 2.63 (H1).

Empirical studies in marketing have shown its substantial contribution to SHV. This follows logically on the fact that marketing is all about building the intangible assets of the firm. The firm's most important intangible asset are its customers, and needs to be valued accordingly. The recently emerged CBV literature in marketing sees customers as assets and makes them the central object of analysis and valuation. Empirical studies in CBV is built up around the CLV concept showing that the sum of all CLVs, known as CE, is a good proxy for the EV. The correlation between CE and the historical share price is 0.695 (H2). CLV and CE models are based on customer margins, retention rates, acquisition costs and a discount rate. An improvement of 100 basis points in the retention rate increases CE by 7.3% (H3). The level of EV EUR 17.8b estimated by the DCF valuation model approximates the level of CE EUR 15.5b estimated by the CE valuation model (H4). Individual customer behavior drives CLV and improvements in CE are linked to improvements in SHV, equals individual customer behavior drives SHV. The variance in customer profitability is largely (CM R^2=0.819; BM R^2=0.701) explained by individual customer purchase behavior (H5). Nine customer behavior value drivers are significantly related to the forecast of customer profitability, hence SHV, for both CM and BM the signs are identical, thus accepting all related hypotheses: retention (positive, H6), cross-sell (positive, H7), up-sell (positive, H8), deep-sell (H9), down-sell (negative, H10), shrink-sell (negative, H11), acquisition (positive, H12), churn (negative, H13) and defection (negative, H14). In addition, in order to forecast several periods ahead a forecast on observed customer behavior is required. As a result, observed customer behavior forecasts future behavior and drives customer profitability, hence SHV (H15). Customers derive value from brands and as a result it drives their loyalty. Increases in customer loyalty drives the firms price premium, and results in incremental CFs to the firm, hence SHV. However, as the impact of brands on SHV is recognized it was not possible to incorporate these effects in the model. Due to serious shortcomings in software and hardware specifications[44] it is highly recommended to run the model, and similar analysis on a server. Incorporating these effects would have increased the number of behavior logit models to be estimated from 18 (2 segments; 9 behaviors) to 72 (2 segments; 9 behaviors; 4 brands), increasing the computed probabilities from 2 to 18 billion, resulting in an estimated 1TB of data. This is simply impossible. Therefore, these brand effects have not been tested, thus the hypotheses (H16 and H17) are not applicable. Then, customer characteristics are related to customer needs and tastes, linking customer characteristics to the purchase decision process. It follows that customer characteristics support in the forecast of customer behavior (H18) and customer profitability (H19) for both CM and BM models. Another variable supporting in forecasting is the customer's relationship age. When the customer relationship age with the firm increases, it also increases its: loyalty, retention

[44] IBM SPSS Statistics 22 (software); Intel i7 + 4GB memory + Windows 7 32-bits and Intel i5 + 16GB memory + SSD + OSX 64-bits

probability, satisfaction and switching costs. In general, the customer relationship age affects its behavior (H20). In addition, it affects customer profitability as well. For early years in the relationship, the direction of the relation is negative, where for later years this becomes positive for both CM and BM models. However, its profitability increases as the relationship age increases, as the negative parameter decreases in size (H21). The final variable supporting in forecasting is share of wallet (SOW). When the customer's SOW increases, it also increases its loyalty. Therefore, the customer's SOW affects its behavior (H22). In addition, it affects customer profitability as well. However, the direction of the relation is ambiguous for both CM and BM customers (H23).

6.2 Comparing DCF and CBB valuation models

A summary of the comparison between DCF and CBB valuation models, revealing the differences and similarities, is reported in Table 27.

Common goal different forecast model | Both DCF and CBB valuation models aim to forecast SHV and result in very similar values. The SHV range from the DCF valuation model falls within the range of the CBB valuation model. The last value range, is a result from low- and high scenarios based on the lower and upper estimated 95% CI bounds. An objective approach in scenario analysis. However, the DCF low- and high scenario values, result from the analyst's view on the development of the breakdown into price and volume components of the key- and operating value drivers. These are drivers are driven by its understanding of the firm's industry dynamics and its competitive position and strategy. Clearly a more subjective approach in scenario analysis.

Different value driver setup | Both DCF and CBB valuation models have a similar value driver setup, however the value drivers themselves are completely different. The value drivers for the DCF valuation model are more product-centric oriented where for the CBB valuation model this is customer-centric oriented. In essence, this setup makes both models two sides of the same coin.

Different analysis approach | Due to the value driver setup both DCF and CBB valuation models have a different approach in analysis. Where the CBB valuation model is clearly an 'inside-out' analysis approach the DCF valuation model has a more ambiguous approach, but essentially is more 'outside-in.'

Different insights | DCF and CBB valuation models provide very different insights. The DCF valuation model insights are mainly on the line item level of the P&L and BS. This provides an overview on for instance, the forecasted revenue growth, EBITDA, EBITDA-margin, CAPEX, NWC, tax-rate and FCF. The development of these items are considered all highly relevant to firm value. However, the CBB valuation model delivers insights on the level of individual customer relationship with the firm. It forecasts future behavior, based on observed behavior, providing insights for instance like: "a customer is less likely to defect in the next period, even though it is observed that it uses less of the same service or product (shrink-sell) during the current period." This detailed insight could be explained as that there is a group of customers (CM) that at first seems to be less engaged with the firm based on their decreased usage and therefore may leave the firm. However, against all odds the results show that they are less likely to leave. This could indicate a more rational type of customer. In general, these kinds of detailed insights can serve as valuable input in developing strategies, tactics and policies, targeted to 'similar behaving' customers or customer-cohorts, in order to stimulate certain customer behavior, thus maximize individual profitability, hence SHV. Based on the different value driver setup and analysis approach, very similar results in valuation, and very different insights it can be concluded that both models are therefore complementary to each other.

Table 27 Comparing DCF and CBB valuation model

	DISCOUNTED CASH FLOW VALUATION MODEL	CUSTOMER BEHAVIOR BASED VALUATION MODEL
DATA		
Availability / accessibility	▪ Publicly available financial data incl. KPIs ▪ Datastreams, annual reports etc.	▪ Big data (internal) ▪ Integrated customer-centric dataset (new developed)
Usability	▪ Readily available for analysis	▪ Extensive data collection ▪ Extensive data preparation
Variables	All variables (line items) from: ▪ Balance sheet ▪ Profit & loss ▪ Cash flow statement ▪ Additional KPIs	Variables (±1,500) from an integrated customer-centric dataset: ▪ Revenues per BSP combination ▪ EBITDA margin (%) on BSP level ▪ Customer behavior (derived) ▪ Product ownership (derived) ▪ Brand (4 different) ▪ Segments (2 different) ▪ Products (29 different) ▪ Number of customers on location ▪ Various customer characteristics (CM and BM)
Level of aggregation	▪ Firm ▪ Brand ▪ Segment ▪ Product	▪ Individual customer (assumption, actual data on unique location level)
METHODOLOGY		
Value drivers	▪ CF discounted at WACC (COC) ▪ ROIC o Price premium ▪ Innovative products ▪ Quality ▪ Brand ▪ Customer lock-in ▪ Rational price discipline o Cost and capital efficiency ▪ Innovative business method ▪ Unique resources ▪ Economies of scale ▪ Scalable product/process ▪ Growth ▪ New products ▪ Sell more ▪ New customers ▪ Gain market share ▪ Bolt-on acquisitions ▪ Innovation (incremental) ▪ Product promotion and pricing ▪ Large acquisitions	▪ CF discounted at WACC (COC) ▪ Customer behavior / profitability o Retention o Cross-sell o Up-sell o Deep-sell o Down-sell o Shrink-sell o Acquisition o Churn o Defection ▪ Customer characteristics o Relationship age o SOW o Various characteristics (CM and BM) ▪ (Brand choice behavior)[45]
Analysis	▪ Key value driver breakdown into price and volume components	▪ Key value driver breakdown into 9 types of customer behavior (derived from observed behavior)
Forecast model	▪ YOY growth extrapolation ▪ Analyst's view on development	▪ Behavior logit model ▪ Profit regression model
Forecast PP	▪ Key- and operating value drivers, driving the line items on the P&L ▪ Future CFs discounted at WACC	▪ Analysis of observed behavior and characteristics, driving the… ▪ Forecast on future behavior probabilities, driving the… ▪ Forecast on future profitability ▪ Future CFs discounted at WACC
Forecast CV	▪ Key value driver formula ▪ CV accounts for about 70% of EV	▪ Key value driver formula ▪ CV accounts for about 70% of EV
Financial adjustments	Obtained EV ▪ (+) NOA ▪ (–) Debt	Obtained EV ▪ (+) NOA ▪ (–) Debt
RESULTS		
SHV	**EUR 10.2–11.8b (2014)**	**EUR 7.8–12.5b (2014)**
CE	**EUR 15.5b (2014)**	

[45] The importance of brand-choice behavior on customer behavior and profitability is acknowledged. However, due to serious shortcomings in software and hardware capabilities concerning the analysis and forecast, the effect is not incorporated in the final model.

6.2.1 Pros and cons

Based on the comparison of the DCF and CBB valuation models, a summary of the pros and cons between DCF and CBB valuation is reported in Table 28.

Table 28 Pros and cons of DCF and CBB valuation models

	DISCOUNTED CASH FLOW VALUATION MODEL	CUSTOMER BEHAVIOR BASED VALUATION MODEL
PROS	**Data** ✓ Publicly available ✓ Financial datastreams (readily prepared data) **Methodology** ✓ DCF is a very common used method in finance, as it relies solely on CFs in and out of the firm ✓ Value driver setup covers the entire 'value-chain', from firm strategy to CF and everything in between **Results** ✓ Can be determined relatively quickly	**Data** ✓ Incorporates big data analytics, creating significant value through improved decision-making (information transparency and information usability frequency) **Methodology** ✓ Relatively high level of objectivity in forecast methodology (algorithm driven model) **Results** ✓ On individual customer level, driving: ✓ Development of strategies, tactics and policies based on detailed insights ✓ Supports manager in pursuing the right balance between growth and ROIC on the customer level
CONS	**Data** ✘ Uses aggregated data **Methodology** ✘ Potentially high subjectivity in forecast, due to analyst's view on the development of key value driver's breakdown ✘ Powerful model, however every assumption has the potential to result in large changes in EV, because: ✘ CV (approx. 70% of the EV) is highly dependent on the accuracy of the forecast	**Data** ✘ Requires extensive internal data ✘ Extensive and complex data collection and preparation ✘ Customer data not available on individual level (but on location level) ✘ Asymmetric data availability (brand and period related) ✘ EBITDA-margin (%) on level BSP combination, hence no customer specific margin, due to the absence of customer specific costs ✘ Limited accessibility to big data warehouse **Methodology** ✘ Extensive and complex modelling ✘ Relies heavily on large quantities of customer data ✘ Brand choice behavior not incorporated in model ✘ Separate 'BM XL' model (a separate model for 'outlier' customers) ✘ Acquisition logit model potentially overestimate and defection logit model potentially underestimates the probabilities and thus SHV, as log EBITDA has not been used as predictor. This potentially causes too high probabilities in the acquisition and defection logit models ✘ Acquisition costs are not taken into account; potentially causing overestimation of SHV results **Results** ✘ Partly depends on choices in econometric modelling, which in turn entails a certain degree of subjectivity

6.3 Limitations of the study

A limitation arises from the continuous tradeoff during this study between the intuitiveness of the model and accurateness of the results. Much time and effort has been put into the construction, preparing and modeling of the data on top of the already challenging integration of both academic fields. The increase of complexity in modeling adds more realism to the model, but potentially reduces its intuition in interpretation and general understanding. However, Donkers et al. (2007) conclude that complex models do not necessarily add predictive capacity in a valuation context. Hence, the tradeoff between intuitiveness and accuracy of the model is not expected to affect the SHV estimate. However, several limitations of this study do have an effect on the model outcomes, resulting in implications for managers and also potential areas for future studies.

Data limitations | A major limitation of this study concerns the *aggregation level* of the integrated customer-centric dataset. The data has been aggregated on the unique location level, such that all available customer information is 'plotted' on the corresponding location. For a situation with more than one customer on a location this causes biased estimates in the first place. The following example will illustrate the most extreme scenario possible causing bias in estimation: "customer 'A' defected from the firm, where customer 'B' was newly acquired by the firm during the same period." The model assumes individual customers, such that in terms of 'dummies' the same customer has a '1' for defection and a '1' for acquisition. The effect of bias in the estimation due to the location aggregated data is not obvious, such that it potentially can underestimate or overestimate SHV.

In addition, *asymmetry in data availability*[46] potentially causes biased estimates as well. However, due to the 'extra data layer' resulting from the extracted customer behavior value driver the impact has been reduced to a minimum. Obviously, missing data is not beneficial for a model heavily relying on large quantities of data. The effect of bias in the estimation due to asymmetrical data availability is not obvious, such that it potentially can underestimate or overestimate SHV.

Then, the *absence of customer specific margin*, potentially causes biased estimates as well. A customer's total EBITDA contribution is the sum of its revenues per BSP combination times the firm level EBITDA-margin (%) for each of the BSP combinations. The effect of bias in the estimation due to the use of 'average margins (%)' is not obvious, such that it potentially can underestimate or overestimate SHV. However, in empirical marketing studies average absolute margins are typically used, such that the more specific setup in this study is preferred.

Finally, due to *limited accessibility into the data warehouse*, the concept of big data analytics is not used to its full potential. In essence the integrated customer-centric dataset contains solely product ownership information, using just a fraction of the enormous size of data available to the firm's analysts. This leaves a wide variety of other data sources like 'web-data' 'mobile data,' 'customer-service data' and many more, unused. Normally, more data leads to more and potentially better predictors, resulting in better estimates. It is however not possible to determine whether not incorporating these data has caused underestimation or overestimation of SHV.

Methodological limitations | Another quite major limitation of this study is the fact that the *effect of brands* has not been incorporated as part of customer behavior and thus profitability. Incorporating customer brand choice behavior in the model would have increased the number of behavior logit models from 18 to 72. It is estimated that this would have increased the computed customer behavior probabilities from 2 to 18 billion, driving the current 150GB of data up to 1TB. This is simply impossible with a 'home configuration.' In addition, it is also impossible to determine whether not incorporating customer brand choice behavior has caused underestimation or overestimation of SHV.

Then, another important limitation is the absence of an '*outlier model*.' Certain BM customers have been eliminated from the analysis, as they were marked as outliers. However, these 'BM XL' customers represent more than half of total BM EBITDA (2014). Therefore, these customers require special attention in analysis and forecasting. This implies that an additional configuration of 4 profit regression models and 9 behavior logit models was needed for these BM XL customers. However, due to limited time and computing power this has not been executed. This limitation potentially underestimates SHV.

Next, another major limitation is the absence of EBITDA contribution (or actually log EBITDA) from the previous period as a predictor in the *acquisition logit model* and *defection logit model.* Adding this predictor for model estimation would not have been an issue. However, for computing all the equations and producing the probability output it would have been troubling. An example is used to clarify the 'strangled equation' situation:

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[46] The development of the integrated customer-centric dataset was a first time attempt. Therefore, revenues from value added services (VAS) have by mistake not been separated from total revenues. As a consequence, valuable insights on customer behavior are 'lost.'

- The $logit\ model_{2015}$ uses among other predictors $\log_{10} EBITDA_{2014}$ as input for computing the $P(acquisition_{2015})$
- Then, $P(acquisition_{2015})$ is used as input among other predictors in $profit\ model_{2015}$ to compute $\log_{10} EBITDA_{2015}$
- Next, $\log_{10} EBITDA_{2015}$ is used as input among other predictors in $logit\ model_{2016}$ that uses among other predictors $\log_{10} EBITDA_{2015}$ as input for computing the $P(acquisition_{2016})$

This process should have been applied for 4 profit regression models 9 behavior logit models for 2 segments, obviously complicating the computations. The limitation arises from the fact that the acquisition models may produce probabilities for already acquired customers, hence potentially causing to overestimate SHV. For the defection model the opposite situation applies, thereby potentially underestimating SHV.

In addition, *acquisition costs* have not been taken into account in the valuation of acquired customers. And newly acquired customers are often not yet profitable due to these costs, therefore a firm need to develop its new customers (Li et al. 2011). Thus, not incorporating acquisition costs causes potentially overestimation of SHV.

Finally, in the forecast of the behavior logit and profit regression models *relationship age* is a *static predictor*, where dynamic is preferred. Or in other words, in case a customer stays with the firm its relationship age for the next period should have been $relationship\ age_{t+1} = (relationship\ age_t + 1 \mid retained_{t+1})$. At first this seems simple to have this incorporated in the model. However, the complexity of forecasting four periods ahead, given the extensive number of forecast equations and slow performance of software and hardware, turning this predictor from static into a dynamic would have come with increased complexity and delay. In addition, due to dataset structure the maximum relationship age of a customer's entire portfolio is chosen to serve as input for the prediction. In theory a customer may retain with the firm, but may churn on its longest relationship product, such that its relationship age plus one overestimates its relationship age. However, it is more likely a customer is retained on its longest relationship product. Thus, a static relationship age in forecasting causes potentially underestimation of SHV.

Limitation on results | Limitations on the result arise initially from the fact that the dataset is aggregated on the unique location level and not on the unique customer level. Interesting insights arise for instance from a *customer ranking based on value*, which is obviously less accurate due to the data limitation. However, ranking customers is out of the scope of this study.

A more complicated matter and potentially a limitation, is the *choices made in econometric modelling* which in turn entails a certain degree of subjectivity into the model and thus the results. Moreover, it is not known how different ways of econometric modeling would affect SHV. However, Donkers et al. (2007) conclude that more complex models do not necessarily deliver better outcomes and thus valuations aren't necessarily more accurate.

6.4 Managerial implications

The use of big data, developed methodology, results and conclusions of this study have implications for both senior executives and managers.

Managerial implication of current data challenges | It is vital that senior executives and managers put *priority on the availability and accessibility* of all customer related data, in order to improve the application of big data analytics. A deeper integration of existing and new big data sources combined with new advanced analytics tools and technology is crucial for a continuous development of new big data analytics applications, ultimately enhancing SHV.

Managerial implication of margin methodologies | Academics have left the topic of margins and costs underexposed. In modeling customer margins at least three aspects of costs need to be considered: marketing, administrative and CAPEX. Basically there are two approaches possible in modeling customer specific margins.

The first approach is *based on accounting systems*. In order to track a customer's marketing costs, a customer-based accounting system[47] is needed. First, acquisition and retention costs need to be separated. Then, marketing overhead costs need to be allocated to either one of them. Next, it is important to see whether administrative and other operating costs are either fixed or semi-fixed. Finally, an activity-based costs accounting system[48] supports in forecasting CAPEX.

The second approach is *based on big data analytics* but has a more experimental nature. The simple idea behind this approach is that big data contains such a large amount of information on a single customer that based on this information costs can be allocated. For instance, let's take the annual costs of a customer service call center. Assuming that in big data each phone call and length are registered for each customer, then costs can be easily allocated to the individual customer. As the customers annual share of total minutes' times the call center costs, results in the customer specific costs.

6.4.1 Directions for future studies

ROIC on the individual customer level | Valuation theory states that improvements in ROIC and growth and the right balance between them drives CFs. Then, CFs discounted at the COC is what ultimately drives SHV. A forward looking ROIC and growth rate are therefore very insightful parameters. With existing models, it is straightforward to determine future growth of an individual customer. However, estimating the future ROIC of an individual customer is more complicated. First of all, because of the already discussed missing 'customer specific costs' component. But mainly because the optimization of investment–return relation is not straightforward on the individual customer level. The estimated future ROIC of an individual customer would certainly bring valuable managerial insights. Thus, the challenge for future studies is to investigate the individual customer investment optimization.

Modeling CV on the individual customer level | The CV across all models and scenarios represents 71–75% of the EV. As the CV has a tremendous impact on the valuation it is important to understand the impact on firm value when CV is determined on the individual customer level. It logically follows that the derivation of the CV on the individual customer level potentially contributes to even more accurate firm valuations. A CV estimation on the individual customer level implies the estimation of a customer specific growth rate and ROIC, as being key input variables in the key value driver formula. In addition, in the forecast of both DCF and CBB valuation models there is accounted for idiosyncratic risk. Both models account also for systematic risk by discounting CFs at the WACC. However, in case of the CV methodology the idiosyncratic risk is more or less incorporated in the assumption on the growth rate and ROIC. Therefore, a customer specific CV estimation is more capable of accounting for different levels of idiosyncratic risk. Thus, the challenge for future studies is to investigate impact of the CV methodology on the individual customer level on total firm value.

[47] Marn & Rosiello (1992): "A customer-based accounting system can support in managing prices and results in superior profitability."

[48] Bowman & Narayandas (2004) and Niraj et al. (2001): "An activity-based costs accounting system supports in obtaining better cost estimates for determining CLV."

6.5 System requirements

The serious shortcoming of software and hardware has been mentioned throughout this report several times. However, this matter has such great impact on the design of this study that it requires full attention by this paragraph. Big data analytics consists of: large quantities of data, extensive data preparation, extensive analysis, complex modeling, heavy duty model estimation and computation. This requires massive computing power and software capabilities. Especially model estimation is a demanding process in terms of computing power. Therefore, it is highly recommended to use server capacity for at least model estimation, but preferably also for preparing data and calculating equations.

Table 29 Historical financials

FINANCIAL STATEMENTS												
Year to	**12/2003a**	**12/2004a**	**12/2005a**	**12/2006a**	**12/2007a**	**12/2008a**	**12/2009a**	**12/2010a**	**12/2011a**	**12/2012a**	**12/2013a**	**12/2014a**
Profit & loss summary (EURm)												
Revenue	12,742	11,872	11,936	12,057	12,632	14,602	13,509	13,398	13,163	9,458	8,472	8,083
EBITDA	5,313	4,594	4,500	4,613	4,614	4,854	4,996	5,274	4,906	3,198	2,727	2,843
Depreciation & amortization	(2,638)	(2,189)	(2,332)	(2,436)	(2,380)	(2,316)	(2,297)	(2,197)	(2,399)	(1,637)	(1,817)	(1,769)
EBIT (operating profit)	2,675	2,405	2,168	2,177	2,234	2,538	2,699	3,077	2,507	1,561	910	1,074
Net interest	(700)	(534)	(533)	(523)	(708)	(703)	(779)	(687)	(780)	(823)	(804)	(520)
PBT	2,407	2,119	1,814	1,710	1,941	1,887	2,036	2,306	1,772	518	262	286
Taxation	(736)	(300)	(360)	(127)	708	(550)	139	(508)	(222)	(204)	31	(47)
Net profit	1,671	1,819	1,454	1,583	2,652	1,332	2,178	1,798	1,550	765	(215)	(584)
Balance sheet summary (EURm)												
Intangible fixed assets	8,583	8,695	9,401	9,051	10,424	10,060	9,832	9,755	9,212	8,458	3,643	3,992
Tangible fixed assets	9,119	8,979	8,338	7,965	7,866	7,736	7,523	7,514	7,533	7,895	5,340	6,606
Current assets	4,105	3,983	3,347	3,058	4,060	3,735	4,689	2,870	2,721	3,098	5,221	3,385
Cash & others	1,839	1,551	1,033	803	1,148	1,199	2,690	823	990	1,286	3,946	2,276
Total assets	24,125	23,661	22,702	21,258	24,797	23,913	24,851	22,737	22,253	22,301	25,872	18,556
Operating liabilities	4,197	4,848	5,316	3,849	6,577	5,761	5,221	5,419	5,609	5,857	5,354	3,757
Gross debt	11,337	9,840	10,273	10,255	12,388	12,581	14,270	13,013	13,483	14,492	14,504	10,703
Net debt	9,625	8,408	9,359	9,573	11,366	11,528	11,715	12,324	12,625	13,301	10,643	8,508
Shareholders' funds	7,359	6,556	5,104	4,196	4,518	3,759	3,841	3,500	2,273	1,334	5,303	4,630
Invested capital	19,510	17,973	16,697	15,687	18,104	17,232	18,828	17,121	16,846	17,383	20,826	15,649
CF summary (EURm)												
CFO	4,436	4,253	4,067	4,451	5,429	4,117	5,180	4,605	4,596	2,596	2,832	2,670
CAPEX	0	(2,106)	(1,865)	(1,729)	(2,938)	(2,196)	(1,963)	(2,181)	(2,209)	(1,447)	(1,568)	(1,697)
CFI	(2,349)	(3,013)	(2,209)	(1,445)	(3,403)	(2,524)	(1,845)	(1,743)	(2,140)	(1,063)	(701)	(1,249)
Dividends	0	(848)	(902)	(993)	(982)	(981)	(1,042)	(1,152)	(1,202)	(979)	(5)	(94)
Change in net debt	9,625	(1,218)	952	213	1,794	162	187	609	301	676	(2,658)	(2,135)
FCF equity	2,087	1,240	1,858	3,006	2,026	1,593	3,335	2,862	2,456	1,533	2,131	1,421

Table 30 Historical KPIs

RATIO, GROWTH AND PER SHARE ANALYSIS												
Year to	**12/2003a**	**12/2004a**	**12/2005a**	**12/2006a**	**12/2007a**	**12/2008a**	**12/2009a**	**12/2010a**	**12/2011a**	**12/2012a**	**12/2013a**	**12/2014a**
YoY % change												
Revenue	-	-6.8	0.5	1.0	4.8	15.6	-7.5	-0.8	-1.8	-28.1	-10.4	-4.6
EBITDA	-	-13.5	-2.0	2.5	0.0	5.2	2.9	5.6	-7.0	-34.8	-14.7	4.3
Operating profit	-	-10.1	-9.9	0.4	2.6	13.6	6.3	14.0	-18.5	-37.7	-41.7	18.0
PBT	-	-12.0	-14.4	-5.7	13.5	-2.8	7.9	13.3	-23.2	-70.8	-49.4	9.2
EPS	-	12.5	-14.0	19.6	81.0	-46.5	73.1	-13.7	-8.1	-78.7	-53.1	-45.5
Ratios (%)												
Revenue/IC (x)	0.7x	0.7x	0.7x	0.8x	0.7x	0.8x	0.7x	0.8x	0.8x	0.5x	0.4x	0.5x
ROIC	-	10.9	13.0	12.5	14.7	24.6	14.2	24.3	14.5	10.3	5.6	15.4
ROE	22.7	27.7	28.5	37.7	58.6	35.6	56.6	51.4	68.2	23.5	5.5	5.2
ROA	6.9	7.7	6.4	7.4	10.7	5.6	8.8	7.9	7.0	1.4	1.1	1.3
EBITDA margin	41.7	38.7	37.7	38.3	36.5	33.2	37.0	39.4	37.3	33.8	32.2	35.2
Operating profit margin	21.0	20.3	18.2	18.1	17.7	17.4	20.0	23.0	19.0	16.5	10.7	13.3
EBITDA/net interest (x)	7.6x	8.6x	8.4x	8.8x	6.5x	6.9x	6.4x	7.7x	6.3x	3.9x	3.4x	5.5x
Net debt/equity	130.8	128.2	183.4	228.1	251.6	306.7	305.0	352.1	555.4	997.0	200.7	183.8
Net debt/EBITDA (x)	1.8x	1.8x	2.1x	2.1x	2.5x	2.4x	2.3x	2.3x	2.6x	4.2x	3.9x	3.0x
CF from operations/net debt	46.1	50.6	43.4	46.5	47.8	35.7	44.2	37.4	36.4	19.5	26.6	31.4
Per share data (EUR)												
EPS	0.67	0.75	0.65	0.78	1.40	0.75	1.30	1.12	1.03	0.22	0.10	0.06

Table 31 One-to-one relations [1 out of 2]

RELATION BETWEEN CUSTOMER AND LOCATION																								
Brand	Brand 1						Brand 4						Brand 2						Brand 3					
Segment	CM			BM			CM			BM			CM			BM			CM			BM		
Period	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14
Product category 1 (in 000)																								
Total number of customers	1,035	989	982	228	219	199	950	839	767	-	-	-	-	854	895	-	162	167	-	-	-	-	-	-
Number of relations 1:1	783	715	664	134	127	116	705	621	561	-	-	-	-	568	588	-	22	24	-	-	-	-	-	-
Relations 1:1 (%)	**76%**	**72%**	**68%**	**59%**	**58%**	**58%**	**74%**	**74%**	**73%**	-	-	-	-	**67%**	**66%**	-	**14%**	**15%**	-	-	-	-	-	-
Product category 2 (Type 1) (in 000)																								
Total number of customers	257	376	342	0	1	2	-	-	-	-	-	-	-	207	229	-	-	-	99	82	64	78	75	68
Number of relations 1:1	248	362	332	0	1	2	-	-	-	-	-	-	-	204	226	-	-	-	97	81	63	67	64	58
Relations 1:1 (%)	**96%**	**96%**	**97%**	**80%**	**84%**	**86%**	-	-	-	-	-	-	-	**98%**	**99%**	-	-	-	**99%**	**99%**	**99%**	**86%**	**86%**	**86%**
Product category 3 (Type 1) (in 000)																								
Total number of customers	491	643	704	0	4	7	-	-	-	-	-	-	-	134	213	-	-	-	18	36	51	2	6	9
Number of relations 1:1	473	629	692	0	4	6	-	-	-	-	-	-	-	132	210	-	-	-	18	35	50	2	6	9
Relations 1:1 (%)	**96%**	**98%**	**98%**	**82%**	**95%**	**95%**	-	-	-	-	-	-	-	**99%**	**99%**	-	-	-	**99%**	**99%**	**99%**	**99%**	**99%**	**97%**
Product category 4 (in 000)																								
Total number of customers	985	913	798	66	63	59	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	913	844	739	64	62	57	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	**93%**	**92%**	**93%**	**98%**	**97%**	**97%**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Product category 5 (Type 1) (in 000)																								
Total number of customers	-	1,064	829	-	337	286	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	1,041	816	-	280	239	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	-	**98%**	**98%**	-	**83%**	**83%**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Product category 6 (Type 1) (in 000)																								
Total number of customers	1,044	1,103	1,072	12	16	24	-	-	-	-	-	-	-	183	202	-	-	-	58	65	76	12	17	22
Number of relations 1:1	1,020	1,077	1,046	11	15	22	-	-	-	-	-	-	-	181	200	-	-	-	58	64	76	11	16	21
Relations 1:1 (%)	**98%**	**98%**	**98%**	**96%**	**94%**	**93%**	-	-	-	-	-	-	-	**99%**	**99%**	-	-	-	**99%**	**99%**	**99%**	**97%**	**97%**	**96%**
Product category 7 (in 000)																								
Total number of customers	-	-	-	138	130	117	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	-	-	126	120	108	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	-	-	-	**91%**	**92%**	**92%**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Product category 8 (in 000)																								
Total number of customers	-	-	-	27	25	22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	-	-	24	22	19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	-	-	-	**90%**	**89%**	**88%**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Product category 9 (Type 2) (in 000)																								
Total number of customers	-	-	19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	-	19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	-	-	**100%**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

One-to-one relations **[2 out of 2]**

RELATION BETWEEN CUSTOMER AND LOCATION

Brand	Brand 1						Brand 4						Brand 2						Brand 3					
Segment	CM			BM			CM			BM			CM			BM			CM			BM		
Period	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14	jun-12	jun-13	jun-14
Product category 10 (Type 2) (in 000)																								
Total number of customers	-	-	194	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	-	194	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	**-**	**-**	**100%**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
Product category 11 (Type 2) (in 000)																								
Total number of customers	-	-	321	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of relations 1:1	-	-	320	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Relations 1:1 (%)	**-**	**-**	**100%**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**

Table 32 Descriptive statistics: purchase rates

Year				2012	2013		2014		
Products				1-19	1-26	1-19	1-29	1-19	1-26
Customers				All	All	Retained	All	Retained	Retained
Retained from year				-	-	2012	-	2012	2013
Total (N=)				**5.008.018**	**7.663.340**	**4.089.873**	**7.875.375**	**3.439.221**	**6.239.525**
Purchase rates									
Product 1	Brand 1	CM	-	18,0%	11,0%	18,5%	10,3%	18,8%	11,5%
Product 2	Brand 4	CM	-	16,1%	9,3%	15,7%	8,3%	15,9%	9,6%
Product 3*	Brand 1	BM	-	3,2%	2,0%	3,4%	1,8%	3,4%	2,1%
Product 4	Brand 1	CM	Type 1	5,0%	4,8%	4,4%	4,0%	3,9%	4,2%
Product 5	Brand 3	CM	Type 1	2,0%	1,1%	1,8%	0,8%	1,4%	0,9%
Product 6*	Brand 1	BM	Type 1	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Product 7	Brand 3	BM	Type 1	1,4%	0,9%	1,4%	0,8%	1,3%	0,8%
Product 8	Brand 1	CM	Type 1	9,6%	8,4%	9,8%	8,9%	10,0%	8,6%
Product 9	Brand 3	CM	Type 1	0,4%	0,5%	0,4%	0,6%	0,4%	0,5%
Product 10	Brand 1	BM	Type 1	0,0%	0,0%	0,0%	0,1%	0,0%	0,1%
Product 11	Brand 3	BM	Type 1	0,0%	0,1%	0,0%	0,1%	0,0%	0,1%
Product 12	Brand 1	CM	Type 1	17,7%	10,0%	16,9%	9,0%	16,8%	9,5%
Product 13	Brand 1	BM	Type 1	1,2%	0,7%	1,3%	0,7%	1,3%	0,8%
Product 14	Brand 1	CM	Type 1	20,8%	14,1%	21,5%	13,5%	22,0%	14,7%
Product 15	Brand 3	CM	Type 1	1,2%	0,8%	1,2%	1,0%	1,2%	0,9%
Product 16	Brand 1	BM	Type 1	0,2%	0,2%	0,2%	0,3%	0,2%	0,2%
Product 17	Brand 3	BM	Type 1	0,2%	0,2%	0,2%	0,3%	0,2%	0,2%
Product 18	Brand 1	BM	Type 1	2,6%	1,6%	2,7%	1,4%	2,6%	1,6%
Product 19	Brand 1	BM	Type 1	0,5%	0,3%	0,5%	0,2%	0,5%	0,3%
Product 20	Brand 2	CM	-	-	9,1%	-	9,2%	-	9,5%
Product 21*	Brand 2	BM	-	-	0,5%	-	0,5%	-	0,5%
Product 22	Brand 2	CM	Type 1	-	2,7%	-	2,8%	-	2,5%
Product 23	Brand 2	CM	Type 1	-	1,7%	-	2,6%	-	1,8%
Product 24	Brand 2	CM	Type 1	-	2,4%	-	2,5%	-	2,3%
Product 25	Brand 1	CM	Type 1	-	13,7%	-	10,4%	-	13,0%
Product 26	Brand 1	BM	Type 1	-	4,0%	-	3,3%	-	4,0%
Product 27	Brand 1	CM	Type 2	-	-	-	0,2%	-	-
Product 28	Brand 1	CM	Type 2	-	-	-	2,3%	-	-
Product 29	Brand 1	CM	Type 2	-	-	-	4,0%	-	-

Table 33 Ownership correlations 2013-2014 (Pearson correlation r-coefficient)

Product type jun-13	Product type jun-14																									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	.86**	.07**	.03**	.06**	.02**	.01**	.01**	.13**	.01**	.01**	.01**	.08**	.04**	.15**	.02**	.02**	.01**	.02**	.00**	.01**	.01**	.00**	-.01**	-.01**	.03**	.04**
2	.07**	.87**	.01**	.03**	.01**	.00**	.00**	.06**	.01**	.00**	.00**	.06**	.02**	.06**	.01**	.01**	.00**	.00**	.00**	.03**	.00**	.01**	.02**	.01**	-.01**	.01**
3	.03**	.01**	.87**	.02**	.01**	.02**	.09**	.00**	.00	.04**	.02**	.02**	.09**	.01**	.00**	.06**	.03**	.18**	.14**	-.01**	.07**	.00**	-.01**	-.01**	.02**	.24**
4	.07**	.04**	.02**	.77**	.00**	.00**	.00**	.29**	-.01**	.00**	.00**	.12**	.02**	.18**	-.01**	.00**	.00**	.00*	.00**	.02**	.01**	.00**	.00**	-.01**	.01**	.01**
5	.03**	.01**	.01**	-.01**	.76**	.00	.00**	-.02**	.20**	.00	0.00	.02**	.01**	-.02**	.14**	.00*	.00**	0.00	.00**	.01**	.00**	-.01**	-.01**	-.01**	.09**	.03**
6	.00**	.00**	.02**	.00**	0.00	.59**	.00**	.00**	.00	.19**	.00*	.00**	.02**	.00**	.00	.15**	.00**	.01**	.00**	0.00	.01**	.00	.00*	.00**	.00**	.02**
7	.01**	.00**	.09**	.00**	.00**	.01**	.79**	-.01**	.00**	.00**	.09**	.00**	.04**	-.02**	.00**	.01**	.09**	.05**	.07**	-.01**	.04**	.00**	-.01**	-.01**	.02**	.14**
8	.13**	.06**	.00*	.28**	-.01**	.00**	-.01**	.79**	-.01**	.00**	.00**	.19**	.03**	.55**	-.02**	-.01**	-.01**	-.02**	-.01**	.03**	.00**	-.02**	.00**	-.01**	-.05**	-.02**
9	.01**	.01**	.00	-.01**	.15**	.00*	.00**	-.01**	.71**	.00**	.00	.03**	.00**	-.01**	.44**	.00**	.00**	.00**	.00**	.01**	.00**	.00**	0.00	.00**	-.01**	-.01**
10	.01**	.00**	.03**	.00**	.00**	.16**	.00**	.00**	.00**	.73**	0.00	.00**	.05**	-.01**	.00**	.39**	.00*	.01**	.00**	.00	.01**	.00**	.00**	.00**	.00**	.01**
11	.00**	.00**	.01**	.00**	.00**	.00**	.06**	.00**	0.00	.00**	.70**	.01**	.01**	-.01**	.00*	.00**	.36**	.00**	.00**	.00*	.01**	.00**	.00**	.00**	.00**	.00**
12	.08**	.06**	.02**	.10**	.02**	.00**	.00**	.17**	.04**	.00**	.01**	.80**	.00**	.16**	.03**	.01**	.01**	.00**	.00**	.05**	.01**	.06**	.04**	.04**	.01**	.00**
13	.03**	.02**	.09**	.02**	.01**	.02**	.04**	.03**	.00**	.03**	.01**	.00**	.85**	.04**	.00**	.06**	.01**	.09**	.06**	.01**	.03**	0.00	.00**	.00**	.00**	.15**
14	.15**	.06**	.01**	.16**	-.02**	.00**	-.02**	.56**	-.02**	-.01**	-.01**	.18**	.05**	.84**	-.02**	-.01**	-.01**	-.02**	-.01**	.03**	.00**	-.03**	-.02**	-.02**	-.07**	-.03**
15	.01**	.01**	.00*	-.01**	.02**	.00*	.00**	-.02**	.46**	.00**	.00*	.03**	.00**	-.02**	.78**	.00**	.00**	-.01**	.00**	.01**	.00**	-.01**	.00**	-.01**	-.01**	-.01**
16	.02**	.01**	.04**	-.01**	.00**	.13**	.00**	-.01**	.00**	.39**	0.00	.01**	.06**	-.01**	.00**	.79**	.00**	.01**	.00**	.00**	.01**	.00**	.00**	.00**	.00**	.02**
17	.01**	.00**	.02**	.00**	.00**	.00**	.03**	-.01**	.00**	.00**	.36**	.01**	.01**	-.01**	.00*	.00**	.75**	.01**	.01**	.00**	.01**	.00**	.00**	.00**	.00**	.02**
18	.02**	.00**	.18**	0.00	.00	.02**	.05**	-.01**	.00**	.03**	.01**	.00**	.10**	-.02**	-.01**	.05**	.02**	.84**	.13**	-.01**	.06**	-.01**	-.01**	-.01**	.01**	.35**
19	.00**	.00**	.14**	.00**	.00**	.01**	.07**	-.01**	.00**	.00**	.00**	.00**	.06**	-.01**	.00**	.01**	.01**	.14**	.87**	-.01**	.04**	.00**	-.01**	.00**	.00**	.19**
20	.00**	.02**	-.01**	.01**	.01**	.00	-.01**	.02**	.01**	.00	.00**	.05**	.01**	.02**	.01**	.00	.00**	-.01**	-.01**	.83**	.02**	.07**	.09**	.08**	-.02**	-.01**
21	.00**	.00**	.05**	.00**	.00**	.01**	.04**	.00**	.00**	.01**	.01**	.01**	.03**	.00*	.00**	.02**	.02**	.05**	.04**	.02**	.77**	.00**	.00**	.01**	.00**	.08**
22	.00**	.01**	.00**	-.01**	-.01**	.00*	.00**	-.03**	-.01**	.00**	.00**	.05**	.00**	-.03**	-.01**	.00**	.00**	-.01**	.00**	.07**	.01**	.73**	.25**	.02**	.03**	.01**
23	-.01**	.01**	-.01**	-.01**	-.01**	.00*	-.01**	-.02**	.00**	.00**	.00**	.05**	.00**	-.03**	-.01**	.00**	.00**	-.01**	.00**	.08**	.00**	.24**	.66**	.42**	-.02**	-.01**
24	-.01**	.01**	-.01**	-.02**	-.01**	.00*	-.01**	-.02**	.00**	.00**	.00**	.05**	.00**	-.03**	-.01**	.00**	.00**	-.01**	.00**	.08**	.01**	.01**	.39**	.76**	-.02**	-.01**
25	.04**	-.01**	.02**	.01**	.09**	.00**	.02**	-.03**	.01**	.00**	.00**	.01**	.00**	-.03**	.01**	.00**	.00**	.01**	.00	-.02**	.00**	.02**	-.02**	-.01**	.86**	-.01**
26	.04**	.01**	.24**	.01**	.03**	.03**	.13**	-.02**	.00**	.03**	.01**	.00	.16**	-.02**	.00**	.07**	.03**	.35**	.17**	-.01**	.09**	.00	-.02**	-.01**	-.01**	.88**

**: p<0.01 (correlation is significant at the 0.01 level, 2-tailed)

*: p<0.05 (correlation is significant at the 0.05 level, 2-tailed)

Table 34 Forecast on key value drivers

Year to	2014a	2015f	2016f	2017f	2018f
Product category 1 revenue drivers					
Product category 1 revenues (EURm)	**1.407**	**1.429**	**1.440**	**1.439**	**1.439**
Customers (BoP 000s)	7.351	7.540	7.734	7.811	7.889
Customers (EoP 000s)	7.540	7.734	7.811	7.889	7.968
YoY growth rate	*2,6%*	*1,0%*	*1,0%*	*1,0%*	*1,0%*
Net sales per average customer (EUR pa)	189	187	185	183	182
YoY growth rate	*-6,6%*	*-1,0%*	*-1,0%*	*-1,0%*	*-1,0%*
Product category 2 revenue drivers					
Product category 2a revenues (EURm)	**253**	**243**	**230**	**220**	**211**
Customers (BoP 000s)	2.667	2.618	2.500	2.400	2.316
Customers (EoP 000s)	2.618	2.500	2.400	2.316	2.247
YoY growth rate	*-1,8%*	*-4,5%*	*-4,0%*	*-3,5%*	*-3,0%*
Net sales per average customer (EUR pa)	96	95	94	93	93
YoY growth rate	*-18,4%*	*-1,0%*	*-0,9%*	*-0,8%*	*-0,7%*
Product category 2b revenues (EURm)	**954**	**931**	**921**	**919**	**917**
Customers (BoP 000s)	2.900	2.941	3.000	3.057	3.112
Customers (EoP 000s)	2.941	3.000	3.057	3.112	3.165
YoY growth rate	*1,4%*	*2,0%*	*1,9%*	*1,8%*	*1,7%*
Net sales per average customer (EUR pa)	327	314	304	298	292
YoY growth rate	*-7,4%*	*-4,0%*	*-3,0%*	*-2,0%*	*-2,0%*
Product category 2c revenues (EURm)	**229**	**242**	**255**	**267**	**279**
Customers (BoP 000s)	1.920	2.003	2.083	2.156	2.220
Customers (EoP 000s)	2.003	2.083	2.156	2.220	2.276
YoY growth rate	*4,3%*	*4,0%*	*3,5%*	*3,0%*	*2,5%*
Net sales per average customer (EUR pa)	117	119	120	122	124
YoY growth rate	*-6,8%*	*1,5%*	*1,5%*	*1,5%*	*1,5%*
Product category 2d revenues (EURm)	**480**	**470**	**461**	**452**	**443**
YoY growth rate	*12,7%*	*-2,0%*	*-2,0%*	*-2,0%*	*-2,0%*
Product category 3 revenue drivers					
Product category 3a revenues (EURm)	**771**	**776**	**755**	**728**	**695**
Customers (BoP 000s)	1.674	1.726	1.735	1.743	1.752
Customers (EoP 000s)	1.726	1.735	1.743	1.752	1.761
YoY growth rate	*3,1%*	*0,5%*	*0,5%*	*0,5%*	*0,5%*
Net sales per average customer (EUR pa)	454	449	434	417	396
YoY growth rate	*-15,1%*	*-1,1%*	*-3,2%*	*-4,0%*	*-5,0%*

	2014a	2015f	2016f	2017f	2018f
Product category 3 revenue drivers (continued)					
Product category 3b revenues (EURm)	**729**	**616**	**543**	**483**	**438**
Customers (BoP 000s)	994	864	812	772	741
Customers (EoP 000s)	864	812	772	741	718
YoY growth rate	*-13,1%*	*-6,0%*	*-5,0%*	*-4,0%*	*-3,0%*
Net sales per average customer (EUR pa)	785	734	685	639	601
YoY growth rate	*6,4%*	*-6,4%*	*-6,7%*	*-6,7%*	*-6,0%*
Product category 3c revenues (EURm)	**336**	**337**	**353**	**368**	**378**
Customers (BoP 000s)	270	265	281	302	328
Customers (EoP 000s)	265	281	302	328	354
YoY growth rate	*-1,9%*	*6,0%*	*7,5%*	*8,5%*	*8,0%*
Net sales per average customer (EUR pa)	1.256	1.236	1.211	1.169	1.110
YoY growth rate	*-9,6%*	*-1,6%*	*-2,0%*	*-3,5%*	*-5,0%*
Product category 4 revenue drivers					
Product category 4 revenues (EURm)	525	499	476	457	441
YoY growth rate	*-15,9%*	*-5,0%*	*-4,5%*	*-4,0%*	*-3,5%*
Product category 5 revenue drivers					
Product category 5 revenues (EURm)	**2.245**	**2.333**	**2.251**	**2.186**	**2.136**
XXX (BoP 000s)	1.635	1.952	1.972	1.993	2.017
XXX (EoP 000s)	1.952	1.972	1.993	2.017	2.043
YoY growth rate	*19,4%*	*1,0%*	*1,1%*	*1,2%*	*1,3%*
Net sales per average XXX (EUR pa)	1.252	1.189	1.136	1.090	1.052
YoY growth rate	*-23,0%*	*-5,0%*	*-4,5%*	*-4,0%*	*-3,5%*
Product category 6 revenue drivers					
Product category 6 revenues (EURm)	**709**	**685**	**672**	**661**	**652**
Customers (BoP 000s)	3.389	3.261	3.228	3.199	3.174
Customers (EoP 000s)	3.261	3.228	3.199	3.174	3.152
YoY growth rate	*-3,8%*	*-1,0%*	*-0,9%*	*-0,8%*	*-0,7%*
Net sales per average customer (EUR pa)	213	211	209	208	206
YoY growth rate	*-0,2%*	*-1,0%*	*-0,9%*	*-0,8%*	*-0,7%*
Product category 9 revenue drivers					
Product category 9 revenues (EURm)	**948**	**926**	**936**	**937**	**929**
XXX (BoP 000,000,000s)	25	23	23	23	23
XXX (EoP 000,000,000s)	23	23	23	23	23
YoY growth rate	-6,4%	0,0%	0,5%	-2,0%	-1,0%
Net sales per average XXX (EUR)	0,039	0,040	0,040	0,040	0,041
YoY growth rate	3,7%	1,0%	0,9%	0,8%	0,7%

Table 35 Forecasted financials

FINANCIAL STATEMENTS					
Year to	**12/2014a**	**12/2015e**	**12/2016e**	**12/2017e**	**12/2018e**
Profit & loss summary (EURm)					
Revenue	8,083	8,127	8,075	8,022	7,968
EBITDA	2,843	3,007	2,988	2,962	2,935
Depreciation & amortization	(1,769)	(1,880)	(1,761)	(1,663)	(1,581)
EBIT (operating profit)	1,074	1,127	1,228	1,300	1,354
Net interest	(520)	(551)	(529)	(471)	(431)
PBT	286	344	457	541	608
Taxation	(47)	(87)	(115)	(136)	(153)
Net profit	(584)	(566)	(482)	(418)	(368)
Balance sheet summary (EURm)					
Intangible fixed assets	3,992	3,805	3,651	3,524	3,419
Tangible fixed assets	6,606	6,190	5,853	5,576	5,348
Current assets	3,385	3,411	3,389	3,367	3,344
Cash & others	2,276	2,288	2,274	2,259	2,244
Total assets	18,556	15,148	14,646	14,230	13,883
Operating liabilities	3,757	2,990	3,196	3,667	3,705
Gross debt	10,703	10,377	10,006	9,024	8,351
Net debt	8,508	8,170	7,813	6,846	6,187
Shareholders' funds	4,630	3,893	3,240	2,651	2,112
Invested capital	15,649	14,589	13,568	12,001	10,792
CF summary (EURm)					
CFO	2,670	2,725	2,681	2,637	2,597
CAPEX	(1,697)	(1,337)	(1,324)	(1,311)	(1,298)
CFI	(1,249)	(498)	(1,546)	(1,801)	(1,356)
Dividends	(94)	(171)	(171)	(171)	(171)
Change in net debt	(2,135)	(338)	(357)	(967)	(659)
FCF equity	1,421	2,227	1,136	836	1,241

Table 36 DCF valuation scenario analysis

High growth
- Higher growth by small acquisitions (5%)
- Maintaining current operating margin

Value during planning period		5,053
Value after planning period (PV CoV)	(+)	14,373
Enterprise value		**19,426**
Excess cash	(+)	1,976
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,867
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**11,831**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR) (per 31/12/2014)		**2.77**
Long term growth rate		1.5%

Margin improvement
- Moderate organic revenue growth (3.5%)
- Program to increase productivity employees

Value during planning period		4,967
Value after planning period (PV CoV)	(+)	13,354
Enterprise value		**18,322**
Excess cash	(+)	2,173
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**11,394**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR) (per 31/12/2014)		**2.67**
Long term growth rate		1.5%

Low case
- Prolonged downturn in B&C market with negative revenue growth (2%)
- Maintaining current operating margin

Value during planning period		4,704
Value after planning period (PV CoV)	(+)	12,405
Enterprise value		**17,109**
Excess cash	(+)	2,195
Joint ventures	(+)	42
Other financial fixed assets	(+)	347
Deferred tax asset	(+)	1,323
Assets held for sale	(+)	8
Loans	(-)	9,397
Other financial liabilities incl. current portion	(-)	1,044
Pension deficit	(-)	316
Revolving credit facility	(-)	0
Current financial liabilities	(-)	0
Other noncurrent liabilities	(-)	64
Equity value (EURm)		**10,203**
Number of shares outstanding (EoP 000,000s)		4,270
Value per share (EUR) (per 31/12/2014)		**2.39**
Long term growth rate		1.5%

Table 37 Input customer equity forecast 2015–2018

VALUES AS INPUT FOR FORECAST				
Year to	**2015**	**2016**	**2017**	**2018**
Cash flow from operations (CFO - EURm) (m)				
DCF valuation model (low case scenario)	2,680	2,637	2,593	2,553
DCF valuation model (high case scenario)	2,838	2,794	2,748	2,707
CBB valuation model (low case scenario)	2,644	2,474	2,417	2,399
CBB valuation model (high case scenario)	2,734	2,622	2,638	2,715
Retention rate (%) (r)				
Low case scenario	89.2%	88.7%	88.2%	87.7%
High case scenario	90.2%	90.7%	91.2%	91.7%
WACC (post-tax) (%) (d)				
Low case scenario	7.2%	7.3%	7.4%	7.5%
High case scenario	7.0%	6.9%	6.8%	6.7%
Growth rate (%) (g)				
Low case scenario	12.7%	12.0%	12.6%	13.3%
High case scenario	11.5%	9.5%	8.9%	8.3%

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