

CUSTOMER PORTFOLIO MANAGEMENT

An Application to Private Wealth Management

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Submitted by:

MCom. Christian Zaum

Heinsbergstraße 12

50674 Köln

Referee: Prof. Dr. Markus Rudolf

Co-Referee: Prof. Dr. Dr. h.c. Jürgen Weber

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Contents

Contents	i
List of Tables	v
List of Figures	vii
List of Abbreviations	ix
List of Essential Symbols	xi
I Theoretical Model Development	1
1 Introduction	3
2 Theory	7
2.1 From marketing to finance	8
2.2 Customer valuation	10
2.3 Customer-based firm valuation	17
2.4 Research gap	23
3 Private Wealth Management	29
3.1 Defining the industry	29
3.2 Applying Customer Portfolio Management	33
3.3 Chapter summary	37
4 Model Development	39
4.1 Dynamic customer-based firm valuation	40

4.1.1	Modeling cash flows	42
4.1.2	Modeling Assets under Management	43
4.2	Customer portfolio optimization	52
4.2.1	Assumptions and conditions	52
4.2.2	Optimization restrictions and transaction costs	56
4.2.3	Objective function	58
4.2.4	Numerical implementation	62
4.3	Chapter summary	63
 II Empirical Application		67
 5 Data and Preliminary Analysis		69
5.1	Data	69
5.1.1	Defining jumps	73
5.1.2	Estimating the discount rate	75
5.2	Preliminary analysis	77
5.2.1	Equity return correlation	80
5.2.2	Test of autocorrelation	82
5.2.3	Stochastic model verification	85
5.3	Chapter summary	88
 6 Results		91
6.1	Model calibration	91
6.1.1	Correlation analysis	92
6.1.2	Stochastic parameter calibration	92
6.2	Valuation of the customer portfolio	96
6.3	Optimization of the customer portfolio	101
6.4	Expansion of the customer portfolio	111
6.5	Managerial implications	119
6.6	Chapter summary	122
 7 Conclusion		125

III Appendix	129
A Maximum Likelihood Estimation	131
B Generating Correlated Random Variables	135
C Distribution Tests of Normality	137
Bibliography	xvii

List of Tables

3.1	International ranking of PWM providers	32
4.1	Model overview	64
5.1	Empirical sample data	72
	(a) Empirical data	72
	(b) Empirical growth rates	72
5.2	Firm-level descriptives	78
5.3	Ljung-Box Q-statistic test	85
5.4	Stochastic model comparison	86
6.1	Segment-level correlation analysis	93
	(a) Correlations of $\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}}$	93
	(b) Correlations of $\frac{NNA_{s,t}}{AuM_{s,t-1}}$	93
	(c) Correlations of $R_{s,t}$	93
6.2	Segment-level parameter calibration	94
6.3	Empirical firm-level parameters	97
6.4	Monte Carlo simulation	98
6.5	Characteristics of the CE probability distribution for the existing customer portfolio	100
	(a) Distribution parameters	100
	(b) Distribution tests of normality	100
6.6	Portfolio optimization parameters	102
6.7	Client segment weight bounds	103
6.8	Client segment weights	104

6.9	Characteristics of the CE probability distribution for the optimal customer portfolio	105
	(a) Distribution parameters	105
	(b) Distribution tests of normality	105
6.10	Stochastic parameters of new client segment	113
	(a) Stochastic process parameters	113
	(b) Correlation structure of $v_{s,t}$	113
6.11	Moment-matching results for $v_{s,t}$	114
6.12	New client segment weights	116
6.13	Characteristics of the CE probability distribution for the optimal expanded customer portfolio	117
	(a) Distribution parameters	117
	(b) Distribution tests of normality	117

List of Figures

2.1	From marketing to finance	8
2.2	How customers generate value	12
2.3	From customer to firm value	19
2.4	Customer Portfolio Management	26
3.1	The wealth pyramid	31
3.2	Importance of strategic areas in the PWM industry	34
3.3	Global HNWI AuM development 2002-2008	35
3.4	Relevance of Customer Portfolio Management to PWM	37
4.1	AuM process	45
4.2	Segment-level cash flow drivers in the PWM industry	47
5.1	Segmentation criteria currently used by PWM providers	70
5.2	MSCI Europe weekly returns and number of monthly jumps	74
5.3	Firm-level AuM development	78
5.4	Development of average PWM client financial market returns and European equity market returns over time	81
5.5	Regression of average PWM client financial market returns on European equity market returns	82
	(a) Regression analysis for full period	82
	(b) Regression analysis for pre-crisis period	82
5.6	Correlograms	84
	(a) Correlogram $\frac{NNA_t}{AuM_{t-1}}$	84
	(b) Correlogram R_t	84
6.1	CE probability distribution for the existing customer portfolio	100

6.2	CE probability distribution for the optimal customer portfolio . . .	105
6.3	Comparison of the empirical cumulative CE probability distribution for the existing and optimal customer portfolio	107
6.4	M-LPM efficient frontier of customer portfolios	109
6.5	CE probability distribution for the optimal expanded customer portfolio	117
6.6	Comparison of M-LPM efficient frontier of customer portfolios . .	119
6.7	Customer segment portfolio transition	120

List of Abbreviations

AuM	Assets under Management
BHHH	Berndt, Hall, Hall and Hausman
bps	basis points
CAGR	Compound Annual Growth Rate
CAPM	Capital Asset Pricing Model
CE	Customer Equity
CEO	Chief Executive Officer
CFM	Cash Flow Margin
CHF	Swiss Franc
CLV	Customer Lifetime Value
CPM	Customer Portfolio Management
CRM	Customer Relationship Management
D	Diffusion Model
DCF	Discounted Cash Flow
e.g.	exempli gratia, for example
FV	Firm Value
HNWI	High Net Worth Individual
i.e.	id est, that is
i.i.d.	independently and identically distributed
JD	Jump-Diffusion Model
LL	Log-Likelihood
LPM	Lower Partial Moment
M-LPM	Mean-Lower Partial Moment
M-V	Mean-Variance
MLE	Maximum Likelihood Estimator

MSCI	Morgan Stanley Capital International
MSI	Marketing Science Institute
NNA	Net New Assets
OPG	Outer Product of Gradients
p.a.	per annum
PB	Private Banking
PM	Profit Margin
PWM	Private Wealth Management
RM	Revenue Margin
RMSE	Root-Mean-Squared-Error
RRA	Return on Retained Assets
s.t.	subject to
UHNW	Ultra High Net Worth
USD	United States Dollars
vs.	versus

List of Essential Symbols

$\mathbf{1}$	Identity matrix
α	Level of significance for statistical hypothesis testing
AD	Anderson-Darling test statistic
$AuM_{s,t}$	Assets under Management of client segment s at time t
AuM_t	Assets under Management aggregated across all client segments at time t (i.e. firm-level Assets under Management at time t)
β	Beta factor of the Capital Asset Pricing Model
c	Constant transaction cost factor
\mathbf{C}	Cholesky decomposition of Σ
CE	Customer Equity
CE^0	Customer Equity of empirically observed customer portfolio composition
\mathbf{CE}^0	Vector of N Customer Equity realizations CE_1^0, \dots, CE_N^0 , generated by means of a Monte Carlo simulation using the empirically observed portfolio composition \mathbf{w}^0
\widehat{CE}	Customer Equity net of transaction costs
\widehat{CE}^*	Customer Equity net of transaction costs of the optimal customer portfolio composition
$\widehat{\mathbf{CE}}^*$	Vector of N Customer Equity realizations net of transaction costs $\widehat{CE}_1^*, \dots, \widehat{CE}_N^*$, generated by means of a Monte Carlo simulation using the optimal portfolio composition \mathbf{w}^*
$CF_{s,t}$	Net cash flow of client segment s at time t
CF_t	Net cash flow aggregated across all client segments at time t (i.e. firm-level cash flow at time t)
CFM	Cash flow margin in percent of earnings before taxes

CLV_i	Customer Lifetime Value of customer i
CLV_s	Customer Lifetime Value of client segment s
CM_i	Contribution margin of customer i
χ^2	Chi-square
χ_{test}^2	Chi-square test statistic
$\text{Cov}[\cdot]$	Covariance function
d	Discount rate
\mathbf{D}	Diagonal matrix of Σ
$DivG$	Dividend growth rate
$DivY$	Current dividend yield
$\Delta AuM_{s,t}$	Change in Assets under Management of client segment s from time $t - 1$ to t
ΔAuM_t	Change in firm-level Assets under Management from time $t - 1$ to t
ΔCF_t	Change in net firm-level cash flow from time $t - 1$ to t
Δt	Unit of time
Δw_s	Deviation of client segment weight w_s from empirically observed segment weight w_s^0 for segment s
δ	Jump volatility of stochastic process
δ_s^2	Jump variance of stochastic process of client segment s
e	Expected counts in bin
$E[\cdot]$	Expected value
$\varepsilon_{s,t}$	Random variable for the diffusion process of $\frac{NNA_{s,t}}{AuM_{s,t-1}}$ for client segment s at time t
ε_t	Random variable for the diffusion process of $\frac{NNA_t}{AuM_{t-1}}$ at time t
η_i	Retention rate of customer i
$f(\cdot)$	Probability density function
$F_e(\cdot)$	Empirical cumulative distribution function
$F_n(\cdot)$	Normal cumulative distribution function
$F_{sn}(\cdot)$	Standard normal cumulative distribution function
$F_{CE^0}(\cdot)$	Cumulative empirical probability distribution function of \mathbf{CE}^0
$F_{\widehat{CE}^*}(\cdot)$	Cumulative empirical probability distribution function of $\widehat{\mathbf{CE}}^*$
$F_{\Upsilon}(\cdot)$	Cumulative Kolmogorov probability distribution

g	Long-term growth rate of net firm-level cash flows
γ	Standardized sample skewness
H	Planning horizon
\mathbf{H}	Hessian matrix
i	customer (or client)
\mathbf{I}	Information matrix
$\hat{\mathbf{I}}$	Information matrix estimator
j_t	Jumps per unit of time Δt at time t
JB	Jarque-Bera test statistic
k	Time lag
κ	Standardized sample kurtosis
K	Total number of time lags
KS	Kolmogorov-Smirnov test statistic
λ	Jump intensity of stochastic process
\mathbf{lb}	Vector of lower segment weight bounds lb_1, \dots, lb_S
lb_s	Lower weight bound for client segment s
$L(\cdot)$	Likelihood function
$\ln L(\cdot)$	Log-likelihood function
$\ln L_D(\cdot)$	Log-likelihood function of a diffusion process
$\ln L_{JD}(\cdot)$	Log-likelihood function of a jump-diffusion process
LPM_n^τ	Lower partial moment of order n with reference level τ
LT_i	Expected lifetime of customer i
m	Number of bins
$MN(\cdot)$	Multivariate normal distribution function
μ	Diffusion drift of stochastic process
μ_s^{NNA}	Diffusion drift of $\frac{NNA_{s,t}}{AuM_{s,t-1}}$ process for client segment s
μ_s^R	Diffusion drift of $R_{s,t}$ process for client segment s
n	order of lower partial moment
N	Number of observations
N_θ	Number of parameters
$N(\cdot)$	Normal distribution function
$NNA_{s,t}$	Net New Assets of client segment s at time t

NNA_t	Net New Assets aggregated across all client segments at time t (i.e. firm-level Net New Assets at time t)
o	Observed counts in bin
ω_i	Growth rate of contribution margin for customer i
ϕ	Jump drift of stochastic process
ϕ_s	Jump drift of stochastic process for client segment s
φ_k	Autocorrelation coefficient for time lag k
φ_k^*	Partial autocorrelation coefficient for time lag k
ψ	Reference level of $E[\widehat{CE}(\mathbf{w})]$
$Poisson(\cdot)$	Poisson distribution function
PM_s	Profit margin (earnings before taxes) in percent of revenue for client segment s
$\text{Prob}(\cdot)$	Probability function
Q	Ljung-Box Q-statistic
ρ^j	Cross-sectional correlation of the number of jumps j between all client segments
$\boldsymbol{\rho}^v$	Cross-sectional correlation matrix of the diffusion process v
ρ_{s_1, s_2}^v	Cross-sectional correlation of the diffusion process v between the pair of client segments s_1 and s_2
\mathbf{R}	Vector of asset returns
R	Asset return
$R_i^{<\tau}$	Asset return i that falls short of reference level τ
R^f	Risk-free return
R^m	Market return
$R_{s,t}$	Return on the average financial portfolio of a PWM client within segment s at time t
R_t	Return on the average financial portfolio of a PWM client across all segments (i.e. at the firm-level) at time t
R_t^*	Residual of regression of R_t on $\{1, R_{t-1}, R_{t-2}, \dots, R_{t-k+1}\}$
\bar{R}	Mean return on the average financial portfolio of a PWM across all segments (i.e. at the firm-level) over the empirical observation period $1, \dots, T$
R^2	Coefficient of determination

$RRA_{s,t}$	Return on Retained Assets of client segment s at time t
RM_s	Revenue margin in percent of AuM for client segment s
$RMSE$	Root-Mean-Squared-Error
s	Client segment
S	Number of client segments s
σ	Diffusion volatility of stochastic process
σ_s^{NNA}	Diffusion volatility of $\frac{NNA_{s,t}}{AuM_{s,t-1}}$ process for client segment s
σ_s^R	Diffusion volatility of $R_{s,t}$ process for client segment s
Σ	Covariance matrix of random vector \mathbf{V}
θ	Parameter vector
θ_0	True parameter vector
θ_c	Vector of correlation coefficients
θ_m	Vector of distribution moments
$\hat{\theta}$	Maximum likelihood estimator of parameter vector
Θ	Parameter space
t	Time period
τ	Reference level of lower partial moment
T	End of a calibration or observation time frame
$TC(\cdot)$	Transaction cost function
TV	Terminal value
\mathbf{U}	Upper triangular matrix of Σ
\mathbf{ub}	Vector of upper segment weight bounds ub_1, \dots, ub_S
ub_s	Upper weight bound for client segment s
$v_{s,t}$	Random variable for the diffusion process of $R_{s,t}$ for client segment s at time t
v_t	Random variable for the diffusion process of R_t at time t
Υ	Kolmogorov distribution
\mathbf{V}	Vector of random variables V_1, \dots, V_N
$\text{Var}[\cdot]$	Variance function
\mathbf{w}	Vector of client segment weights w_1, \dots, w_S
\mathbf{w}^0	Vector of empirically observed client segment weights w_1^0, \dots, w_S^0
\mathbf{w}^*	Vector of optimal client segment weights w_1^*, \dots, w_S^*
w_s	Weight of client segment s

w_s^0	Empirically observed weight of client segment s
w_s^*	Optimal weight of client segment s
w^{max}	Global maximum of client segment weight
w^{min}	Global minimum of client segment weight
x	Empirical observation
\mathbf{x}	Vector of empirical observations x_1, \dots, x_N
\bar{x}	Mean of empirical observations \mathbf{x}
ξ	Client segment weight tolerance
\mathbf{y}	Vector of \mathbf{x} that is sorted by size and standardized by its mean and standard deviation
Y_s	Jump size of client segment s
\mathbf{Z}	Vector of standard normal random variables Z_1, \dots, Z_N

Part I

Theoretical Model Development

Chapter 1

Introduction

Since the advent of the value-based management concept, the ultimate goal of many firms operating in competitive markets has become the maximization of shareholder value (Rappaport, 1986). Because shareholder value is defined as the present value of all future cash flows and the realization of these future cash flows is uncertain, these firms in fact strive to maximize the present value of expected future cash flows. By and large, the stream of expected future cash flows is generated by customer revenues. Consequently, Rappaport (1998) notes that “[...] without customer value there can be no shareholder value” (p.8). However, because the firms’ resources are scarce and customers consume these resources, only a limited number of customers can be served. Hence, firms have to maximize the present value of expected future cash flows from a limited set (or portfolio) of customers. In order to do so, firms need to focus their available resources on the portfolio of customers that can be expected to generate the highest cash flows at an acceptable level of risk. In order to enable firms to identify this value-maximizing customer portfolio, our study sets out to develop a comprehensive Customer Portfolio Management (CPM) model.

The exact nature of any theoretically derived CPM model depends on the type of firm it is applied to, because the dynamics of customer value creation are industry-specific (Bolton, Lemon and Verhoef, 2004). This study chooses to develop the CPM model in the context of the private wealth management (PWM) industry, because it is highly relevant to decision makers within this industry as a strategic tool that supports the allocation of resources to the ac-

quisition and retention of clients. The reason for this is threefold. First, the PWM business model is centered around long-term client relationships, making the acquisition and retention of clients the most important strategic area (PricewaterhouseCoopers, 2009). Second, the level of competition in the PWM industry is high,¹ increasing the pressure to allocate scarce resources in the most effective and efficient way. Third, as the last financial crisis has shown, the PWM business model is highly vulnerable to periods of economic downturn (Capgemini and Merrill Lynch, 2009), further increasing the pressure to reduce risks by active client relationship management. Besides being highly relevant to the PWM industry, the development and application of the proposed model is also particularly feasible here. This is due to the industry's unique set of characteristics, such as contractual, long-term client relationships, fairly stable margins and the availability of client segment-level data over an extended period of time.

The first part of this study is devoted to the theoretical development of our CPM model, drawing to a large extent on insights from the literature on customer valuation and customer-based firm valuation that have introduced the concepts of Customer Lifetime Value (CLV) and Customer Equity (CE). We develop a dynamic customer-based firm valuation model that is conceptually similar to a recent model developed by Kumar and Shah (2009). However, instead of employing a structural stochastic model to capture the dynamics of the cash flow generation process, we follow Krafft, Rudolf and Rudolf-Sipötz (2005) and Hogan, Lehmann, Merino, Srivastava, Thomas and Verhoef (2002), who suggest to employ reduced-form stochastic models that are commonly used for modeling the value of financial assets. Compared to structural stochastic models, this methodology lowers data requirements and construct measurability issues substantially (Chintagunta, Erdem, Rossi and Wedel, 2006). Furthermore, since a significant part of client value dynamics is tied to financial market developments, it is only appropriate to use stochastic models that are commonly employed to capture the dynamics of financial markets. In a next step, we extend this dynamic customer-based firm valuation model by applying financial portfolio selection theory (Markowitz, 1952) to it and develop a portfolio optimization algorithm that is in line with share-

¹See for example the professional reports of PricewaterhouseCoopers (2007; 2006; 2005; 2004), Capgemini and Merrill Lynch (2007), IBM (2005) and Oliver Wyman (2006), but also academic studies, such as Foehn (2006).

holder value maximization. The application of financial portfolio optimization techniques to the management of customer portfolios has recently been called for by both Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram (2006) and Terho and Halinen (2007).

In the second part of our study, we apply the proposed theoretical CPM model to an empirical case, using a set of proprietary client segment-level data from one of the world's largest PWM institutions. In a preliminary analysis of the empirical data and in the course of our empirical application, we are able to validate all assumptions made during our theoretical model development. The results from our empirical application confirm that the proposed CPM model is able to identify the customer portfolio that maximizes value and at the same time accounts for the risk preferences of our sample firm as the investor in the customer portfolio. Furthermore, our results demonstrate that this firm can realize substantial diversification effects, arising from the value dynamics across different customer assets, by holding a balanced customer portfolio. This allows the firm to increase the expected value of the customer portfolio with a lower than proportional increase in the attached cash flows risks. We conclude that managers can realize substantial benefits in terms of shareholder value by basing their resource allocation decisions regarding customer acquisition and retention strategies on the results from the proposed CPM model. Finally, our study shows that this CPM model cannot only be employed to optimize the existing portfolio of customer assets, but can also be used to support the strategic decision-making process regarding the expansion of the existing customer portfolio.

Our study makes several contributions to the literature. First, we extend the concept of customer-based firm *valuation* (e.g. Gupta, Lehmann and Stuart, 2004; Krafft, Rudolf and Rudolf-Sipötz, 2005) to customer-based firm value *optimization*. By moving from valuing and managing individual customer relationships in isolation to assessing the contribution of individual customer relationships to the portfolio of customers as a whole, we address an important research gap that has been identified by Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram (2006) and Johnson and Selnes (2004). Furthermore, in line with Kumar and Shah (2009) and in contrast to prior research in the field of customer valuation and customer-based firm valuation, our study is

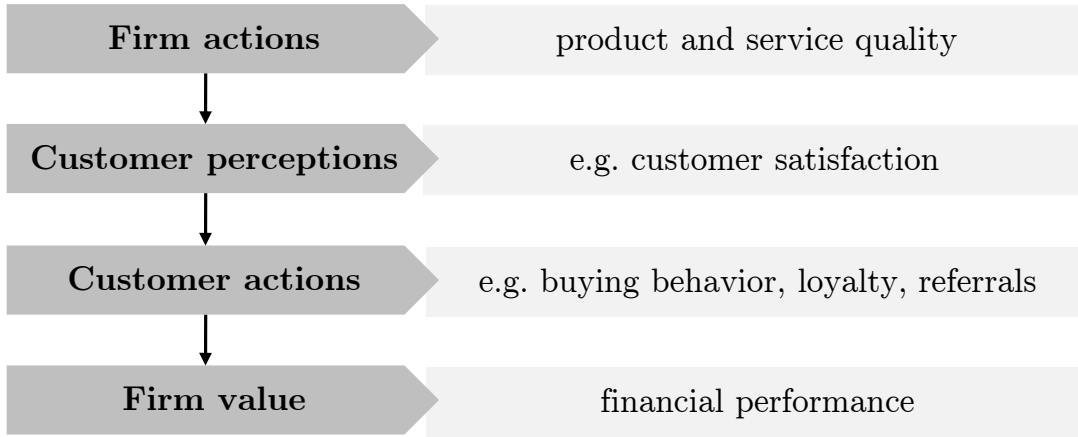
unique in that it not only accounts for the ability of customer relationships to contribute value by “accelerating and enhancing cash flows”, but also by “lowering the volatility and vulnerability of cash flows” (p.2, Srivastava, Shervani and Fahey, 1998). Moreover, ever since Johnson and Selnes (2004) introduced the conceptual framework of customer portfolio management dynamics, academics throughout the field have demanded that future models of customer value should account for these dynamics (Kumar, Lemon and Parasuraman, 2006). To the best of our knowledge, so far the only examples of empirical implementations of customer portfolio dynamics can be found in the studies of Homburg, Steiner and Totzek (2009) and Buhl and Heinrich (2008). The former study models customer dynamics by the switching behavior of customers between segments over time (i.e. customer migration). In contrast, Buhl and Heinrich (2008) focus on the implementation of a customer portfolio framework that draws on observable, historical measures of return and risk in order to account for the presence of customer dynamics. Our study adds to the understanding of customer dynamics within the portfolio by explicitly modeling them in the form of correlations in the customer value generation process. Finally, our study adds to the literature on PWM, an industry that has only recently begun to inspire the interest of the research community and as a whole still lacks a deeper academic understanding.

The remainder of this dissertation is structured as follows. Chapter 2 provides a review of the related literature and identifies the literature gap that this study seeks to address. In chapter 3, we characterize the PWM industry and motivate in more detail why this industry in particular has been chosen as a context for this study. Building on prior research in the field of customer valuation and customer-based firm valuation and accounting for the peculiarities of the PWM industry, chapter 4 is dedicated to the actual development of the CPM model and concludes the first part of this study. Part II is devoted to the empirical application of the proposed, theoretical CPM model and begins with a presentation of the empirical data in chapter 5. This chapter also comprises a preliminary analysis of the data that validates the various assumptions that are made during the theoretical model development. The results of the empirical application of the proposed CPM model are presented and discussed in chapter 6. Finally, chapter 7 summarizes and concludes.

Chapter 2

Theory

In this chapter, we review the relevant literature, providing the reader with a thorough theoretical background, thus setting the stage for the development of a Customer Portfolio Management (CPM) model. The chapter begins by outlining the interface between the disciplines of marketing and finance in section 2.1. The literature on this interface, which has been coined the financial impact literature throughout the marketing discipline, has inspired most of the research that is of direct relevance for the development of a CPM model. This research can be divided into two main streams. The first one is devoted to the valuation of customer relationships and is discussed in section 2.2. The second one, presented in section 2.3, builds on the first stream and concentrates on what is known as customer-based firm valuation. Both streams have successfully linked customer relationships to firm value and have ultimately contributed to raising the financial accountability of marketing expenditures. Nevertheless, so far the literature has failed to develop a comprehensive model that capitalizes on these findings in order to actively manage a portfolio of customer relationships. This gap in the literature is outlined in section 2.4. This study contributes to closing this gap by extending the concept of customer-based firm *valuation* to customer-based firm value *optimization*.

Figure 2.1: From marketing to finance

2.1 From marketing to finance

In order to develop a CPM model, it is necessary to value customers. The literature on customer valuation is situated in the interface between the disciplines of marketing and finance (i.e. the science for generating and the science for managing cash). According to Gupta and Zeithaml (2006), the entire literature dedicated to this interface can be disaggregated into the following four components: firm actions, customer perceptions, customer actions and firm value. The logic behind this framework is that firm actions, which include all efforts geared towards achieving the overall product and service quality, result in certain customer perceptions, such as for example a certain degree of customer satisfaction. These unobservable customer perceptions then manifest themselves in observable behavior in the form of customer actions, among them a certain buying behavior, loyalty and referrals. By influencing the revenues and costs of a firm, customer actions contribute to the firm's overall return or value, which is most often expressed as financial performance. This framework and the interrelationships of its components are visualized by figure 2.1.

Because each of these components clearly results from the one preceding it, this framework has also been termed service-profit chain (e.g. Heskett, Jones, Loveman, Sasser and Schlesinger, 1994; Kamakura, Mittal, de Rosa and Mazzon, 2002), return on quality (Rust, Moorman and Dickson, 2002; Rust, Zahorik and Keiningham, 1995), return on marketing (Rust, Lemon and Zeithaml, 2004) or

marketing productivity (Rust, Ambler, Carpenter, Kumar and Srivastava, 2004). The framework was first introduced as a way to make marketing actions financially accountable. Both practitioners and academics had called for this, fearing that the new focus on shareholder value would otherwise lead to a severe underinvestment in the financially unaccountable marketing activities (Aaker and Jacobson, 1994; Day and Fahey, 1988; Stein, 1989). Since then, research activity in this field has especially been fueled by Srivastava, Shervani and Fahey (1998), who developed a conceptual framework to demonstrate that, by influencing customer behavior, marketing initiatives can increase shareholder value by:

1. “accelerating and enhancing cash flows [and by]”
2. “lowering the volatility and vulnerability of cash flows.” (p.2)

In 2004, the Marketing Science Institute (MSI) made the financial accountability of marketing actions one of its top research priorities (Lehmann, 2004), leading to the emergence of an entire stream of research dedicated to justifying the role of the marketing discipline in a finance-dominated world. Rao and Bharadwaj (2008) have recently contributed to this literature. Using a theoretical model, the study demonstrates that marketing actions are linked to a firm’s expected cash flows, can reduce firm cash needs and ultimately determine shareholder wealth.

While relatively few studies focus on the development of integrative frameworks, most research on the interface between marketing and finance is devoted to the establishment of specific links between any two of the four components depicted in figure 2.1. Apart from Gupta and Zeithaml (2006), two excellent overviews of this literature are provided by Petersen, McAlister, Reibstein, Winer, Kumar and Atkinson (2009) and Srinivasan and Hanssens (2009).

The recent surge in interest in customer relationship management (CRM) and its associated customer metrics, most prominently customer satisfaction, has led researchers to explore the link between customer satisfaction and different measures of financial performance. Measures of financial performance analyzed include, but are not limited to, profit (Rucci, Kirn and Quinn, 1998), stock price (Fornell, Mithas, Morgeson III and Krishnan, 2006; Ittner and Larcker, 1998; Luo and Homburg, 2008), Tobin’s q (Anderson, Fornell and Mazvancheryl, 2004), return on assets (Hallowell, 1996), return on investments (Anderson

and Mittal, 2000; Anderson, Fornell and Rust, 1997; Anderson, Fornell and Lehmann, 1994), abnormal earnings (Aksoy, Cooil, Groening, Keiningham and Yalcin, 2008; Nayyer, 1995), cash flows (Gruca and Rego, 2005) and most recently even corporate bond markets (Anderson and Mansi, 2009). Albeit some variation in the results, due to firm-, industry- and country-specific effects and the nonlinear nature of the link itself, all studies come to the conclusion that an improvement in the level of customer satisfaction is significantly and positively related not only to a firm's financial performance, but also to investor perceptions about the firm.

However, as Kamakura, Mittal, de Rosa and Mazzon (2002) show, customer satisfaction alone does not necessarily lead to higher financial performance, but has to be accompanied by a firm's ability to transform positive customer perceptions into actual customer behavior beneficial for the firm. That is why another stream of the literature is devoted to the link between customer perceptions and behavior, the results of which show that for instance an increase in customer satisfaction generally increases retention rates (Bolton, 1998; Hallowell, 1996; Rust and Zahorik, 1993), revenues (Ittner and Larcker, 1998), cross-selling opportunities (Loveman, 1998), number of customers (Ittner and Larcker, 1998) and share-of-wallet (Loveman, 1998).

The literature on the interface between marketing and finance described above is commonly referred to as financial impact literature throughout the marketing discipline. It has inspired researchers to develop novel approaches to value customers in order to strengthen the final link of the service-profit chain, namely the link between customer actions and firm value. These approaches are outlined in the next section.

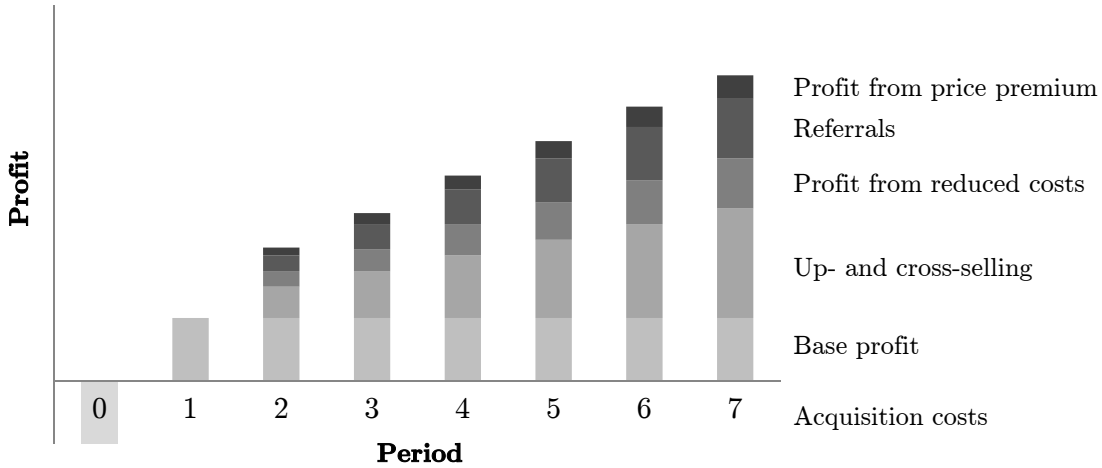
2.2 Customer valuation

Early approaches to the valuation of customers make use of historic, deterministic, univariate measures, such as past sales or past contribution margin, in order to estimate the value a particular customer is likely to contribute to the firm in the future.

Although most industries have adopted these approaches for the valuation of their customers, the results are at best mixed. More specifically, many firms across different industries have found the concentration on customers deemed the most valuable according to historic, univariate measures to be fatally flawed. For example, in the context of private wealth management (PWM), the focus on the historic contribution margin for the valuation of clients has led many providers to focus their acquisition and retention efforts on the most wealthy and hence most profitable clients. However, many PWM institutions soon had to realize that these clients are not only substantially more difficult and costly to retain, but also resource consuming to acquire, so that asset growth is limited. Moreover, many of these clients are eager to pursue highly risky investment strategies, resulting in very volatile profits.

As a consequence, practitioners and academics have called for heightened research efforts on how customers generate value for the firm in order to discover superior measures for customer valuation. Some of the insights gained by these research efforts have already been pointed out in the preceding section, but those most relevant for the development of a new approach to customer valuation are discussed next.

Over a customer's lifetime one can identify three events that determine the customer's value to the firm: acquisition, retention and defection. However, it is important to note that these events can only be identified for contractual customer relationships, because the points in time for all three events are clearly defined by the contract. Because upon defection the customer is viewed as forever lost for the firm, the approach to account for contractual customer relationships is also called the 'lost-for-good' approach (e.g. Berger and Nasr, 1998). This stands in contrast to the 'always-a-share' approach, used for noncontractual settings, in which individual customer buying decisions have to be predicted and in which the firm is assumed to have a relationship with every potential customer (e.g. Rust, Lemon and Zeithaml, 2004; Venkatesan and Kumar, 2004). In their seminal paper on the value of customer retention and loyalty, Reichheld and Sasser (1990) identify the major sources of profitability and hence value across the customer lifetime events mentioned above for contractual customer relationships. These sources are depicted in figure 2.2.

Figure 2.2: How customers generate value

Source: Reichheld and Sasser (1990).

As the figure illustrates, acquiring new customers is generally costly for firms, leading to a loss or negative profit upon customer acquisition. From thereon, customers are assumed to generate a certain base profit that remains constant over the remaining duration of the relationship. Once a customer defects and the relationship ceases to exist, the entire profitability of the customer disappears. Nevertheless, as long as firms are successful in retaining customers, a number of effects lead to changes (generally assumed to be positive) in the profitability of customer relationships over their lifetime. First of all, in case customers respond positively to the up- and cross-selling efforts of firms, the profitability of the relationships will rise. Second, over the duration of the relationships, firms often become more efficient in serving customers, which reduces costs and thus increases profitability. Third, in case customers are satisfied with the products and services of a firm, they usually issue referrals within their social network, which in turn might lead to new customer acquisitions for that firm. In that case, the profitability of newly acquired customers is counted towards the profitability of the customers who issued the referrals, since they induced the relationships in the first place. Finally, additional profits may arise over time, if the customers' price sensitivity declines and firms are able to extract a higher profitability from existing relationships by charging price premia.

An alternative way of classifying these value drivers has been proposed by Stahl, Matzler and Hinterhuber (2003). In particular, the authors identify four sources of customer lifetime value that can be linked to the value drivers identified by Reichheld and Sasser (1990): a customer's base potential, a customer's growth potential, a customer's networking potential and finally, a firm's learning potential regarding a specific customer. Customer base potential comprises both, the acquisition cost that needs to be incurred to acquire a customer in the first place, as well as the contribution margin or level of profitability a customer brings into the relationship from the beginning. Customer growth potential accounts for a customer's susceptibility to up- and cross-selling efforts and a firm's ability to increase profits by negotiating price premia. Referrals or positive word-of-mouth are captured by a customer's networking potential. Finally, a firm's learning potential with regard to a specific customer includes a firm's ability to realize efficiency gains and thus to increase the profits from the relationship over the customer's lifetime by reducing the costs to service him.

The insights gained from the research discussed above have contributed significantly to the development of a novel approach to the valuation of customers. This approach is termed Customer Lifetime Value (CLV) and was introduced by Dwyer (1989) and Jackson (1992). Its further development was mainly driven by Blattberg and Deighton (1996), Berger and Nasr (1998) and Blattberg, Getz and Thomas (2001). In contrast to the early attempts to customer valuation, which involve historic, univariate measures, such as past sales or past contribution margin, to predict the future value of a customer to a firm, the CLV is a forward looking, multivariate measure. Essentially, its computation entails the prediction of all expected future cash flows from a customer relationship over the customer's entire lifetime (i.e. the expected duration of the relationship). These future cash flows can be thought of as a summary measure for all aspects of customer and firm behavior (i.e. all revenues and costs that arise from the relationship). These cash flows are then discounted to their present value to account for differences in their timing. Finally, the discounted future cash flows over the expected customer lifetime are summed to arrive at the CLV measure. Essentially, the computation of CLV is conceptually analogous to the discounted cash flow (DCF) method commonly employed in the finance discipline to value financial assets and firms.

Assuming that the future cash flows of a customer relationship can be predicted with a high degree of accuracy, the CLV should in theory reflect the ‘true’ customer value. Because the cash flows for each future period of a customer’s lifetime are inherently hard to estimate in practice, they are usually approximated by the current (or expected) average contribution margin¹(CM) of a customer in the most basic specification of the CLV (Mulhern, 1999). Therefore, despite the fact that cash flows (or the contribution margin) can be expected to vary for each period t , for simplicity they are often assumed to remain constant over time. This leads to the following basic specification of the CLV for customer i over his expected lifetime (LT) and with discount rate d :²

$$CLV_i = \sum_{t=0}^{LT_i} \frac{CM_i}{(1+d)^t} \quad (2.1)$$

This CLV model specification has two obvious shortcomings. First, it only captures the direct monetary effects of a customer relationship and therefore neglects the sometimes substantial value of positive network effects through referrals or word-of-mouth. In fact, Reichheld (2003) suggests that the key to business growth lies in positive network effects and claims that the number of referrals is the only figure firms need to maximize in order to succeed. Additionally, in a contemporaneous study, Hogan, Lemon and Libai (2003) are able to show that the value of a lost customer over time is not only a function of lost purchases, but also a function of lost word-of-mouth, which often induces purchases by potential new

¹The contribution margin is an accounting measure of profitability, which can differ substantially from the actual net cash flow for a given period, due to the application of the matching principle required by current accounting standards. The matching principle distinguishes between the recognition of revenues and expenses and cash in- and outflows. More specifically, expenses are recognized when obligations are incurred and offset against revenues which are generated from those expenses, no matter when the actual cash flow occurs. Cash flows, on the other hand, are recognized upon the actual cash payment irrespective of the timing of the related obligation. The difference between accounting profits and cash flows is called accruals. Despite the fact that accounting profits and cash flows can differ substantially at any single point in time, Preinreich (1937) and Lücke (1955) prove that the net present value using accounting profits is always equal to the one using cash flows, since the sum of all accruals over the entire investment period must equal zero. This insight is called the Preinreich-Lücke-Theorem.

²This specification is used for the valuation of an existing customer relationship, for which we are only interested in the residual value. In case we want to value a customer that is yet to be acquired, the acquisition costs have to be subtracted from the present value as initial investment costs.

customers. While this already demonstrates the importance of positive network effects, Villanueva, Yoo and Hanssens (2008) further establish that the marginal CLV of customers that are acquired via referrals is higher than that of customers acquired by firm-induced marketing activities. Stated differently, referrals are not only valuable because they lead to the acquisition of new customers and thus generate further purchases, but also because customers acquired via referrals are themselves more valuable than customers acquired through regular marketing channels. Because the referral value of a customer is inherently hard to measure, the proponents of the CLV measure stated above do not explicitly account for. In particular, they argue that because a high CLV is by itself an indication of a satisfied customer and satisfied customers are known to issue more referrals, the referral value of a customer should be positively correlated with the CLV measure. However, using data from a financial services and telecommunications firm, Kumar and Leone (2007) demonstrate that the CLV is often independent from customer referral value. The explicit inclusion of customer referral value in the estimation of the CLV thus remains an open issue.

The second, and even more severe shortcoming of the CLV specification in equation 2.1, is its deterministic nature. In particular, it does not allow the value of the customer to increase or decrease over time. Specified in such a way, the customer is valued similar to an investment that needs to be made today (the acquisition cost), pays regular constant coupons over a certain time horizon in the future (the contribution margin and the customer lifetime), and whose value needs to be discounted to its present value to reflect the different timing of payments and thus the time value of money. Therefore, the model neglects the value dynamics over time and the substantial risk attached to the realization of future values. Because the contribution margin in equation 2.1 is most often proxied by the current level of customer profitability, the specification assumes that customer profitability is persistent over time and that the current level of profitability is a good estimate of future profitability. The findings of Campbell and Frei (2004) cast significant doubt on this conjecture by showing that a substantial amount of 1-year ahead customer profitability cannot be explained by current profitability.

To address some of these shortcomings, several extensions of this basic CLV model in equation 2.1 suggest to include a linear growth rate (ω) for the con-

tribution margin. Furthermore, instead of using a sometimes arbitrary estimate for expected customer lifetime, some researchers suggest to estimate the CLV for an infinite period of time, accounting for lifetime expectations using a retention rate η (i.e. a probability for customer repeat buying or being ‘alive’ in the next period). The latter has been particularly propagated by Gupta and Lehmann (2005), who show that using a specific estimate of expected customer lifetime generally leads to an overestimation of the CLV. The resulting specification of the CLV can be written as:

$$CLV_i = \sum_{t=1}^{\infty} \frac{\eta_i^t CM_i (1 + \omega_i)^{t-1}}{(1 + d)^t} \quad (2.2)$$

Thus, given a certain contribution margin (CM) and a positive growth rate (ω), the value of a customer i generally increases with an increase in the retention rate (η). This is in line with the widespread belief that customer relationships generally become more valuable over time and that acquiring a new customer is often more expensive than retaining an existing one (Reichheld and Sasser, 1990). However, as Reinartz and Kumar (2003) note, customer relationships may continue, but deteriorate. They show that the duration of a customer relationship on its own does not automatically translate into higher profitability. Similarly, and in contrast to the view of Reichheld and Sasser (1990), Du, Kamakura and Carl (2007) argue that a decline in a customer’s share of wallet might have more adverse effects for a firm than the termination of the entire relationship.

While these findings question the view that long-term customer relationships are always more valuable, few studies have tried to explicitly model customer value dynamics over time, in order to capture the risk inherent in the future development of customer cash flows. This is especially true for contractual customer relationships, since they are generally perceived as being less risky and the required parameters can better be estimated. The value of noncontractual customer relationships, in contrast, can fluctuate quite dramatically over time. This has led to a focus of CLV research efforts on noncontractual relationships. In particular, the literature has developed very sophisticated probability models for the purpose of making predictions about whether an individual will be an active customer in the future and if so, what his buying behavior will be. Unlike the

CLV models for contractual relationships, the specification of the CLV for noncontractual relationships therefore allows the contribution margin to vary over time, addressing one of the most severe shortcomings of the CLV measure described in equation 2.2. This, however, comes at the price of estimation risk. In a very recent publication, Fader and Hardie (2009) give an excellent overview of these probability models and their use throughout the customer valuation literature.

Despite these recent advances in the modeling of customer value dynamics, especially in the context of noncontractual relationships, the estimation of the ‘true’ customer value remains uncertain and some researchers have voiced substantial scepticism regarding the derived CLV estimates. A prominent example is the study by Malthouse and Blattberg (2005), which demonstrates empirically that due to the low accuracy of the prediction of future customer value, a large portion of customers are misclassified as either high- or low-value customers. This in turn leads to wrong managerial decisions regarding the allocation of resources away from seemingly low-value customers to seemingly high-value ones. As a result, the firm incurs substantial misclassification costs. In a more recent study, Wübben and von Wangenheim (2008) posit that regarding customer valuation, simple managerial heuristics often perform at least as well as sophisticated CLV probability models. They conclude that existing CLV models should only be implemented in managerial practice with a lot of care and identify a number of areas for their improvement.

Although, the developed CLV models to date are far from being perfect and substantial room for improvement still exists, the CLV literature has influenced the thinking of researchers and practitioners throughout the marketing discipline in a profound and irreversible way. In particular, the concept of CLV has led:

“[...] to a very interesting and important evolution in marketing thinking - away from the ‘Customer is king’ to the ‘Customer is cash’.”
(p.14, Johnson and Selnes, 2005)

2.3 Customer-based firm valuation

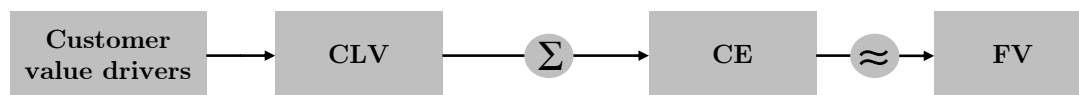
In their seminal paper, Gupta, Lehmann and Stuart (2004) demonstrate that the concept of CLV is not only useful for valuing customers, but also for valuing

firms. Based on the realization that the concept of CLV is essentially a DCF-based valuation on the customer level, one can approximate the market value of an entire firm by summing up the CLV's of all the firm's customers. This is because we know from the finance discipline that investors value a firm by forming expectations about the future cash flows generated by this firm and aggregating their discounted (i.e. their present) value. Therefore, the methodology is virtually the same, only the unit of analysis on which future cash flow expectations are formed varies (i.e. customer vs. firm). Thus, assuming that all cash flows of a firm are operating cash flows (i.e. generated directly by customer exchange relationships), the CLV summed over all customers, referred to as Customer Equity (CE) in the literature, should in theory equal firm value (FV) determined by the DCF method. This concept has been coined customer-based firm valuation in the literature and is illustrated by figure 2.3, which, in a similar form, can be found in a recent study by Kumar and Shah (2009). Note, however, that here firm value corresponds to the value from the perspective of the firm's shareholders only, the equivalent of the market capitalization of the firm. This stands in contrast to the finance discipline, where the concept of firm value encompasses the value from the perspective of both shareholders and creditors and therefore usually comprises the market value of total net debt.

Although Gupta, Lehmann and Stuart (2004) were the first to formally establish the link between valuing customers and valuing firms, the concept of CE had already been advocated by Blattberg and Deighton (1996) and Blattberg, Getz and Thomas (2001) a few years earlier. However, the latter studies focus more on the formulation of marketing strategies aimed at achieving a higher CE in order to make marketing actions more accountable (see section 2.1) and less on customer-based firm valuation. Mathematically, the original specification of CE can be written as follows:

$$CE = \sum_{i=1}^N CLV_i \quad (2.3)$$

where N is the number of customers that can be replaced by the number of customer segments S in case the CLV is computed at the customer segment-level instead of at the level of the individual customer. It is, however, important to

Figure 2.3: From customer to firm value

note that while equation 2.3 only includes the sum of the CLV's of all *existing* customers (Blattberg, Getz and Thomas, 2001; Blattberg and Deighton, 1996), later studies extended this definition of CE to also comprise the CLV's of all *future* or *potential* customers (Rust, Lemon and Zeithaml, 2004). While this extension seems reasonable considering that much of the value, especially of growing firms, lies in the potential to generate cash flows from future customers, it introduces the additional challenge of estimating the number of customers for each future point in time.

Gupta, Lehmann and Stuart (2004) are able to provide the first empirical evidence for the strong conceptual link between customer and firm valuation. For three out of five firms sampled, the authors are able to provide a fairly close approximation of their empirical market value using customer valuation techniques.³ For the estimation of the number of future customers, the authors employ an S-shaped function that is similar to the Bass (1969) diffusion model, which has been used for projecting the number of customers before. The authors convincingly show that customer-based firm valuation techniques can provide reasonable estimates of firm value, when more traditional financial methods do not work, namely for young growth companies with negative earnings. As many of these young growth companies are characterized by a small number of customer relationships, whose average value is low (e.g. internet firms), the estimation of the number of future customers becomes the dominant value-driver in customer-based firm valuation.

Building on this insight, Krafft, Rudolf and Rudolf-Sipötz (2005) exclusively focus on modeling the process of future customer acquisitions for growth companies. They argue that the value of growth companies largely depends on whether a given firm is able to reach a certain critical number of customers. Beyond this point, the self-reinforcing effect of referrals made by satisfied customers (i.e.

³Also see Gupta and Lehmann (2005).

positive word-of-mouth) is strong enough to propel the number of customers to ever higher values until market saturation is reached. If a firm is unable to reach the critical number of customers, the study argues that the referrals of dissatisfied customers (i.e. negative word-of-mouth) will dominate and the firm will quickly cease to exist. The authors model these dynamics using a momentum process, whose inversion (i.e. mean reversion process) is commonly employed for modeling interest rate changes in the finance discipline. The model is able to distinguish between a scenario in which the critical level for the number of customers is surpassed and one in which the firm fails to reach this critical value. Depending on the scenario, the model adjusts the diffusion process accordingly, while accounting for momentum dynamics. Using numerical examples, the study concludes that the proposed process is well suited for modeling the development of customer numbers for growth companies.

In a very recent study, Libai, Muller and Peres (2009) extend these customer diffusion models, developing a more complete framework for modeling the number of future customers that accounts for competition and customer attrition in the context of service companies. The authors argue that to fully understand the dynamics of the customer acquisition and retention process of a growth company, it is important to account for a number of different effects that were neglected in the past. On the one hand, future customers cannot only be acquired from a pool of ‘nonusers’ (also referred to as the remaining market potential, which can include both, completely new customers and customers who disadopted the service in the past⁴), but they can also switch from competitors (which is referred to as ‘churn’). On the other hand, the firm cannot only lose customers who disadopt a service, but also customers who switch to competitors. Using a diffusion model that accounts for both disadoption and churn, the authors are able to estimate firm value using a customer-based valuation technique with relatively small errors. For six, out of a pool of seven different firms, the study computes firm values over three consecutive quarters that on average deviate by only 17.7% from the empirical market values. The authors argue that the remaining error is mainly

⁴Note, that this definition of the remaining market potential breaks with the tradition of viewing lost contractual customer relationships in service industries as ‘lost-for-good’. Unlike the ‘lost-for-good’ approach, Libai, Muller and Peres (2009) explicitly allow for the possibility that a customer who disadopts a service rejoins the firm at a later point in time.

caused by cash generating activities by the firms that are not associated with customer-related business activities. Because investors incorporate these other activities in their expectations regarding future growth opportunities, they are reflected in stock prices, but are not fully captured by the employed model.

While the studies described above show the strong theoretical and empirical link between the concept of CE and firm (shareholder) value, Bauer and Hammerschmidt (2005) first establish this link algebraically. The authors focus on the portion of firm value that is left unexplained by CE. While Bauer and Hammerschmidt (2005) agree that the lion's share of firm value is captured by CE, they also point to the existence of firm value drivers that are not customer-specific and hence not included in CE, but which firms nevertheless often face. These value drivers include fixed costs that cannot directly be allocated to individual customers, financing costs such as investments in working and fixed capital, taxes, but also non-operating assets. Ignoring these value drivers leads to a discrepancy between CE and firm value. The relative size of this discrepancy depends on the degree to which these value drivers are relevant, which in turn depends on the type and activity of the specific firm.

In a more recent publication, Skiera, Wiesel and Schulze (2009) employ a very similar model, reducing the discrepancy between CE and firm value from the perspective of shareholders to non-operating assets, non-equity claims and indirect customer-related expenditures, the latter being a summary measure for all costs that are not driven by individual customers (e.g. administrative costs, investments and taxes). In contrast to Bauer and Hammerschmidt (2005), this study also assesses the empirical fit of the developed model. For this purpose, the authors use customer-level data from two publicly traded internet service providers. Due to the contractual nature of customer relationships in this industry, the authors employ a customer cohort-based approach for the estimation of CE. For both firms the study is able to compute firm (shareholder) values that are close to their empirical market capitalizations. However, Skiera, Wiesel and Schulze (2009) note that CE on its own substantially under- or overestimates the true firm value in the case of the two selected firms. But, the consideration of the proposed additional value components successfully closes the gap between CE and firm value. As indicated above, the usefulness of CE as a proxy for firm value

from the perspective of shareholders therefore depends on the relative importance of these indirect and customer-unrelated value components.

All of the studies above treat CE as a value that exclusively depends on the size of future cash flows, which in turn depend on the number of future customers and their respective profitability. Srivastava, Shervani and Fahey (1999; 1998) further point out that the firm's customers, or market-based assets as they are denoted by the authors, create value not only by "accelerating and enhancing cash flows, [but also by] lowering the volatility and vulnerability of cash flows" (p.2). In other words, while one may have the same expectations regarding the level of future cash flows of two separate entities, the risks inherent in these cash flows can differ substantially. This results in different market valuations, because assuming efficient markets, stock prices reflect the risk-adjusted present value of all future cash flows. However, as Kumar and Shah (2009) note, cash flows from CLV or CE computations are not risk-adjusted. As a result, it is not surprising that the strength of the empirical link between CE and firm value can vary dramatically. In the latest and most successful attempt to link the concept of CE to firm value (i.e. market capitalization), Kumar and Shah (2009) try to close this gap in the literature by explicitly modeling and accounting for the risk of CE. Using historic customer-level data, the authors estimate both, CE and the market capitalization of two firms (one operating in a business-to-business and one in a business-to-consumer context). To account for the risk inherent in the cash flow estimation, the authors employ the weighted-average (weighted by profitability) share-of-wallet across customers to capture cash flow vulnerability and the variance of CE as a proxy for the volatility of future cash flows. The latter proxy is estimated by generating a distribution of possible values of CE using a Monte Carlo simulation technique. CE, as well as the two proxies for cash flow risk, are estimated with monthly frequencies over a 2.5 year period. Market capitalization is then regressed on all three factors to determine their explanatory power. Including the lagged market capitalization of the firms as an additional explanatory variable to account for omitted variables, the authors are able to explain close to 80% of the variance in the firms' market values over time. As expected, the results indicate that the two proxies for cash flow risk significantly

increase the explanatory power and hence strengthen the link between the concept of CE and firm value.

To summarize, the literature discussed above convincingly demonstrates that the concept of valuing a firm's customer base is conceptually very similar to firm valuation. It is therefore not surprising that CE is a good proxy for the value of a firm. This is especially true if firm cash flows are exclusively operational in nature and can directly be linked to individual customers or customer segments and if the risks attached to the realization of future cash flows are accounted for.

2.4 Research gap

Despite some of its shortcomings, overall the concept of CLV has proven to be useful for identifying valuable customers and for managing resources aimed at optimizing the value of individual customers or customer segments. Venkatesan and Kumar (2004) for instance show that compared to other, more traditional customer-based metrics, the CLV measure is superior in selecting customers that will provide higher profits in future periods. Furthermore, their results suggest that future profits are likely to increase, when managers design resource allocation rules consistent with maximizing CLV. Although, the value of these findings to marketing practitioners is beyond doubt, Gupta and Zeithaml (2006) rightfully note that "while this micromarketing is useful from an operational perspective, it must be aggregated at a higher level to [...] be useful [...] for senior managers" (p.724). As we have shown in the preceding section, the concept of CE has filled this gap to a certain extent. However, research so far has only established the link between CE and firm value and has proposed customer-level strategies aimed at increasing this value and making marketing actions financially more accountable (e.g. Kumar and Petersen, 2005). To the best of our knowledge, a comprehensive framework that attempts to extend the concept of customer-based firm valuation to customer-based firm value *optimization* to date does not exist. At a first glance this may seem surprising, since firm value approximated by CE is simply the sum of all CLVs. However, the problem is far more complex than figure 2.3 might at first suggest.

In a deterministic world, in which the CLV of each customer or customer segment can be determined with absolute certainty, the maximization of (customer-based) firm value is equivalent to maximizing the sum of all CLVs. This is achieved by focussing all resources on the customer or customer segment that generates the highest future cash flows. Obviously, we do not live in a deterministic world and despite the fact that there have been tremendous advances in the predictive power of some of the developed models, a great amount of uncertainty regarding the realization of predicted future cash flows still prevails. Moreover, the uncertainty of predicting future cash flows at the customer-level is even higher than at the firm-level, due to the lower level of aggregation (e.g. Malthouse and Blattberg, 2005; Wübben and von Wangenheim, 2008). In a very recent study, Kumar and Shah (2009) point out that this uncertainty is one of the major reasons for the discrepancy between CE and firm value. Accordingly, they propose to adjust CE for risk to strengthen the link between CE and firm value. While this might indeed enhance the theoretical link between both constructs and therefore help improve customer-based firm valuation, it is not useful for decision makers within the firm, whose goal is the maximization of firm value. The reason is that it only increases the awareness for risk, but does not provide decision makers with a tool to manage the value-reducing effect of risk, because it does not account for customer dynamics within the customer portfolio. However, as the literature on customer relationships has shown, “customers evolve over time and, consequently, become more or less valuable in future periods” (p.70, Homburg, Steiner and Totzek, 2009), making the inclusion of customer dynamics in the valuation of customers one of the top current research priorities (Kumar, Lemon and Parasuraman, 2006). Neglecting the role of customer dynamics leads to managerial decisions that consider each customer or customer segment in isolation. Kumar and Shah (2009), for example, propose CRM strategies that exclusively target high CLV customers, without considering the potentially adverse effects of these strategies on the value of the overall portfolio. While their approach increases firm value measured by market capitalization, thus adding to shareholder value, there is still room for improvement.

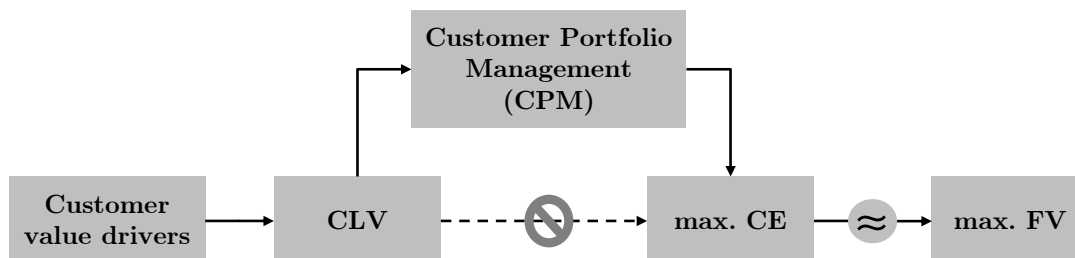
The avenue for improvement has most clearly been formulated in a recent publication by Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and

Sriram (2006). More specifically, in their overview of future research topics in the field of CLV modeling, they call for “moving from a customer to a portfolio of customers.” In particular, they claim that:

“[l]ocally optimal decisions regarding the acquisition and development of customers may in some cases be globally suboptimal from the broader business perspective. For example, in some financial services settings (e.g. credit cards), current CLV measurement practices that focus on the expected value of a customer may predict that high-risk customers are more valuable than low-risk ones. Acting on this information, the marketing manager will focus on acquiring these high-risk customers. However, the financial markets expect a firm to have a portfolio of customers that comprises a mix of low- and high-risk customers. Locally optimal behavior by the marketing manager may therefore be suboptimal for the firm.” (p.150)

As a result, Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram (2006) demand that “to assess the risk of customers, we need to derive expressions for the distribution (or at least the variance) of CLV. We need to develop models for valuing a portfolio of customers and develop rules that guide the marketing manager to undertake actions that maximize the value of the portfolio rather than the value of the next-acquired customer” (p.150). Finally, they suggest that “the large base of finance literature on portfolio optimization can certainly serve as a source of insights for researchers wishing to explore this topic” (p.150).

Our study can be viewed as a direct response to this call for future research. In particular, we propose a model that not only explicitly accounts for the uncertainty of estimating future cash flows at the customer-level, but also accounts for the dynamics within the portfolio of customers. While the former makes sure that risks are appropriately considered at the customer-level, the latter ensures that we account for diversification effects when aggregating cash flows from the customer- to the firm-level. This enables us to value not only the current portfolio of customers, but also to optimize and manage the customer portfolio over time, thus maximizing firm value in line with both return and risk considerations. As

Figure 2.4: Customer Portfolio Management

proposed by Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram (2006), this model to a large extent applies financial modeling and portfolio optimization techniques to the topic of customer-based firm valuation. In line with Johnson and Selnes (2004), it will be referred to as the Customer Portfolio Management (CPM) model in the following. Figure 2.4 visualizes how this CPM model uses customer-based firm valuation techniques to maximize firm value in an uncertain world.

The idea of managing a firm's portfolio of customers or customer segments is not completely new. Early approaches to analyze and manage a portfolio of customers involve simple static and often two dimensional graphical models.⁵ However, only very recently have researchers started to embrace the idea of dynamic, multivariate models addressing the research request of Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram (2006), at least to a certain extent. In fact, in line with Homburg, Steiner and Totzek (2009), we find that with the exception of a few managerial studies (e.g. Dhar and Glazer, 2003; Ryals, 2002) and an overview of current customer portfolio analysis practice (Terho and Halinen, 2007), only very few academic studies have addressed the topic in a sound manner.

In particular, Johnson and Selnes (2004), who pioneered the field of customer portfolio dynamics, have laid the conceptual groundwork for customer portfolio management. More specifically, they develop a set of propositions regarding the theoretical value of loose and close customer relationships to the firm. Loose relationships, they argue, generate higher economies of scale for the firm in ser-

⁵For recent examples see Sanchez and Sanchez (2005), Storbacka (1997) and Zolkiewski and Turnbull (2002).

vicings these customers and yield a higher probability of favorable relationship development in the future. On the other hand, close relationships are on average more valuable to the firm at present. Consequently, a mix of loose and close relationships should in theory lead to higher customer portfolio value. The authors conclude from this theoretical discussion that:

“[m]oving the conceptual framework [of customer portfolio management dynamics] to an empirical and applied level is a challenge and an opportunity for both academics and practicing managers.” (p.15, Johnson and Selnes, 2004)

To a certain extent, this gap in the literature is closed by Homburg, Steiner and Totzek (2009) and Buhl and Heinrich (2008). In particular, Homburg, Steiner and Totzek (2009) are able to empirically demonstrate the importance of accounting for customer dynamics, modeled by customer switching behavior between segments over time, within a portfolio of customers. More specifically, they show that ignoring customer dynamics leads to a misestimation of customer values. Nevertheless, they fail to provide a comprehensive model based on which resource allocation decisions can be made that optimize the current portfolio of customers in a way consistent with overall firm value maximization. While Buhl and Heinrich (2008) concentrate their efforts on developing a customer portfolio model that is able to support resource allocation decisions by means of an empirical case study, their research in turn lacks an explicit model of the customer value generation process. Instead, the authors draw on observable, historical measures of return and risk in order to account for the presence of customer dynamics. Our study adds to the literature by providing a comprehensive Customer Portfolio Management model that explicitly models customer dynamics in the value generation process of customers and supports value-maximizing resource allocation decisions. In the words of Johnson and Selnes (2004), we thus aim to:

“open the eyes of the marketing community to focus more on accumulated value creation of a customer portfolio, not on the value created in single relationships.” (p.15)

Chapter 3

Private Wealth Management

This chapter introduces the reader to the private wealth management (PWM) industry, pointing out the relevance as well as the feasibility of the application of Customer Portfolio Management (CPM) to PWM. In the first section of this chapter, we focus on defining and characterizing the PWM industry by pointing out the boundaries of PWM to related services, such as institutional wealth management and retail banking, but also by characterizing a typical PWM client and describing the service offerings PWM comprises. Finally, we present the characteristics of typical players within this industry and provide an overview of the competitive situation. Section 3.2 motivates the application of CPM to the PWM industry. On the one hand, this is achieved by illustrating the relevance of CPM to decision makers within this industry. On the other hand, we argue that the development and application of a CPM model is particularly feasible in the context of PWM, given its unique set of characteristics. Section 3.3 concludes the chapter with a brief summary.

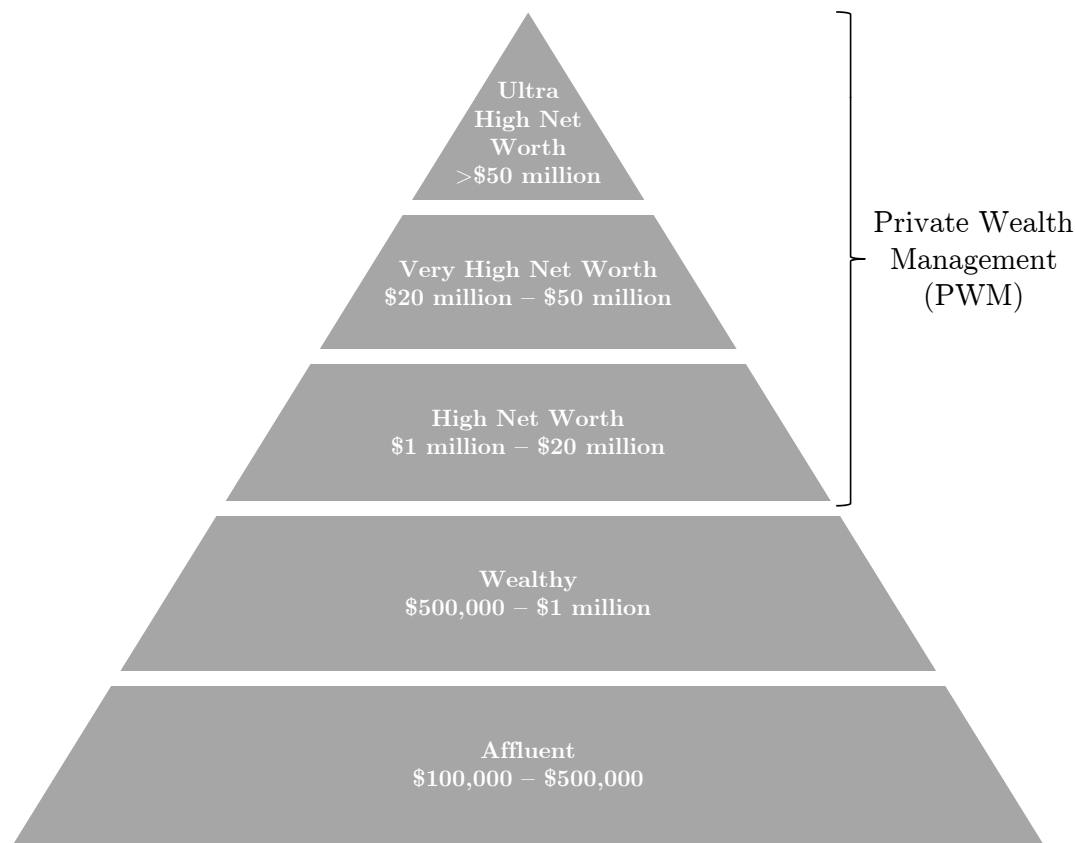
3.1 Defining the industry

Assets can be managed for private individuals or institutions. While the latter is commonly referred to as institutional asset management, the former is most often termed private wealth management. There are three primary factors that distinguish the wealth management needs of individual investors from those of institutions:

1. Individuals are more often guided by emotions in their decision making and are known to develop a certain personal attachment to some of their assets, leading to irrational investment behavior.
2. Individuals have a finite lifetime, which limits the time horizon of many investments and also creates investment needs specific to a certain stage of the lifetime.
3. Individuals' investment returns are subject to a variety of personal taxes that require investment management techniques that meet the objectives of specific tax structures and optimize after tax returns.

In order to adequately address these specific wealth management needs, financial service providers are required to commit a large amount of resources to each client. Service provision is therefore only worthwhile, if the client disposes of substantial wealth.

The distribution of wealth among individuals is often illustrated by a wealth pyramid similar to the one in figure 3.1. The figure illustrates that the bulk of the world's private wealth is concentrated in the hands of a few. These individuals are often referred to as High Net Worth Individuals (HNWIs) and together make up the top of the pyramid. The lower end of the wealth pyramid (which to a large degree is not shown in figure 3.1) is typically serviced by retail banks, who offer standardized products and services to their clients in order to realize enough economies of scale to make the management of limited assets owned by many clients worthwhile. As we move up in the wealth pyramid, economies of scale are less likely to be required in order to service the clients while still making a profit, and therefore products and services become more customized. Starting at a certain level of wealth, financial service providers do no longer refer to retail banking, but instead denote the collection of products and services offered to wealthy individuals as private wealth management (PWM). Most often, these services do not only include an exclusive and highly customized form of sophisticated investment advice, but also comprise value added services that go far beyond the offerings of retail banking, such as succession planning for entrepreneurs or the management of social as well as human wealth (Meiers and Schilling, 2007). Generally, PWM services offer a much more attractive profit margin to financial service providers

Figure 3.1: The wealth pyramid (total personal wealth in USD)

Source: PricewaterhouseCoopers (2009).

than retail banking services, while at the same time having very low capital requirements compared with other banking activities (McKinsey&Company, 2009). As illustrated by figure 3.1, these exclusive PWM services are typically offered to wealthy individuals with liquid assets in excess of 1 million USD. Considering that these HNWI's often use a number of different financial institutions to manage their wealth, the typical PWM account for any particular wealth management institution usually comprises at least 300,000 to 500,000 USD of liquid assets.¹

In practice, the division of clients into these two broad segments (i.e. retail banking and PWM) can vary substantially among financial service providers

¹In a large-scale survey among European PWM providers, IBM (2005) establishes that the average client uses between two to three service providers. Most of the average client's wealth (around 60%) is, however, allocated to his principle provider, while the other 40% are shared by all other providers.

Table 3.1: International ranking of PWM providers by AuM in 2008

Rank	Company/Business unit	AuM ^a	Market share ^b
1	UBS Wealth Management	1,391	4.2
2	Bank of America Private Wealth Management ^c	979	3.0
3	Morgan Stanley Smith Barney ^d	678	2.1
4	Credit Suisse Wealth Management	607	1.9
5	HSBC Private Bank	352	1.1
6	Deutsche Bank Private Wealth Management	228	0.7
7	Goldman Sachs Private Wealth Management	215	0.7
8	Barclays Private Wealth Management	212	0.6
9	Wells Fargo Private Bank ^e	204	0.6
10	Citigroup Private Bank ^f	200	0.6
	Total top 10 players	5,066	15.5
	Total market volume ^g	32,800	100.0

^a Assets under Management (AuM) in billion USD.

^b Market share in %.

^c Including Merrill Lynch Wealth Management acquired January 1, 2009.

^d Joint venture of Morgan Stanley and Citigroup as of January 13, 2009. Estimated AuM are from Morgan Stanley Global Wealth Management Group and Smith Barney's fee-based AuM.

^e Including Wachovia Wealth Management acquired January 1, 2009.

^f Excluding Smith Barney.

^g Figure estimated by Caggemini and Merrill Lynch (2009).

Source: Swiss Banking Institute (2009).

and often depends on the business strategy and positioning of the particular bank. While universal commercial banks that offer retail banking services to the broad public typically also have a private wealth management business unit, a large fraction of HNWI are clients of financial service providers that specialize in private wealth management only. In Europe, especially in German-speaking countries, these specialized institutions are often non-incorporated banking institutions and thus denoted as private banks. The services these institutions offer to their wealthy clients are often referred to as private banking (PB) services, because they are rendered on a more personal level compared to mass-market retail banking. As table 3.1 shows, the largest PWM institutions can be found among the universal commercial banks. However, the top 10 PWM providers together only account for 15.5% of the total market size. Although, there has

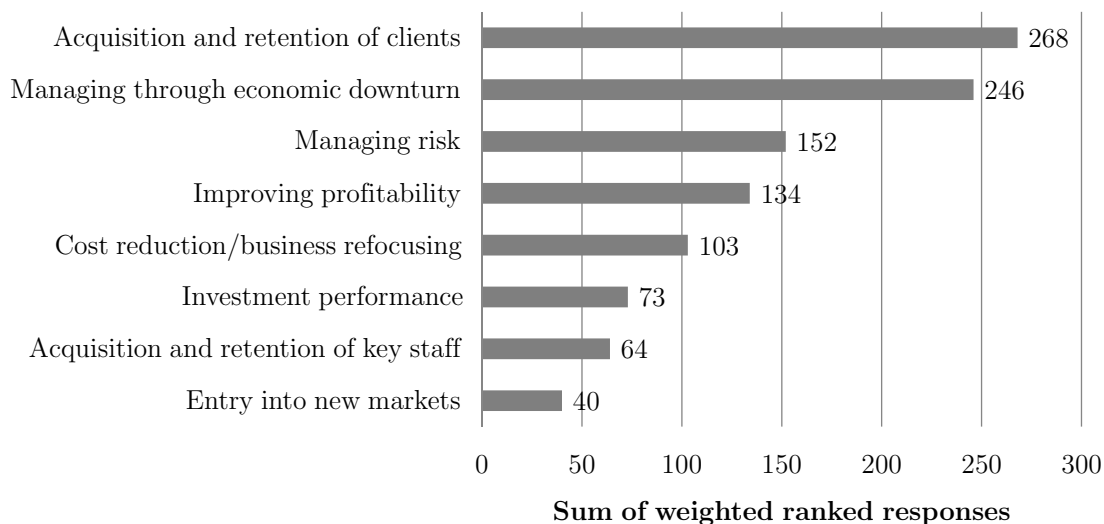
been an unprecedented level of consolidation in the PWM market, mostly caused by financial distress of some institutions in the wake of the financial crisis (see notes of table 3.1), the overall level of concentration remains low. Because this low market concentration is coupled with a high attractiveness of offering PWM services, the industry is characterized by high levels of competition over the finite pool of HNWI assets.

3.2 Applying Customer Portfolio Management

This study chooses to develop and apply the CPM model in the context of the PWM industry, for two reasons. First, in this industry strategic tools that support managers in their decision making regarding the allocation of scarce resources to the acquisition and retention of customers are highly relevant. Second, the development and application of such a data-intensive model in this industry is feasible.

Retail banking services are very standardized and transparent, so that clients can easily switch between providers. Because of this and in order to realize the necessary economies of scale, providers focus on product offerings to acquire and retain clients in retail banking. In contrast, PWM services, as discussed above, are extremely customized and clients are usually in very long-term, trustful relationships with their bankers. Accordingly, PWM providers focus more on client relationships than on product offerings. As a consequence, the management of client relationships is central to the PWM business model and tools that support managers in making decisions related to the allocation of resources to the acquisition and retention of clients are highly useful. As illustrated by figure 3.2, a recent survey among Chief Executive Officers (CEOs) of PWM institutions around the world confirms that the most important strategic area in the PWM industry today is the acquisition and retention of clients.

A sustained period of attractive profit margins and growth has attracted a substantial number of competitors into the PWM industry over the last years,

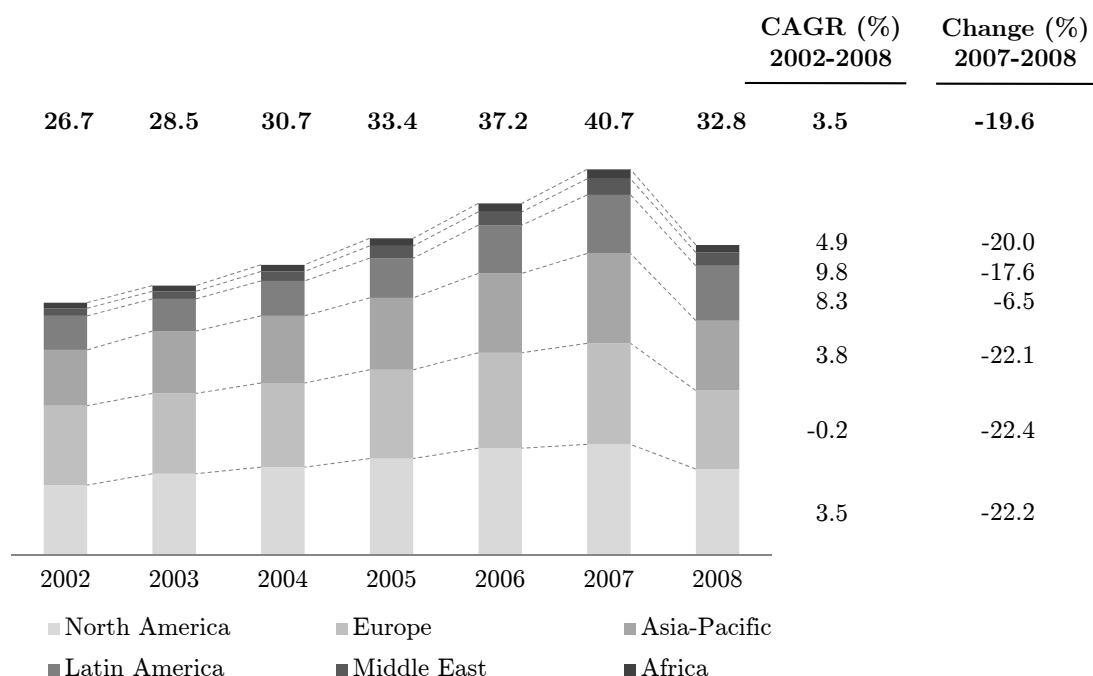
Figure 3.2: Importance of strategic areas in the PWM industry

Source: PricewaterhouseCoopers (2009).

including multi-family offices, hedge funds and other specialist providers.² As pointed out above, this has led to a surprisingly low market concentration, given the fact that the PWM industry can be regarded as a mature industry. Furthermore, due to the stable and profitable business model, the industry has neglected the issue of innovation (Foehn, 2006). Both aspects have contributed to a significant increase in the level of competition. As a result, the acquisition of new client assets has become considerably more resource consuming (especially in the more mature markets of Europe and North America) and the barriers for clients to switch PWM providers are very low nowadays (IBM, 2005). Since “the war for clients intensifies” (p.8, PricewaterhouseCoopers, 2005), PWM providers have been prompted to shift from purely offensive marketing strategies to more defensive strategies, regarding their client acquisition and retention efforts. Rather than exclusively focussing on volume (i.e. client asset) growth³, firms have realized that the identification and retention of profitable client relationships plays a central role in order to successfully face the high level of competition. From the

²This increase in the level of competition in the PWM industry has been identified by a number of professional reports, including PricewaterhouseCoopers (2007; 2006; 2005; 2004), Capgemini and Merrill Lynch (2007), IBM (2005) and Oliver Wyman (2006).

³Ten years ago, these purely offensive, volume-driven strategies dominated the PWM industry (see PricewaterhouseCoopers, 1997).

Figure 3.3: Global HNWI AuM development 2002-2008 (in trillion USD)

Source: Capgemini and Merrill Lynch (2009).

Note: CAGR=compound annual growth rate

perspective of PWM managers, it is therefore important to know which clients to retain and grow in order to effectively and efficiently allocate scarce firm resources. According to a professional industry report by IBM (2005), “banks need to make more conscious choices about the type of clients they pursue” (p.11). In a similar vein, in a recent study on customer valuation in the PWM industry Foehn (2006) notes that at the heart of the evaluation of the current and future success of a PWM institution should lie “the composition, retention and revision of its [...] value-maximizing customer portfolio” (p.3, translated into English).

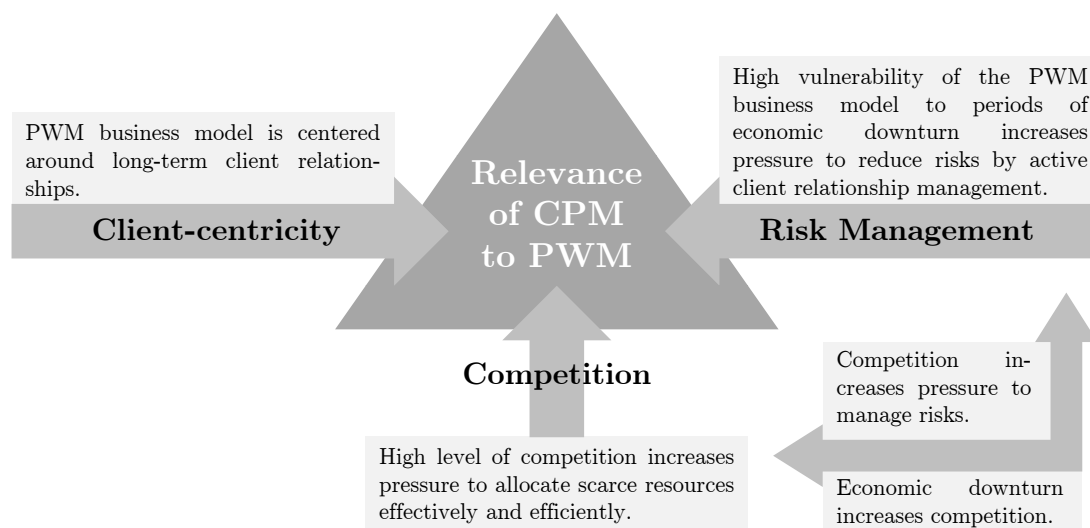
Furthermore, PWM providers around the globe have recently experienced how vulnerable their otherwise very stable business model can be, when facing a large financial crisis. From the year 2007 to 2008, Assets under Management (AuM), the driving force behind cash flow generation in the fee-based PWM industry, were subject to massive devaluations by on average 20% on a global scale, thus lowering revenues by approximately the same amount (see figure 3.3). However, the degree to which institutions were affected by these crisis events varied signif-

icantly by both region and wealth segment. Especially in regions in which equity markets do not play a central role in financial markets, such as Latin America, asset devaluations were significantly more moderate. In contrast, institutions focused on serving clients of the Ultra High Net Worth (UHNW) segment were particularly affected. This is, because these clients invested in complex, structured products that were most affected by the financial crisis (Boston Consulting Group, 2009). Although, market participants tend to ignore this fact, severe asset devaluations during periods of crisis are a common and recurring phenomenon in financial markets. Therefore, strategic tools, such as the proposed CPM model, that allow PWM providers to manage clients in order to reduce overall firm-level exposure to financial market fluctuations by identifying a balanced customer portfolio with regard to both value and risk, are highly relevant. This is confirmed by figure 3.2 above, which shows that ‘managing through economic downturn’ has been identified as the second most important strategic area by CEOs of PWM institutions around the globe.

Finally, it is important to note the interdependencies between the level of competition, the recent economic downturn and the need to manage risks. On the one hand, the significant decrease in AuM on a global scale has led to a substantial decline in market size, which aggravates the already fierce level of competition in the PWM industry even further. A recovery of the market size to pre-crisis levels is not expected before 2013 (Boston Consulting Group, 2009). On the other hand, the higher level of competition has increased the pressure on PWM providers to manage risks, in order to defend their market share and eventually even gain a competitive advantage.

Figure 3.4 summarizes and visualizes the discussion above. Overall, we conclude that due to the client-centricity inherent in PWM services, as well as the intensification of the competition and the heightened importance of risk management in the aftermath of the recent financial crisis, the proposed CPM model is of high relevance to strategic decision makers in the PWM industry.

The development and application of the proposed CPM framework is particularly feasible in the context of the PWM industry, for two main reasons. First, the cash flow generation process on the client segment-level is relatively simple to model. The reason is that revenues in the PWM industry are based on fees

Figure 3.4: Relevance of Customer Portfolio Management to PWM

and commissions that are earned based on the volume of clients' AuM. This together with the fact that the revenue margin is fairly stable when aggregated on the segment-level, enables us to focus on modeling the segment-level sales volume directly instead of the exact number of client relationships. Moreover, these revenues are earned continuously over the entire duration of the contractual, long-term client relationship and are thus independent of individual buying decisions. Second, client segmentation criteria are clearly defined and often apply to individual clients over an extended period of time. On the one hand, this reduces the migration of clients between segments, making the development of client segments largely independent of each other. On the other hand, this ensures the availability of long-term segment-level data required for the calibration of the proposed CPM framework. Both of these characteristics make the PWM industry highly appropriate for the context of this study.

3.3 Chapter summary

This chapter introduces the PWM industry to the reader and motivates the application of the proposed CPM model to this particular industry. In contrast to institutional wealth or asset management providers, PWM institutions specialize

in the provision of wealth management services to wealthy individuals. Individuals in this target group typically dispose of substantial wealth of more than USD 1 million, are referred to as HNWIs and have sophisticated wealth management needs that cannot be addressed by standardized retail banking products and services. Consequently, they are offered exclusive, highly sophisticated and customized products and services that are collectively referred to as PWM services. As the market for PWM services is one of the most attractive financial service offerings in terms of profitability and stability, over time many different providers have attempted to gain a market share, resulting in a rather fragmented and highly competitive market.

The study chooses to develop the CPM model in the context of and to apply it to the PWM industry, because it is highly relevant to decision makers within the industry as a strategic tool that supports the allocation of resources to the acquisition and retention of customers. This is, because, first, the PWM business model is centered around long-term client relationships, making the acquisition and retention of clients the most important strategic area. Second, the level of competition is high, which in turn increases the pressure to allocate scarce resources in the most effective and efficient way. Third, the last financial crisis has shown the high vulnerability of the PWM business model to periods of economic downturn. Given the high level of competition, this increases the pressure to reduce risks by active client relationship management. Finally, the development and application of the proposed model is particularly feasible in the context of the PWM industry, due to its unique set of characteristics, such as contractual, long-term client relationships, fairly stable margins and the availability of segment-level data over an extended period of time.

Chapter 4

Model Development

In order to develop a Customer Portfolio Management (CPM) model, it is necessary to determine how the firm generates value from its customers over time. Without customers a firm has no value. Customers are the reason firms exist. They are the ones generating the lion's share of all cash flows and therefore keep the firm alive. As pointed out in chapter 2, these ideas are at the heart of what the literature calls customer-based firm valuation (e.g. Gupta, Lehmann and Stuart, 2004) and they guide us in our own model development. In particular, our study follows Johnson and Selnes (2004), who state on page 15 that:

“[t]he overall value of a firm's customer portfolio [(i.e. its customer equity)] is an aggregation of the contribution from individual exchange relationships over time.”

Before engaging in the actual model development, it is important to note that similar to prior work in this field, our study develops a CPM model on a segment-level and all customers within one segment are assumed to be homogeneous (Homburg, Steiner and Totzek, 2009; Johnson and Selnes, 2004). Because the purpose of any CPM model is to determine the optimal weighting of customer segments in the portfolio of the firm and individual customers are indivisible, it is necessary to value and weigh customer segments (Buhl and Heinrich, 2008). The assumption that all customers within one segment are homogenous with respect to all value-relevant characteristics allows us to view the individual customer as the smallest divisible unit of the customer segment asset.

The CPM model is developed in two steps. In the first section of this chapter, we develop a dynamic model setup that allows us to value the contribution of individual client segments to the overall customer portfolio or firm value in the private wealth management (PWM) context over time. Building on this, in section 4.2, we propose a methodology for optimizing the value of the existing customer portfolio derived in the first step by shifting firm resources among customer segments. Finally, the last section summarizes and concludes.

4.1 Dynamic customer-based firm valuation

As pointed out in the previous chapter, the literature has shown both, analytically (Bauer and Hammerschmidt, 2005; Skiera, Wiesel and Schulze, 2009) and empirically (Gupta, Lehmann and Stuart, 2004; Libai, Muller and Peres, 2009), that the concept of Customer Equity (CE) is a good approximation of firm value. As a result, we can conclude that our goal of firm value maximization can be achieved by maximizing a firm's CE. From the discussion in section 2.3 we know that in case the Customer Lifetime Value (CLV) is computed on the customer segment-level, CE is equal to the sum of the CLVs across the total number of customer segments S , hence it can be written as:

$$CE = \sum_{s=1}^S CLV_s \quad (4.1)$$

Furthermore, the literature on customer valuation discussed in section 2.2 shows that, unlike individual customers, customer segments have no finite expected lifetime. As a consequence, segment-level CLV (CLV_s) is computed as the sum of future net segment-level cash flows, $CF_{s,t}$, discounted with discount rate d over an infinite time horizon:

$$CLV_s = \sum_{t=1}^{\infty} \frac{CF_{s,t}}{(1+d)^t} \quad (4.2)$$

Substituting equation 4.2 into equation 4.1 thus yields:

$$CE = \sum_{s=1}^S \sum_{t=1}^{\infty} \frac{CF_{s,t}}{(1+d)^t} \quad (4.3)$$

Under the assumption that the net cash flows on the firm-level at time t (CF_t) represent the sum of net segment-level cash flows over all customer segments s , equation 4.3 becomes:

$$CE = \sum_{t=1}^{\infty} \frac{CF_t}{(1+d)^t}, \quad \text{with} \quad CF_t = \sum_{s=1}^S CF_{s,t} \quad (4.4)$$

Mathematically, CE is thus the sum of all discounted future net firm-level cash flows. Note, however, that in contrast to the DCF approach to firm valuation, these firm-level cash flows are assumed to arise exclusively from customer exchange relationships. At the end of a calibration or observation time frame T , CE can also be written as:

$$CE = \sum_{t=T+1}^{\infty} \frac{CF_t}{(1+d)^{t-T}} \approx \sum_{t=T+1}^{T+H} \frac{CF_t}{(1+d)^{t-T}} + \frac{TV}{(1+d)^H} \quad (4.5)$$

As equation 4.5 shows, the infinite sum is usually approximated by the sum of all net cash flows over a planning horizon H and a terminal value TV . This terminal value requires the estimation of a long-term growth rate g of net firm-level cash flows and is calculated as in Gordon (1959) as:

$$TV = \frac{CF_{T+H+1}^{Firm}}{d-g} \quad (4.6)$$

For the computation of TV and CE based on equation 4.5, we therefore require an estimate for the long-term growth rate g of net firm-level cash flows as well as a discount rate d to discount future cash flows. The latter is the risk-adjusted discount rate, which we propose to approximate by the return required by equity holders for the particular PWM provider. This approach is not only the one most commonly used in the academic literature and in practice to approximate risk-adjusted discount rates, but also reflects the fact that the study is interested in maximizing the shareholder value of the firm. Although, it is often difficult

to determine the risk premium that adequately reflects the risk of the expected future firm-level cash flows, the study opts for this method rather than for the risk-neutral asset valuation alternative proposed by Schwartz and Moon (2001). While the risk-neutral asset valuation technique allows discounting future cash flows by the readily available risk-free rate, it requires the formation of risk-neutral expectations. As Krafft, Rudolf and Rudolf-Sipötz (2005) argue, the formation of risk-neutral expectations in the absence of required market data on the customer base is hardly possible.

4.1.1 Modeling cash flows

Equation 4.4 shows that the net firm-level cash flow in any period $t \in \{T + 1, \dots, T + H + 1\}$ is equal to the sum of net segment-level cash flows over the number of customer segments S . The underlying cash flow generation process is very industry-specific. Hence, we have to account for the peculiarities of the PWM industry presented in chapter 3 from this point onwards. In the PWM industry revenues are generated by fees and commissions on the underlying volume of Assets under Management (AuM). Furthermore, the industry is characterized by a high proportion of variable costs, resulting in a relatively stable cost/income ratio.¹ Consequently, we make the simplifying assumption that at the segment-level all margins are constant and cash flows are therefore only driven by AuM (i.e. sales volume). This assumption is reasonable, considering that profitability develops for each client relationship individually over time, as discussed in chapter 2, and the aggregation of these individual client profitability margins at different lifetime stages are likely to even out on the segment-level. Hence, the net cash flow of segment $s \in \{1, \dots, S\}$ in period t can be approximated by:

$$CF_{s,t} = AuM_{s,t} \times RM_s \times PM_s \times CFM \quad (4.7)$$

where $AuM_{s,t}$ is the volume of AuM of segment s at time t , the revenue margin RM_s is revenue in percent of AuM for segment s (i.e. the average management fee for assets of client segment s), the profit margin PM_s represents earnings before

¹The Swiss Banking Institute (2009) shows that on a country-level the cost/income ratios in the PWM industry generally remained within a close corridor of 60-70% over the past 10 years, a very mild fluctuation compared to other industries.

taxes as a percentage of the revenue for segment s and the cash flow margin CFM is cash flow in percent of earnings before taxes. The cash flow margin is required to isolate cash flows that are attributable to a firm's shareholders from the ones attributable to other stakeholders (e.g. taxes, minority interests). This distinction is important, because we are interested in maximizing the firm value from the perspective of the firm's shareholders, implying that only cash flows attributable to them are value-relevant. Note, while operating expenses reflected by the profit margin can be specific to a certain client segment, the attribution of cash flows to different stakeholders of a firm is determined on the firm-level and thus constant across client segments (as indicated by the missing segment index for CFM in equation 4.7).

4.1.2 Modeling Assets under Management

From the discussion above we can conclude that the only dynamic variable and therefore the principle value driver of PWM client segments is the level of AuM. Based on this insight, the study focuses on modeling AuM in the following. Since the level of current segment-level AuM can be observed, we are only interested in the change in AuM over the planning horizon H .

According to the theory discussed in chapter 2, we can attribute changes in AuM of a particular client segment to three major events over the lifetime of the clients belonging to that segment: acquisition, retention and defection. However, while the bulk of the academic literature so far has used these three events to model the number and duration of individual customer relationships, this study applies them to AuM on a client-segment level. This distinction is important, because from the perspective of modeling individual customer relationships, an increase in for instance the sales volume of an existing customer would be classified as a customer retention event. In contrast, from the perspective of AuM (i.e. sales volume) it is an acquisition event. This shift in perspective is made for two reasons. First, it reflects the peculiarities of the PWM industry, because in terms of value on the segment-level it is hardly relevant whether new assets are acquired through the acquisition of entirely new client relationships or by the increase in the level of AuM of existing relationships. Second, it dramatically reduces data

requirements, because only information on the segment-level change of AuM is required, instead of information on the status of individual client relationships over time.

In the context of PWM, the acquisition and defection of assets is typically captured by the variable net new assets (NNA). This variable denotes the difference between acquired and lost AuM within a specified period of time. The change in the level of AuM that is not due to the acquisition and defection of assets is caused by financial market returns ($R_{s,t}$) over the period $t - 1$ to t , earned on the level of retained assets in period $t - 1$ for segment s (i.e. $AuM_{s,t-1}$). This is a peculiarity of the PWM industry and implies that the revenue base (i.e. AuM) can change even without a change in client behavior, simply because it is determined by the value of the underlying financial assets. Throughout the rest of the study we refer to the changes in segment-level AuM arising from financial market returns as return on retained assets (RRA). On the segment-level s at time t it is defined as:

$$RRA_{s,t} = R_{s,t} \times AuM_{s,t-1} \quad (4.8)$$

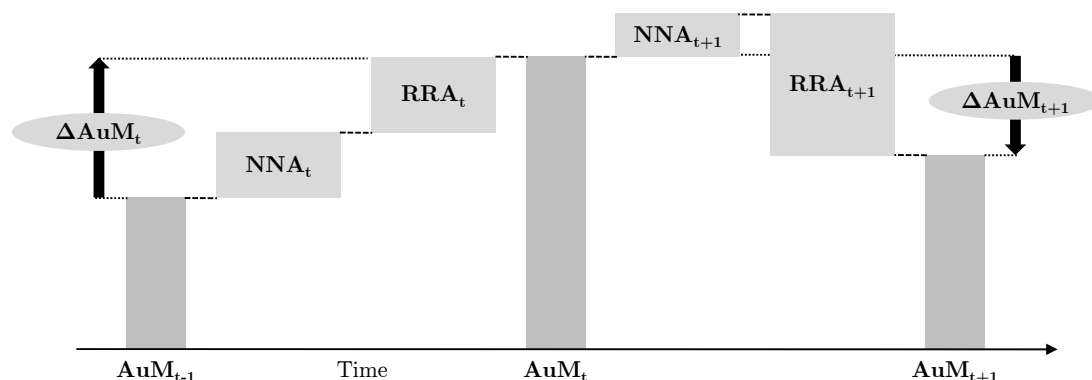
The total absolute change in AuM (ΔAuM) for each period in time is thus the sum of two components, NNA and RRA. The AuM process is visualized by figure 4.1. Mathematically, the AuM of segment s in period t can be written as:

$$\begin{aligned} AuM_{s,t} &= AuM_{s,t-1} + \underbrace{RRA_{s,t} + NNA_{s,t}}_{\Delta AuM_{s,t}} \\ &= AuM_{s,t-1}(1 + R_{s,t}) + NNA_{s,t} \end{aligned} \quad (4.9)$$

As pointed out above, the development of NNA is determined by the acquisition and defection of client assets. Both events in turn can involve the establishment of new or the defection of existing client relationships in their entirety, but can also refer to the acquisition of new and loss of existing assets from existing clients. The following paragraphs discuss both situations and the reasons behind these events in the context of PWM in more detail.

New client relationships often arise from referrals by existing clients that are satisfied with the service quality they receive. This is especially true for services

Figure 4.1: AuM process



such as PWM, which build on discreet, trustful personal relationships and where direct advertising efforts are regarded as blunt. In fact, in a large-scale survey among PWM providers in German-speaking countries, Meiers and Schilling (2007) find referrals to be the most important acquisition channel. While this was the first academic study to establish this fact, many professional reports have come to a similar conclusion ever since. In a recent global survey among 130 PWM institutions, PricewaterhouseCoopers (2006), for example, finds that “referral from existing clients dominates as the top source of new business” (p.12). It is important to note here that the value of new assets acquired through referrals is generally attributed to the issuer of the referral.² That makes it necessary to assume that referrals are only issued and received within the same customer segment so that the asset acquisition rate of one segment is independent from the one of other segments, an assumption that is reasonable following the argumentation of von Wangenheim and Bayón (2007). In particular, these authors demonstrate that the likelihood a receiver of a referral actually acts on the referral (i.e. his conversion rate) is an increasing function of the similarity between the issuer and receiver of the referral. It is therefore very likely to find both parties within the same customer segment.

In contrast to client acquisitions, defections of entire client relationships in the PWM industry are often triggered by client relationship managers switching to

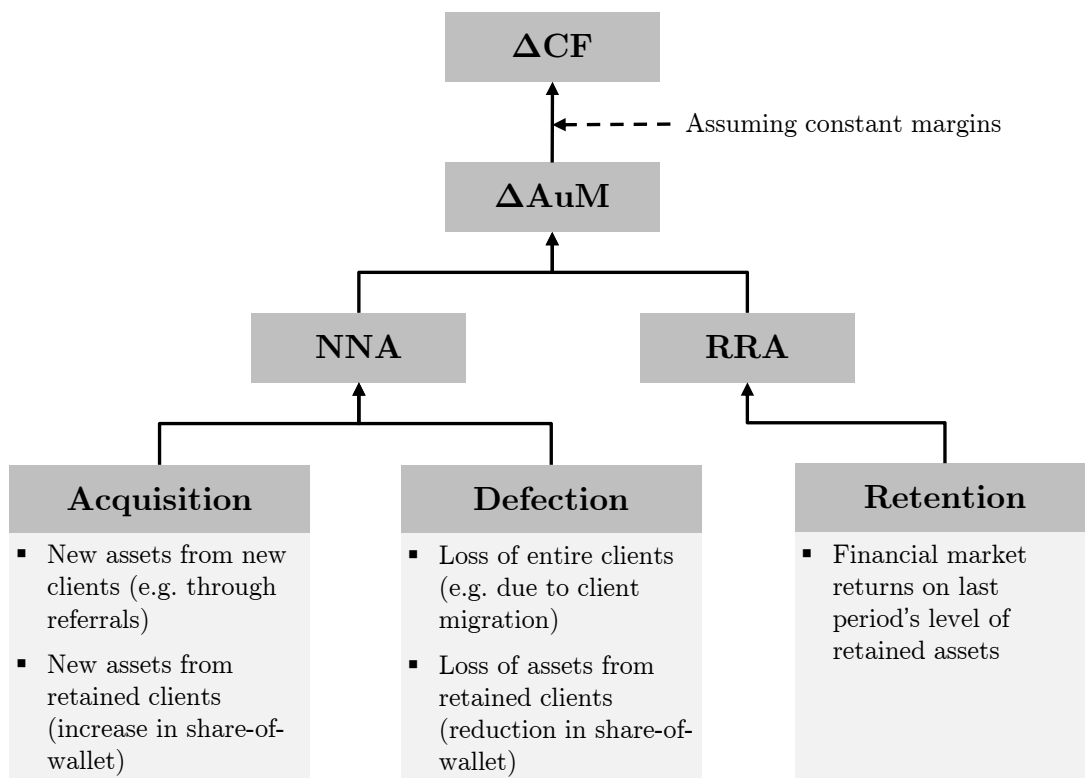
²For a detailed discussion of the referral value refer to chapter 2.

other firms and taking their clients with them (i.e. client migration). They can, however, also be caused by the demise of a client.³

Both, the acquisition and defection of assets can also originate from retained clients by an increase or a reduction in their share-of-wallet. The level of the share-of-wallet in turn is a function of the client's loyalty, which has ultimately been linked to the level of service quality and resulting client satisfaction. While Anderson and Sullivan (1992) show this for firms in general, Horn (2009) and Seiler (2010) have recently confirmed this link in the context of PWM. Since we are interested in *changes* in the level of the share-of-wallet, we need to determine the drivers behind changes in the level of client satisfaction. These changes are unlikely to be caused by systematic factors, such as the quality of reporting or the external environment. According to Seiler (2010), they rather depend on segment- or even client-specific factors like the performance of the client's portfolio and the personal relationship with the respective client relationship manager, which can vary dramatically across clients and over time. We can therefore conclude that changes in the level of the share-of-wallet are unlikely to appear in a systematic manner across segments, but can vary across and sometimes even within client segments.

In contrast to the development of NNA, which is largely determined by client behavior, the development of RRA is exclusively determined by the valuation of the underlying financial assets retained by the PWM provider. It is therefore unrelated to customer lifetime dynamics and instead depends on financial market dynamics. Nevertheless, it is a key driver of changes in segment-level AuM and therefore net cash flows over time. Moreover, the development of RRA is likely to impact all client segments in a systematic way, since all client assets are to a higher or lesser degree invested in the same financial markets. This discussion on the development of AuM and its components, as the underlying segment-level cash flow drivers in the context of PWM, is summarized and visualized by figure 4.2. Having identified the relevant drivers behind the dynamics of AuM and its components, we now turn to specifying the stochastic processes to capture these dynamics.

³See p. 252 of Galasso (1999) for a detailed list of the primary reasons for customer defections in the PWM industry.

Figure 4.2: Segment-level cash flow drivers in the PWM industry

As pointed out in chapter 2, employing stochastic processes for modeling the central drivers of customer segment value is in line with recent calls throughout the related academic literature. Although some researchers have responded to these calls, their attempts are all restricted to non-contractual customer relationships and to the development of structural models (see Kumar and Shah (2009) for a very recent example). While these structural models have the advantage of being directly related to the individual, theoretic value drivers, making their parameters easily interpretable, they are generally very demanding in terms of data requirements and are known to exhibit construct measurability issues (Chintagunta, Erdem, Rossi and Wedel, 2006). We therefore implement reduced-form stochastic models that are commonly employed for modeling the value of financial assets. This methodology is in line with recent studies by Krafft, Rudolf and Rudolf-Sipötz (2005) and Hogan, Lehmann, Merino, Srivastava, Thomas and Verhoef (2002), who suggest the application of stochastic financial models

to the valuation of customers. We further regard the application of a reduced-form stochastic model to capture the value of PWM client segments as highly appropriate for a number of reasons. First, it dramatically reduces the number of parameters that need to be estimated and therefore substantially reduces data requirements. Second, segments are formed so that the number of clients within one segment is large enough to even out any unusual client-level events, increasing parameter estimation accuracy. Third, the estimation accuracy is further enhanced by the fact that the value generation process of clients that are in long-term contractual relationships with the firm is much less volatile than for non-contractual relationships, which have the additional risk of individual customer buying decisions. Fourth, the economic interpretation of specific customer value drivers, as made possible by using structural models, is not the central goal of this study. Finally, because the return on a PWM client's financial assets is a central driver of value for the PWM provider, the application of stochastic models that have already been successfully applied for modeling financial asset returns and tested extensively in the financial discipline is only logical. For these reasons, this study specifies reduced form stochastic models for capturing the dynamics of the NNA and RRA developments similar to Merton (1976) and Jorion (1988).

The absolute values of NNA and RRA are scaled by last period's AuM in order to transform them into growth rates. Equation 4.9 therefore becomes:

$$\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}} = \frac{NNA_{s,t}}{AuM_{s,t-1}} + \frac{RRA_{s,t}}{AuM_{s,t-1}} = \frac{NNA_{s,t}}{AuM_{s,t-1}} + R_{s,t} \quad (4.10)$$

The time series of the growth rates $\frac{NNA_{s,t}}{AuM_{s,t-1}}$ and $R_{s,t}$ is assumed to exhibit stochastic independence. This assumption is a necessary prerequisite for applying the proposed stochastic processes to model changes in each of the two variables and will be verified empirically in section 5.2.2. In particular, we assume that the dynamics of the NNA ($\frac{NNA_{s,t}}{AuM_{s,t-1}}$) process follow a simple diffusion process and, similar to Jorion (1988), can hence be described by:

$$\frac{NNA_{s,t}}{AuM_{s,t-1}} = \mu_s^{NNA} \Delta t + \sigma_s^{NNA} \varepsilon_{s,t} \sqrt{\Delta t} \quad (4.11)$$

where μ_s^{NNA} and σ_s^{NNA} represent the diffusion drift and volatility parameter of the NNA process for segment s , respectively, $\varepsilon_{s,t}$ is a standard normal random

variable and Δt represents the unit of time. As pointed out above, this model specification requires the diffusion process to exhibit no autocorrelation. Moreover, we do not expect $\varepsilon_{s,t}$ to be significantly correlated across segments. This follows directly from the theoretical discussion above, which reveals that neither the acquisition nor the defection of entire or partial client relationships are driven by systematic factors.

The dynamics of the financial market return ($R_{s,t}$) process are not as easily captured by a stochastic model. As has been shown by extensive empirical research, financial market returns, depending on the particular asset class, are far from being normally distributed (e.g. Sheikh and Qiao, 2010). In fact, for equity returns Merton (1976) finds that large deviations from the long-term mean (especially downside) are observed more often than expected under the assumption of normally distributed returns. Consequently, he proposes to add a jump component to the diffusion process in order to account for the probability of price changes of extraordinary magnitude. This jump component can be thought of as representing macro-economic shocks that affect all assets at a particular point in time. Jorion (1988) shows that this so called mixed jump-diffusion model better captures the dynamics of the empirical distribution of both equity and foreign exchange returns. More recently, Das and Uppal (2004) confirm empirically the presence of these simultaneous jumps in international equity markets and the importance of the jump component in stochastic processes employed to capture return dynamics and for subsequent portfolio selection. In the context of the valuation of customers and customer portfolios, the above mentioned jumps are typically referred to as ‘demand shocks’ and were first modeled by Johnson and Selnes (2004). Similar to the model specification used by Jorion (1988), the $R_{s,t}$ process can thus be written as:

$$R_{s,t} = \mu_s^R \Delta t + \sigma_s^R v_{s,t} \sqrt{\Delta t} + Y_s j_t \quad (4.12)$$

where μ_s^R and σ_s^R represent the diffusion drift and volatility parameter of the financial market return process for segment s , respectively and $v_{s,t}$ is a standard normal random variable. The random variable j_t reflects the number of jumps per unit of time Δt and is drawn from a Poisson distribution with mean λ . Accordingly, the jump intensity is specified by λ . The jump size Y_s is log-

normally distributed with mean ϕ_s and variance δ_s^2 , or stated equivalently as $\ln Y_s \sim N(\phi_s, \delta_s^2)$. Again, while we assume no autocorrelation for all random variables, we hypothesize the following correlation structure for the cross-section (i.e. across client segments). Because the jump events represent macro-economic shocks or crisis events that affect all segments at the same point in time, the stochastic process for the number of jumps j is correlated with $\rho^j = 1$ across all segments (e.g. Das and Uppal, 2004). The fact that j affects all segments equally is also indicated by the missing segment index for the variable itself and for the corresponding distribution parameter λ . Although all segments are affected by crisis events at the same point in time, the effect (i.e. the jump size) is expected to vary in a systematic way across segments. The reason behind this are variations in the financial portfolio composition across client segments, whose aggregate values are systematically affected to a differing extent by financial crisis events. Consequently, the jump size Y_s for each segment is drawn from a distribution with a segment-specific mean and variance, which are expected to capture the characteristic effect of crisis events on a particular client segment. We further need to assume a cross-sectional correlation structure for the diffusion process $v_{s,t}$, because it is drawn from the same distribution for each segment, but is still expected to be correlated across segments. Again, this is because of systematic variations in the financial portfolio composition across segments. We therefore expect financial market developments to affect the value of these financial portfolios in a similar, but not necessarily equal way, even in the absence of a crisis event. For example, in the case of geographic client segments, we expect to observe significant differences in the composition of the average financial portfolio across client segments due to the presence of the well-documented home bias in the selection of financial assets.⁴ Because the composition of financial portfolios differs across segments, recent news or (non-crisis) events that impact financial

⁴The home bias refers to the tendency of investors to hold an over-proportional share of domestic assets in their portfolio. This bias was first documented by French and Porterba (1991) and Tesar and Werner (1995). Since then, several studies have examined the determinants of the home bias, which include transaction costs (Glassmann and Riddick, 2001), exchange rate risk (Fidora, Fratzscher and Thimann, 2006), information barriers (Ahearne, Grierer and Warnock, 2004), corporate governance issues (Dahlquist, Pinkowitz, Stulz and Williamson, 2003) and lack of familiarity (Bekaert and Wang, 2009; Portes and Rey, 2005). For HNWIs the home bias has been documented by Capgemini and Merrill Lynch (2009).

markets affect these portfolio to varying degrees. Consequently, we hypothesize a time-invariant correlation matrix $\boldsymbol{\rho}^v$ for the cross-section of the diffusion process $v_{s,t}$, whose elements lie between 0 and 1. Mathematically, this correlation matrix can be written as:

$$\boldsymbol{\rho}^v = \begin{bmatrix} 1 & \rho_{1,2}^v & \cdots & \rho_{1,S}^v \\ \rho_{2,1}^v & 1 & \cdots & \rho_{2,S}^v \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{S,1}^v & \rho_{S,2}^v & \cdots & 1 \end{bmatrix} \quad (4.13)$$

Each element of the cross-sectional correlation matrix $\boldsymbol{\rho}^v$ represents a Pearson correlation coefficient.

Having specified the processes for valuing client segments and using equation 4.10, we are now able to generate a time series of AuM over a planning horizon H from the following equation:

$$AuM_{s,t} = AuM_{s,t-1} \left(1 + \underbrace{\frac{NNA_{s,t}}{AuM_{s,t-1}}}_{\Delta AuM_{s,t}/AuM_{s,t-1}} + R_{s,t} \right) \quad (4.14)$$

The equation above enables us to derive a probability distribution of CE and thus customer portfolio value. Following Kumar and Shah (2009), we generate the CE probability distribution by simulating a large number of N possible CE realizations (by Monte Carlo simulation), employing the NNA and financial market return processes from equations 4.11 and 4.12, whose parameters are calibrated in such a way that they capture the dynamics of the AuM process of a specific PWM provider. The currently observed level of AuM for each client segment (i.e. $AuM_{s,0}$) constitutes the initial value for the stochastic AuM process. Following equation 4.14, the first period AuM ($AuM_{s,1}$) therefore is equal to:

$$AuM_{s,1} = AuM_{s,0} \left(1 + \frac{\Delta AuM_{s,1}}{AuM_{s,0}} \right) \quad (4.15)$$

Initializing the proposed stochastic model in this way generates a distribution of N realizations of CE that reflects the empirically observed composition of the client segment portfolio and yields the vector $\mathbf{CE}^0 = \{CE_1^0, \dots, CE_N^0\}$. The

expected value of CE^0 ($E[CE^0]$) represents an approximation of current firm value from the perspective of shareholders.

4.2 Customer portfolio optimization

Now that we are able to generate the CE probability distribution for the existing portfolio of PWM client segments, we turn to optimizing the portfolio of client segments in order to maximize firm value. This step involves the application of financial portfolio selection theory to the problem of customer portfolio management (Buhl and Heinrich, 2008; Terho and Halinen, 2007; Gupta, Hanssens, Hardie, Kahn, Kumar, Lin, Ravishanker and Sriram, 2006). However, before we resume with the development of our model, we briefly describe the assumptions we make and how they relate to those made by financial portfolio selection theory as defined by Markowitz (1952). This is important when applying theory originally developed for financial assets to customer assets.

4.2.1 Assumptions and conditions

First and foremost, the application of financial portfolio selection theory requires the divisibility of assets. In finance, this condition is easily met, since the underlying asset is usually a firm (in the case of equity) and the value of the firm is divisible through a mostly large number of shares. Individual customers, however, are not divisible. Therefore, as pointed out above and similar to prior studies in this field (e.g. Homburg, Steiner and Totzek, 2009; Buhl and Heinrich, 2008; Johnson and Selnes, 2004), our model instead values the contribution of homogeneous customer segments to the value of the firm as a whole. Assuming that all customers within one segment are homogenous with respect to all value-relevant characteristics and that the number of customers within each segment is large, allows us to view the individual customer as the smallest divisible unit of the customer segment asset. In addition to satisfying the necessary condition of asset divisibility, this approach also has the added advantage of producing a more reliable and stable valuation of customer assets. This is, because many singular

and extreme events related to individual exchange relationships even out when aggregated on the customer segment-level.

Second, financial portfolio selection theory implies that investors are price takers, meaning that investors cannot influence the value of an asset by altering their level of investment in that asset, i.e. the weighting of that asset in their portfolio. However, in the rare event that an investment in (or divestment of) in any asset, be it financial or otherwise, is significant relative to the total supply of that asset, it will influence the asset's value. Therefore, subject to the condition that the pool of potential customers belonging to a particular customer segment is large, we assume that the value of customer assets is independent of their weighting within the portfolio.

Third, financial portfolio selection theory assumes frictionless markets, meaning that assets can be traded in absence of transaction costs. However, because the presence of transaction costs is an empirical fact, many recent portfolio optimization models explicitly account for them (see Brandt, Santa-Clara and Valkanov (2009) for a recent example). Transaction costs for customer assets are arguably even larger than those for financial assets. The reason is that customers are more costly to acquire and divest compared to financial assets. Acquiring new customers is especially costly when the demand for a particular customer asset is very high relative to its supply. In that case the costs of acquiring additional "units" (i.e. customers) of that particular asset (i.e. segment) may prove to be prohibitive. In the PWM industry this is presently the case for the most wealthy client segment, as PWM providers are in fierce competition for the very few individuals actually belonging to that particular segment. With respect to customer divestments, the literature on word-of-mouth effects finds that the reduction of acquisition and retention efforts (i.e. divestments) of customer assets may culminate in customer dissatisfaction and negative word-of-mouth, substantially increasing the costs of these strategies (e.g. Anderson, 1998; Richins, 1983). Because of their apparent importance, our portfolio optimization model accounts for transaction costs. For the purpose of simplification, we assume transaction costs to be constant for all customer assets across time.

Fourth, in order to determine a global optimum where portfolio value is maximized and portfolio risk minimized, financial portfolio selection theory, as defined

by Markowitz (1952), requires at least one of the following two conditions to hold. Either asset returns are normally distributed or the investor is risk-averse and his utility function is thus concave. While we do not expect the former condition to be met in our study, due to the presence of jumps in the customer value generation process, we assume the latter condition to hold. More specifically, since it is our goal to maximize shareholder value and shareholders can be expected to be risk-averse on aggregate, it is reasonable to assume that the firm, who acts in the shareholders' best interest, is a risk-averse investor in customer assets. Although, emotional biases may cause individual shareholders to deviate from risk-averse behavior as the extensive literature on behavioral finance has shown (e.g. Barberis and Thaler, 2003), the preferences of shareholders on aggregate can be expected to be in line with risk-aversion. The key reason for this is that the largest equity holdings of a given public firm are usually in the hands of institutional shareholders, whose preferences are expected to be driven by rational decisions and who are less susceptible to emotional biases. Having established that shareholders on aggregate are risk-averse, it is important to note that a fundamental assumption regarding the concept of risk aversion in the financial discipline is the positive relationship between risk and return. More specifically, an investor who wants to achieve a higher expected return on his portfolio of financial assets must accept more risk (Lintner, 1965; Sharpe, 1964). In contrast to financial assets, the general relationship between risk and value of portfolios comprising customer assets is less clear, because the value of customer assets is not determined by mechanisms of demand and supply in the market place. Nevertheless, we expect to find a positive relationships between risk and value of customer portfolios in the PWM industry for two reasons. First, corporate finance theory tells us that any firm operating in a competitive environment should theoretically be pressured by its owners to invest only in projects with the highest (lowest) possible return (risk) for a given level of risk (return) in order to maximize firm value (Dixit and Pindyck, 1994). If a firm, for instance, were to expand its operations into a new customer segment, the firm would be pressured by its owners to pursue the investment only in case the expected value from the new customer segment justifies the additional risk. Second, as pointed out above, the value of a customer asset in the PWM industry is to a large extent driven by the returns on the underlying

portfolios of financial assets. Consequently, we expect the positive relationship between risk and return of the underlying financial portfolio of each customer asset to determine, at least partly, the relationship between risk and value of the portfolio of customer assets as well.

Finally, we follow Markowitz (1952) and assume that the investment opportunity set, in our case the set of customer assets available for investment, is constant over the investment horizon.⁵ This assumption simplifies an intertemporal problem of optimizing the customer portfolio over an extended period of time (i.e. the entire investment horizon) to a one-period portfolio allocation problem.⁶ Faced with a one-period investment into a customer portfolio, we can conclude that optimizing CE by finding optimal client segment weights today (i.e. in period 0), optimizes CE or firm value for the entire investment period as well (Sharpe, 1987). Moreover, the consumption of firm capacity (and therefore firm resources) by a PWM client segment is mainly determined by its AuM. Accordingly, the client segment weight w_s is time-invariant and its empirically observed level w_s^0 can be defined as the ratio of the empirically observed segment-level AuM ($AuM_{s,0}$) divided by the empirically observed firm-level AuM (AuM_0), or mathematically as:

$$w_s^0 = \frac{AuM_{s,0}}{AuM_0} \Leftrightarrow AuM_{s,0} = w_s^0 \times AuM_0 \quad (4.16)$$

Substituting this definition of $AuM_{s,0}$ into equation 4.15 reveals how the weighting of client segments $\mathbf{w} = \{w_1, \dots, w_S\}$ in the customer portfolio determines the value of next period segment-level AuM and ultimately CE of the customer portfolio. Finding an appropriate algorithm to identify the optimal

⁵The alternative would be to allow the investment opportunity set to change over time, i.e. an intertemporal portfolio allocation problem. While an increasingly large body of literature is dedicated to the topic of intertemporal asset allocation, the models that have been developed remain largely theoretical. In fact, closed-form solutions only exist for some very special cases (Merton, 1990) and the complexity of the problem grows geometrically with the number of assets and state variables, in case a numerical approximation is attempted (Lee, 2000). Moreover, the relatively high illiquidity of customer assets compared to financial assets (see the discussion on transaction costs above) makes a dynamic adjustment of portfolio weights on a continuous basis during the investment horizon infeasible.

⁶See Merton (1969) and Merton (1990, chapter 5) for the mathematical details.

composition of client segment weights $\mathbf{w}^* = \{w_1^*, \dots, w_S^*\}$ is therefore the aim of the following sections.

4.2.2 Optimization restrictions and transaction costs

From this definition of client segment weights $\mathbf{w} = \{w_1, \dots, w_S\}$, it is clear that the optimization of the client segment portfolio can only be conducted with at least two important restrictions. First, the sum of all client segment weights must be equal to one, because the sum of segment-level AuM is equal to the firm-level AuM. Second, the client segment weights must be positive, because negative segment-level AuM cannot arise. Hence, the portfolio optimization is restricted by at least the following two conditions:

$$\mathbf{w}'\mathbf{1} = 1 \wedge \mathbf{w} \geq 0 \quad (4.17)$$

Apart from these minimum segment weight restrictions, we impose a number of additional restrictions on the portfolio optimization problem. First of all, we define upper and lower boundaries for the segment weights to avoid extreme (corner) solutions and to ensure a minimum degree of diversification. Rudolf and Zimmermann (1998) show that imposing such restrictions on the optimization algorithm leads to more stable results when facing estimation risk. In line with this finding, Buhl and Heinrich (2008) also make use of segment weight bounds in their customer portfolio optimization. To reduce the number of parameters that would have to be estimated for each segment, we employ a maximum segment weight tolerance factor ξ that is used to construct an interval with a lower and upper bound around the empirically observed, non-optimal segment weights $\mathbf{w}^0 = \{w_1^0, \dots, w_S^0\}$. As the empirically observed segment weights can be very close to 0 or 1, we also have to define a global minimum and maximum segment weight to avoid boundaries below 0 or above 1. These global boundaries are set at a minimum of w^{min} and a maximum of w^{max} , where w^{min} and $w^{max} \in [0, 1]$. The

lower and upper bound ($\mathbf{lb} = \{lb_1, \dots, lb_s\}$ and $\mathbf{ub} = \{ub_1, \dots, ub_s\}$, respectively) for each segment s and for $\xi \in [0, 1]$ are therefore given by:

$$\begin{aligned} \mathbf{lb} &\leq \mathbf{w} \leq \mathbf{ub} \\ \Leftrightarrow \max[w^{\min}, \mathbf{w}^0 - \xi] &\leq \mathbf{w} \leq \min[\mathbf{w}^0 + \xi, w^{\max}] \end{aligned} \quad (4.18)$$

Second, we consider transaction costs in the portfolio optimization problem to account for the fact that such costs are expected to be high when dealing with client assets. Clients are both difficult to acquire and divest. Especially large-scale divestment efforts are known to cause significant negative network (word-of-mouth or referral) effects.⁷ We therefore implement a transaction cost function $TC(\mathbf{w})$, similar to the one in the recent study by Brandt, Santa-Clara and Valkanov (2009). This function expresses the expected costs of optimizing the portfolio of customer segments as a percentage of CE and takes the following form:

$$TC(\mathbf{w}) = c \sum_{s=1}^S |\Delta w_s| \quad (4.19)$$

where Δw_s is the deviation of segment weight w_s from the empirically observed weight w_s^0 for client segment s and $c \in [0, 1]$ is the constant transaction cost factor. The resulting value for the transaction cost function depends on the sum of all Δw_s and always lies between 0 and 1. To derive CE net of transaction costs (\widehat{CE}), the value of the transaction cost function is multiplied with the CE that is generated with the altered composition of segment weights $\mathbf{w} \neq \mathbf{w}^0$. Accordingly, \widehat{CE} is defined as:

$$\widehat{CE}(\mathbf{w}) = CE(\mathbf{w}) \times (1 - TC(\mathbf{w})) \quad (4.20)$$

and represents the objective variable of our optimization algorithm. Therefore, the higher the deviation of a more optimal weight vector \mathbf{w} from the empirically observed segment weights \mathbf{w}^0 , the higher the reduction in the optimized CE and therefore firm value. Hence, the transaction cost function constrains the optimization to search for optimal solutions in the direct vicinity of \mathbf{w}^0 . Apart from

⁷In particular, Anderson (1998) finds that dissatisfaction produces more negative word-of-mouth than satisfaction produces positive word-of-mouth.

the recent study by Brandt, Santa-Clara and Valkanov (2009), similar implementations of transaction costs within portfolio optimization algorithms can be found throughout the academic literature. Prominent examples include Hong (2004), Hong and Loewenstein (2002), Leland (2000) and Davis and Norman (1990).

4.2.3 Objective function

We now turn to a discussion regarding the objective function within the optimization algorithm that ensures that the optimized client segment portfolio is indeed preferred over any other combination of client segments. Since Markowitz (1952), portfolio optimization models in the financial discipline typically optimize the return of a portfolio due to the favorable statistical properties of returns compared to the absolute values. As this study is interested in optimizing the CE of a customer portfolio, we optimize the absolute value of the portfolio, an approach that has already been implemented by Roy (1952) in the early days of modern financial portfolio theory.

Similar to the portfolio selection model of Markowitz (1952), we are interested in optimizing the portfolio of client segments with respect to two distinct dimensions, value and risk. The objective is to find the portfolio weights that maximize the value (i.e. the CE) of the customer portfolio while minimizing its risk. To achieve both goals simultaneously, we have to formulate measures for both value and risk and combine them into one objective function that has to be optimized.

In the financial discipline two different approaches are usually employed for maximizing value while minimizing risk by means of a single function. The first approach is based on the concept of utility maximization.⁸ Instead of optimizing both value and risk separately, the investor's preferences are assumed to follow a particular utility function that represents a combination of both value and risk. Maximizing the investor's utility will consequently result in the optimization of value and risk simultaneously. The problem with this approach, however, is that assumptions have to be made regarding the functional form of the investor's

⁸The concept of utility maximization was first introduced by Bernoulli (1738) and is thus often referred to as the Bernoulli principle. The theoretical foundation for the Bernoulli principle was developed by von Neumann and Morgenstern (1947) and takes the form of axioms of rationality.

utility that is generally not observable. Moreover, depending on the chosen utility function, further parameters need to be estimated (e.g. risk aversion parameters). Therefore, while this approach might be able to describe investor preferences more precisely, it also introduces substantial model risk. In this respect, the second approach is superior to the first one as it summarizes both value and risk in a simple ratio, called risk-value model, and therefore requires no assumptions regarding the exact shape of the investor's utility function. For this reason, we decide to implement a risk-value model as our objective function. Although, risk-value models are often criticized for their lack of theoretical foundation, we meet this criticism by choosing a risk-value model that has been proven to be consistent with a certain class of utility functions.

According to Kumar and Shah (2009) and Buhl and Heinrich (2008), the expected value of the CE distribution is a good measure of the customer portfolio value. Although, we agree in principle that the expected value is an appropriate measure for value for a given CE distribution, our portfolio optimization faces essentially two distinct CE distributions, one for the existing composition of customer assets and one for the optimal customer portfolio. Therefore, in line with prospect theory (Kahneman and Tversky, 1979), we propose to measure the value of the optimal customer portfolio by the expected value of the CE probability distribution in excess of a benchmark or reference level. Our reference level is the expected value of CE that can be realized without actively managing the portfolio of customer segments (i.e. $E[CE^0]$). This choice of a reference level is consistent with our goal of maximizing the value of CE and therefore firm value.

In contrast to the measure for value, the choice of an appropriate measure for risk is less obvious and the financial discipline has developed numerous alternatives to measure risk ever since the seminal paper of Markowitz (1952). In the context of customer portfolios, Kumar and Shah (2009) are the first ones to propose a measure of risk. In line with Markowitz (1952) and Sharpe (1966), they measure risk as the volatility of the CE probability distribution that is generated by means of Monte Carlo simulation.⁹ We deviate from this approach in our

⁹Although, Buhl and Heinrich (2008) also propose to employ the volatility as a measure of risk in the optimization of customer portfolios, their approach measures the volatility from a time series of historic cash flows, instead, leading to a static and backward-looking measure of risk compared to the approach employed by Kumar and Shah (2009).

study and employ a different measure of risk. The reason is that the volatility is only a good measure of risk under the assumption of a symmetrical probability distribution, because it treats downside and upside deviations from the expected value equally. This assumption cannot be made in our study, as we expect the CE probability distribution to be non-normal and hence non-symmetrical due to the presence of jumps (i.e. downside events) in the valuation model. Thus, the assumption of normality would substantially underestimate the downside risk of the customer portfolio value. Consequently, we propose to employ a measure of risk that does not require any assumptions regarding the functional shape of the CE probability distribution. The literature on financial asset allocation is extensive and proposes numerous possible alternatives to volatility as risk measures in the case of non-normal asset return distributions (for a recent example see Sheikh and Qiao (2010)). However, most alternative measures still require the estimation of explicit distribution parameters of higher than second order to describe the observed probability distribution and are therefore not completely independent of the functional shape of the distribution. We choose the lower partial moment (LPM) as our measure of risk, because it is one of the few measures that does not require any assumptions regarding the true probability distribution parameters. This measure of risk was first proposed by Bawa (1978). Although, the LPM measure has been used in asset allocation since then, the interest in this risk measure has peaked only recently due to the mounting evidence of non-normal asset returns and the nonparametric characteristics of this measure. Instead of relying on a single point estimate, the determination of the LPM comprises a full probabilistic description of all relevant uncertainties of future cash flows or returns. In general, the LPM of order n for a vector of N discrete asset returns \mathbf{R} is defined as:

$$\text{LPM}_n^\tau[\mathbf{R}] = \sum_{i=1}^N \text{Prob}(R_i^{<\tau}) (\tau - R_i^{<\tau})^n \quad (4.21)$$

where $R_i^{<\tau}$ denotes the values of R_i that fall short of the minimum return specified by τ and $\text{Prob}(R_i^{<\tau})$ is the probability of R_i falling short of τ . In this study, the asset return observations \mathbf{R} are equal to the CE observations net of transaction costs $\widehat{\mathbf{CE}}$ that are viewed as the returns of our customer segment

portfolio. In line with our choice of the reference level above, the variable τ is set to the value of $E[CE^0]$. Depending on the choice of order n , the LPM measure is interpreted in different ways. Choosing the LPM of order $n = 0$, results in a measure that can be interpreted as the probability of downside deviations from the minimum return. If we choose $n = 1$, the LPM is equal to the expected downside deviation from the minimum return. Finally, by choosing $n = 2$, we get the variance of downside deviations from the minimum return.

For the purpose of our study, we choose $n = 1$, because the LPM of order 1 combines the probability with the expected value of downside deviations. Moreover and more importantly, the literature has shown that minimizing the LPM of order 1 as a measure of risk, while simultaneously maximizing the expected (excess) value of a return distribution, results in asset allocation decisions that are consistent with decisions based on risk-averse utility functions (Fishburn, 1977). As pointed out in section 4.2.1, we assume that the firm is a rational and risk-averse investor in the portfolio of customer assets, representing the preferences of its shareholders on aggregate. Hence, maximizing the expected (excess) value, while minimizing the LPM of order 1 of the CE probability distribution, will maximize shareholder value. Consequently, our specification of LPM in equation 4.21 becomes:

$$\text{LPM}_1^{E[CE^0]}[\widehat{CE}] = E[\max(E[CE^0] - \widehat{CE}, 0)] \quad (4.22)$$

The resulting objective function has been used by many studies that deal with portfolio management problems and non-normally distributed asset returns and has been termed mean-lower partial moment (M-LPM) measure. A recent comparison of this M-LPM measure with the mean-variance (M-V) measure, which is in line with the tradition of Markowitz (1952), can be found in Jarrow and Zhao (2006). The authors conclude that in case of portfolios with event risk for downside loss-averse investors, the M-LPM measure is the appropriate objective

function that needs to be maximized. In line with Jarrow and Zhao (2006), our portfolio optimization algorithm can therefore be written as:

$$\begin{aligned}
\max_{\mathbf{w}} \quad & \frac{\mathbb{E}[\widehat{CE}(\mathbf{w})] - \mathbb{E}[CE^0]}{\text{LPM}_1^{\mathbb{E}[CE^0]}[\widehat{CE}(\mathbf{w})]} \\
\text{s.t.} \quad & \mathbf{w}'\mathbf{1} = 1 \\
& \mathbf{w} \geq 0 \\
& \mathbf{lb} \leq \mathbf{w} \leq \mathbf{ub}
\end{aligned} \tag{4.23}$$

We employ $\widehat{CE}(\mathbf{w})$ as our objective variable in the portfolio optimization algorithm to account for transaction costs, as outlined in section 4.2.2 and defined in equation 4.20. Hence, in case the client segment weights remain unchanged (i.e. $\mathbf{w} = \mathbf{w}^0$), it holds that $TC(\mathbf{w}) = 1$ and $\widehat{CE} = CE^0$. Apart from transaction costs, the portfolio optimization algorithm in equation 4.23 is subject to the optimization constraints detailed in equations 4.17 and 4.18.

4.2.4 Numerical implementation

In line with Jarrow and Zhao (2006), we opt for a numerical solution to the optimization problem in expression 4.23 since analytical expressions for LPM_n^{τ} are unavailable and integration has to be done numerically. In line with Kumar and Shah (2009) and as described in section 4.1.2, we begin our analysis by generating a probability distribution of CE with the existing, empirically-observed customer segment weights \mathbf{w}^0 by means of Monte Carlo simulation. From this distribution of CE we are able to infer the reference level $\mathbb{E}[CE^0]$. Following Jarrow and Zhao (2006), we then turn to applying a sequential quadratic programming optimization algorithm in order to alter the customer segment weights \mathbf{w} in such a way so as to maximize expression 4.23. In particular, the optimization algorithm is implemented in the numerical computing environment of MATLAB using the constraint nonlinear optimization function `fmincon`. The optimization tolerance for the objective function is set to 10^{-6} to ensure that the optimal customer segment weights are estimated with a reasonable degree of accuracy. The composition of client segment weights that maximizes expression 4.23 is given by $\mathbf{w}^* = \{w_1^*, \dots, w_S^*\}$. The distribution of N realizations of CE

net of transaction costs ($\widehat{\mathbf{CE}}$) that is generated with \mathbf{w}^* is denoted accordingly by $\widehat{\mathbf{CE}}^* = \{\widehat{CE}_1^*, \dots, \widehat{CE}_N^*\}$.

4.3 Chapter summary

Equipped with the theoretical background on customer valuation and customer-based firm valuation, as well as the characteristics and particularities of the PWM industry outlined in the previous two chapters, this chapter develops a comprehensive model to value and optimize the customer portfolio of a typical PWM provider. This Customer Portfolio Management model is developed in two steps.

In a first step, we develop a dynamic customer-based firm valuation model, whose cash flow generation process is adjusted to meet the particularities of the PWM industry. This model identifies the Assets under Management (AuM) of a particular client segment as the primary source of value dynamics. Consequently, in the following the study focuses on modeling the dynamics of the AuM process. For this purpose, we divide the change in AuM into two components: the net new assets (NNA) component, which is related to the acquisition and defection of client assets, and the return on retained assets (RRA) component, which captures the financial market returns earned on last period's volume of retained assets. Applying the theory on customer valuation from chapter 2 and the characteristics of the PWM industry discussed in chapter 3, the dynamics of each of these value components are hypothesized to follow a distinct stochastic process with a specific correlation structure. The resulting model setup enables us to value the empirically observed composition of the client segment portfolio.

In a second step, we develop a methodology for optimizing the empirically observed customer portfolio consistent with the concept of shareholder value maximization. We begin by discussing and addressing the assumptions and conditions of financial portfolio selection theory in order to be able to apply theory originally developed for financial assets to customer assets. Next, we implement a number of optimization restrictions and transaction cost provisions that directly follow from the application of financial theory to customer assets. Finally, we develop an objective function for our portfolio optimization algorithm that is in line with the concept of shareholder value maximization and employs measures

Table 4.1: Model overview

Step	Equation	Reference
1	$\frac{NNA_{s,t}}{AuM_{s,t-1}} = \mu_s^{NNA} \Delta t + \sigma_s^{NNA} \varepsilon_{s,t} \sqrt{\Delta t}$	(4.11)
	$R_{s,t} = \mu_s^R \Delta t + \sigma_s^R \nu_{s,t} \sqrt{\Delta t} + Y_s j t$	(4.12)
2	$AuM_{s,t} = AuM_{s,t-1} \left(1 + \frac{NNA_{s,t}}{AuM_{s,t-1}} + R_{s,t} \right)$	(4.14)
	where $AuM_{s,1} = AuM_{s,0} \left(1 + \frac{\Delta AuM_{s,1}}{AuM_{s,0}} \right)$	(4.15)
	with $AuM_{s,0} = w_s^0 \times AuM_0$	(4.16)
	and $\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}} = \frac{NNA_{s,t}}{AuM_{s,t-1}} + R_{s,t}$	(4.10)
3	$CF_{s,t} = AuM_{s,t} \times RM_s \times PM_s \times CFM$	(4.7)
4	$CF_t = \sum_{s=1}^S CF_{s,t}$	(4.4)
5	$CE = \sum_{t=T+1}^{\infty} \frac{CF_t}{(1+d)^{t-T}} \approx \sum_{t=T+1}^{T+H} \frac{CF_t}{(1+d)^{t-T}} + \frac{TV}{(1+d)^H}$	(4.5)
	with $TV = \frac{CF_{T+H+1}^{Firm}}{d-g}$	(4.6)
Valuing the customer portfolio		Optimizing the customer portfolio
6	simulate N realizations of CE using the empirically observed segment weights $\mathbf{w} = \mathbf{w}^0$ to yield \mathbf{CE}^0	simulate N realizations of CE using any \mathbf{w} to yield \mathbf{CE}
7	from \mathbf{CE}^0 infer $E[CE^0]$ and $LPM_1^{E[CE^0]}[CE^0]$ as measures of value and risk	compute \mathbf{CE} net of transaction costs determined using equations (4.19) and (4.20) to yield $\widehat{\mathbf{CE}}$
8		from $\widehat{\mathbf{CE}}$ infer $E[\widehat{\mathbf{CE}}]$ and $LPM_1^{E[\widehat{\mathbf{CE}}]}[\widehat{\mathbf{CE}}]$ as measures of value and risk
9		maximize expression (4.23) to find the optimal segment weights $\mathbf{w} = \mathbf{w}^*$ that yield $\widehat{\mathbf{CE}}^*$

Note: This table summarizes the methodology of valuing and optimizing customer portfolios comprising private wealth management client segments detailed in chapter 4.

of value and risk for customer portfolios that build on recent findings in the field of customer valuation and portfolio analysis as well as recent financial studies.

Table 4.1 provides an overview of the theoretically derived Customer Portfolio Management (CPM) model. In the first five steps the table illustrates how the CE of a portfolio comprising PWM client segments is computed based on the stochastic models for the NNA and financial market return processes. The table also reveals at which point the client segment weights are introduced to determine the ultimate CE as a function of the portfolio weighting. Depending on the subsequent purpose, table 4.1 then proceeds to summarize how to derive a measure of portfolio value and risk by means of Monte Carlo simulations in order to value and optimize the empirically observed customer portfolio.

This chapter concludes part I of this study. Part II is devoted to the empirical application of the proposed, theoretical CPM model developed in part I, using a set of unique proprietary data.

Part II

Empirical Application

Chapter 5

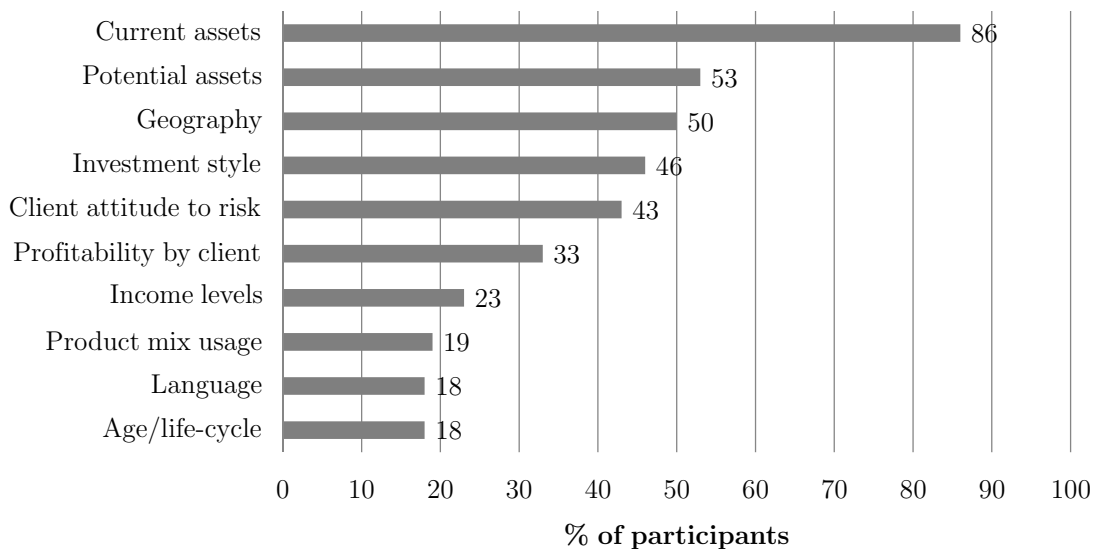
Data and Preliminary Analysis

After having developed a theoretical Customer Portfolio Management (CPM) model in part I of this study, we now proceed to applying the proposed model to an empirical case. On the one hand, this allows us to verify the adequacy of the various assumptions that were made during the theoretical model development. On the other hand, it illustrates the potential benefits of implementing such a model in the real business world. While this chapter focuses on the former point, the latter aspect is covered next in chapter 6.

This chapter is organized as follows. Section 5.1 describes the data sources for the empirical case study and the measurement of the required variables. Section 5.2 performs a preliminary analysis, which presents the empirical data and validates the various assumptions of chapter 4. The chapter concludes with a brief summary in section 5.3.

5.1 Data

The data used for the empirical case study is from the Credit Suisse Group, whose private wealth management (PWM) business unit is one of the world's largest PWM institutions with total AuM of 712 billion CHF as of June 2009. In fact, referring to table 3.1 in chapter 3 of this study, Credit Suisse Wealth Management ranked fourth among the largest providers of PWM services by AuM in the world in 2008. For a total of three client segments, the institution has provided us with data on the monthly development of AuM and NNA for the period January

Figure 5.1: Segmentation criteria currently used by PWM providers

Source: PricewaterhouseCoopers (2009)

2006 - August 2009. The values for the time series of segment-level financial market returns $R_{s,t}$ can be directly derived from the time-series of AuM and NNA using equation 4.9. The three client segments are formed based on current AuM and geography. These are two of the most common segmentation criteria used by PWM providers, as can be seen in figure 5.1. Only High Net Worth Individuals (HNWIs) with total AuM above one million CHF are included. While Credit Suisse Wealth Management operates worldwide, all clients considered in this study are from Europe. Although, these three client segments only represent a subsample of all available client segments of Credit Suisse Wealth Management, the study assumes that these three segments represent all available segments and treats the aggregation of AuM and NNA for these segments as firm-level variables in the following. Similarly, we regard the CE of the customer portfolio as being an approximation to firm value. This assumption, however, does not influence the results in any way and is only made for the purpose of argumentation.

Because the PWM business model is build upon a high degree of confidentiality, obtaining sensitive data on such a detailed level is very difficult. Consequently, the data provided is anonymous and has been proportionally distorted. This means that although the segmentation criteria are known, the identification of segments is impossible, because the exact segment cut-offs applied by Credit Suisse Wealth

Management are kept secret. Furthermore, while the relative changes of the actual time series for each segment are preserved in their distorted counterparts, the absolute levels are obscured with a different factor for each segment, so that even the share of segment AuM relative to total AuM (i.e. the portfolio weights) are distorted. Altogether, these measures make it impossible to draw conclusions that could possibly lead to the identification of any of the clients or that could be valuable from a competitors point of view. Unfortunately, this limits our ability to interpret the results and validate their economic intuition. Most importantly, however, the data is sufficient for the purpose of our analysis, since our basic data requirements are met: homogeneity of clients within one segment, as well as data on the historical development of the key cash flow drivers within the PWM industry, namely AuM and its components (i.e. NNA and RRA), over an extended period of time. Moreover, the heterogeneity across segments is sufficient to reveal significant differences in the value dynamics of each individual client segment. This is important, because the results of the proposed CPM model and therefore the benefits of implementing it for a given PWM provider, are directly dependent on the potential to realize diversification effects and therefore rely on the presence of systematic differences across customer assets. Table 5.1 reports an excerpt of the empirical sample data provided by Credit Suisse Wealth Management. While table 5.1a provides a first impression of the absolute values of the empirical data, table 5.1b presents an excerpt of the segment-level AuM and NNA growth rates as well as the financial market returns derived from the absolute values in table 5.1a.

All other required information regarding the cash flow generation process is extracted from the quarterly financial statements of the Credit Suisse Group. This includes all relevant margins (i.e. revenue margin, profit margin and cash flow margin) as well as the long-term annual AuM growth rate. Although, our model initially requires the estimation of the revenue and profit margin on the segment-level, we further simplify the model by assuming that these margins are the same across all segments. While we would have preferred to use segment-level data, we were unable to obtain estimates for these margins at the segment-level for confidentiality reasons.

Table 5.1: Empirical sample data

(a) Empirical data (in million CHF).

Period	Segment $AuM_{s,t}$			Segment $NNA_{s,t}$		
	1	2	3	1	2	3
Jan 06	15,821	382	3,165	43.9	2.6	83.1
Feb 06	16,049	386	3,218	18.2	-0.9	12.3
Mar 06	16,272	378	3,274	74.4	-4.9	16.8
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Aug 09	14,314	347	4,382	-118.2	-2.9	-1.4

Note: Excerpt of the monthly data provided by Credit Suisse Wealth Management over the historical period January 2006 - August 2009 for client segments 1 to 3.

(b) Empirical growth rates (in %).

Period	Segment $\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}}$			Segment $\frac{NNA_{s,t}}{AuM_{s,t-1}}$			Segment $R_{s,t}$		
	1	2	3	1	2	3	1	2	3
Jan 06	-	-	-	-	-	-	-	-	-
Feb 06	1.44	0.91	1.66	0.12	-0.24	0.39	1.32	1.15	1.27
Mar 06	1.39	-1.96	1.76	0.46	-1.28	0.52	0.93	-0.69	1.23
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Aug 09	-0.07	-1.26	0.86	-0.83	-0.82	-0.03	0.75	-0.44	0.89

Note: Own calculations based on the empirical data partly shown in panel a and using equation 4.9.

The revenue margin (RM) is calculated in percent of AuM (i.e. similar to an average management fee) and is measured net of interest and trading expenses. This definition of the revenue margin is chosen, because PWM providers usually report their revenues net of interest and trading expenses in their financial statements. Because the financial statements are only issued on a quarterly frequency and we need an estimate of the revenue margin for monthly AuM data, the average quarterly revenue margin is divided by 3. Similarly, the average quarterly revenue margin is multiplied by 4 to obtain the annual margin. All other margins do not require this adjustment, because they are exclusively based on income statement positions instead of balance sheet accounts. This implies that the numerator and denominator of these margins increase proportionately over

time, leaving the ratios unchanged. The profit margin (PM) is the percentage of earnings before taxes to total revenue (again net of interest and trading expenses). Finally, the cash flow margin (CFM) is calculated as the ratio of net cash flows attributable to the firm's shareholders to earnings before taxes, essentially accounting for taxes and minority interests. Both, the revenue and profit margin, are estimated for all available quarters, namely from the fourth quarter of 2001 to the second quarter of 2009, and are averaged over this period. The estimation period for the cash flow margin is only from the first quarter of 2004 to the second quarter of 2009 (i.e. 22 quarters), in order to avoid distortions due to the substantial structural break in the minority interest position of the Credit Suisse Group at the end of 2003.

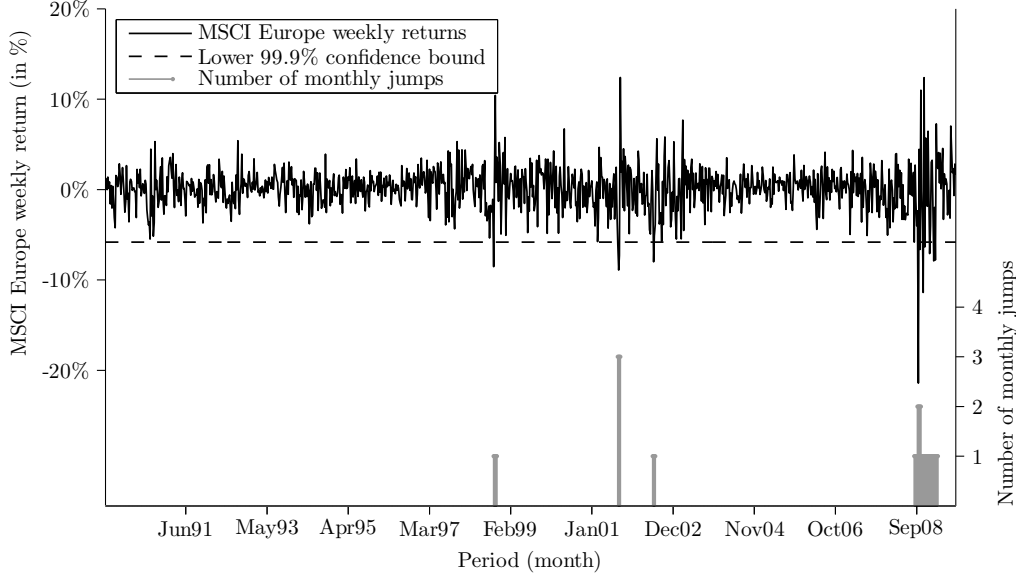
The growth rate that is required for the estimation of the terminal value within the CE calculation is approximated by the long-term year-on-year total AuM growth rate. This assumption is reasonable, considering that the cash flow dynamics are only dependent on the development of AuM in our model. The growth rate is based on the full history of available quarterly data. As the first observation of total AuM is for the fourth quarter of 2001, the first observation of the year-on-year AuM growth rate is for the fourth quarter of 2002 and the last for the second quarter of 2009. The average year-on-year AuM growth rate over this sample period is 5%.

Last but not least, the study relies on the estimation of two variables that are not readily observable and consequently require further analysis. The first is the incidence of jumps over the time period of the historical data. This variable is needed to calibrate the stochastic process of segment-level financial market returns $R_{s,t}$. Second, we require an appropriate discount rate to discount future cash flows. The methodology for estimating both variables is discussed in the following two sections.

5.1.1 Defining jumps

In theory, the incidence of jumps should be inferred from the time series of segment-level financial market returns $R_{s,t}$ itself. However, disentangling jumps from the diffusion process is generally difficult when dealing with discretely ob-

Figure 5.2: MSCI Europe weekly returns and number of monthly jumps from August 1989 - August 2009



served time series, especially when the frequency of the time series is low and the observation period relatively short, as in our case.¹ Consequently, we need to make use of a closely correlated time series that can be observed with a higher frequency and for a longer time period. For this purpose, we choose equity market returns that seem to be the natural choice for such a correlated time series, since the dynamics of equity market returns should be closely mirrored by the financial market returns on the average financial portfolio of a particular PWM client segment (i.e. the $R_{s,t}$ process).² Assuming a deterministic diffusion volatility as well as independently and identically distributed (i.i.d.) returns, Merton (1976) proposes that jumps can then be defined as outliers of the return distribution.

This study chooses the well-diversified Morgan Stanley Capital International (MSCI) Europe index to reflect equity market returns. This choice reflects the expectation that the sample, which consists exclusively of European clients, will be largely invested in European equities, due to the home bias within the average

¹See Ait-Sahalia (2004; 2002), Andersen, Benzoni and Lund (2002) and Bandorff-Nielson and Shepard (2004).

²For an analysis of the correlation between $R_{s,t}$ and equity returns see section 5.2.1 of this study.

client's financial portfolio (see section 4.1.2). Using weekly return data from the Thomson Reuters Financial Datastream service, we estimate the mean and the standard deviation of the MSCI Europe index return for a period of 20 years and count the number of incidences in each month that equity returns are below the 99.9% confidence interval around the mean.³ This methodology, which is visualized by figure 5.2, produces a monthly time series with values from 0 to 4 for each month. We only consider downside jumps, since we expect the incidence of jumps to be symmetric. The validity of this conjecture can easily be inferred visually from figure 5.2.

5.1.2 Estimating the discount rate

The overarching goal of this study is the maximization of firm (i.e. shareholder) value. The discount rate should, therefore, represent the required rate of return from the perspective of the firm's equity holders. For the firm this required or expected return on equity is equivalent to the cost of equity (i.e. the cost of raising additional equity to finance the investment in customer assets). We measure the cost of equity using the two most widely employed methods, namely the Capital Asset Pricing Model (CAPM) approach, as well as the dividend yield approach.

The CAPM approach (Lintner, 1965; Sharpe, 1964) requires the estimation of the following equation:

$$E[R] = R^f + \beta(E[R^m] - R^f) \quad (5.1)$$

where $E[R]$ is equal to the required or expected rate of return by equity holders or the cost of equity from the firm's point of view, R^f is the risk-free rate of return, $E[R^m]$ is the expected market return and β represents the beta factor.

The risk-free return R^f is obtained from the zero-coupon yield curve for Switzerland for a maturity of 15 years as of September 1st, 2009, constructed by the Thomson Reuters Financial Datastream service. To avoid short-term effects, we

³We use weekly rather than daily returns to avoid the inclusion of trading noise. Trading noise refers to short-term stock price fluctuations that arise from trading activity that is based on non-fundamental data. As a result, the trading activity is often irrational and erratic, causing price and risk levels based on high-frequency data to diverge from expectations (DeLong, Shleifer, Summers and Waldmann, 1990).

do not employ the current, but the 12 months average yield of 3.06%. The beta factor β is equal to the ratio of the covariance of stock returns to the variance of market returns. We measure stock returns by the returns on the Credit Suisse Group stock⁴ and market returns by the returns on the Swiss Market Index, to which the Credit Suisse stock belongs. For a 20 year history of monthly return data⁵ (adjusted for dividend payments) from the Thomson Reuters Financial Datastream service, we thus estimate a beta factor of 1.48 (this estimate is significant at the 1% level). For consistency reasons, the expected return on the market $E[R^m]$ is estimated using the same stock index over the same time period with the same return frequency as for the beta factor estimation, resulting in an annualized market return of 8.75%. Employing equation 5.1 this yields an expected return estimate of 11.45%.

Our second approach to measuring expected return or cost of equity, the dividend yield approach, is derived from the Gordon Growth model (Gordon, 1959) and takes the following form:

$$E[R] = DivY(1 + E[DivG]) + E[DivG] \quad (5.2)$$

where $DivY$ is the current dividend yield and $E[DivG]$ represents the expected dividend growth rate.

For a five-year history of monthly Credit Suisse dividend yield and price data obtained from the Thomson Reuters Financial Datastream service, we estimate the current annual dividend yield at 2.82%, using the average annualized dividend yield. We further assume that the best estimate for the expected dividend growth rate is the current dividend growth rate, which is estimated from the same data over the same time period at 7.64%. Compared to the CAPM approach, the dividend yield approach results in a slightly lower expected return estimate of

⁴Although we would prefer to use the stock returns of Credit Suisse Wealth Management, stock returns are only available on the business group level. We are aware that this results in a cost of equity estimate that represents the risk profile of the Credit Suisse Group as a whole and that this risk profile might differ from the one of the standalone PWM business.

⁵Similar to our reasoning above, we argue that a higher frequency of returns would bias the results by introducing short-term trading noise, while a lower return frequency would lack the required number of observations to achieve a robust estimate of the beta factor. We also employ shorter estimation periods for robustness, but do not find substantial deviations from our previous results.

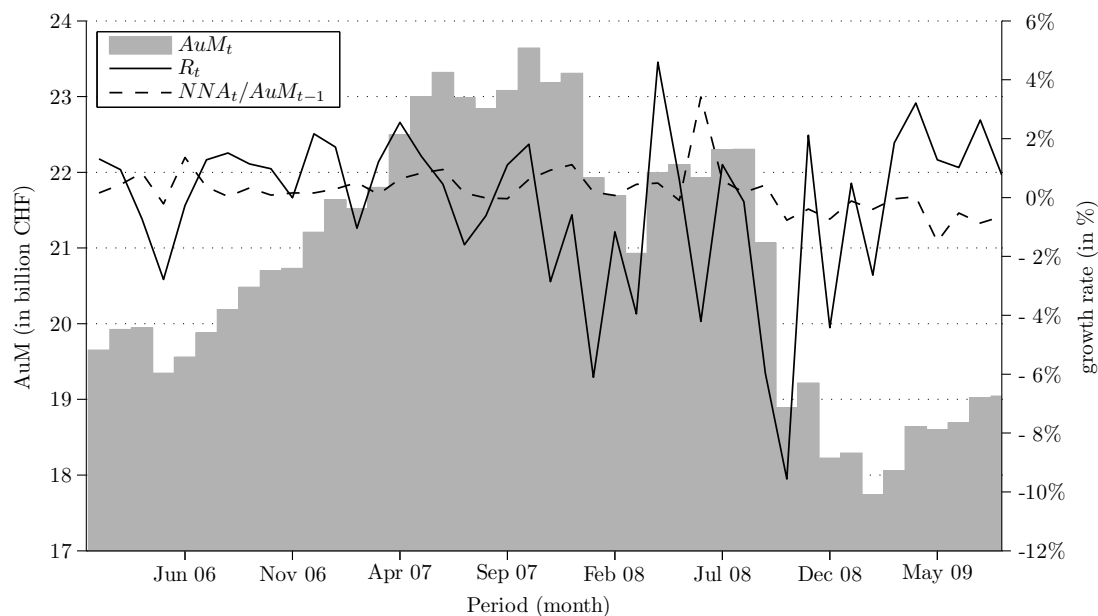
10.67%. We regard the average of the two estimates, 11.06%, as a robust estimate of the true expected return or cost of equity and hence use it as our discount rate d in the following.

5.2 Preliminary analysis

Our preliminary analysis serves the twofold goal of introducing the proprietary data set to the reader by presenting detailed descriptives and of empirically validating the various assumptions that were made during the theoretical model development. For the purpose of brevity and simplicity and due to the proprietary nature of the data, descriptives and analysis results are presented on the aggregated firm-level only. Consequently, the segment-level data for the total AuM growth ($\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}}$), the NNA process ($\frac{NNA_{s,t}}{AuM_{s,t-1}}$) and financial market returns ($R_{s,t}$) presented in table 5.1b are aggregated across all client segments, thus yielding the firm-level time series $\frac{\Delta AuM_t}{AuM_{t-1}}$, $\frac{NNA_t}{AuM_{t-1}}$ and R_t that represent the AuM-weighted average of the segment-level data. Note, however, that the results are quantitatively similar and qualitatively the same to those on the segment-level. Therefore, none of the relevant conclusions drawn in this section is influenced by this choice.

Both, figure 5.3 and table 5.2, suggest that while the effect of NNA on the overall AuM growth ($\frac{\Delta AuM_t}{AuM_{t-1}}$) is only small (on average around one-third of the total change), financial market returns (R_t) account for the lion's share of total AuM growth (on average around two-thirds of the total change). Furthermore, while the financial market return process is very volatile, sometimes leading to drastic changes in the level of total AuM (especially negative changes), the development of NNA is much more stable. Additionally, the total AuM growth and financial market return processes exhibit high negative skewness. In line with this, the distribution means are much smaller compared to the medians. This fact strongly indicates the absence of normality regarding in the distribution of both, total AuM growth and financial market returns. This conclusion stands in opposition to the one for the NNA process, for which the mean and median are substantially closer together, indicating normality of the underlying distribution.

Table 5.2 reveals that the variance of the different margins necessary to transform AuM to net cash flows based on equation 4.7 is relatively low and exhibits

Figure 5.3: Firm-level AuM development**Table 5.2:** Firm-level descriptives

	Growth rates (in %)			Margins (in %)		
	$\frac{\Delta AuM_t}{AuM_{t-1}}$	$\frac{NNA_t}{AuM_{t-1}}$	R_t	RM	PM	CFM
Mean	0.00	0.22	-0.22	0.10	39.2	60.4
Median	0.53	0.15	0.76	0.10	38.9	60.4
Volatility	2.83	0.75	2.79	0.01	3.5	12.3
Minimum	-10.33	-1.50	-9.56	0.08	31.8	28.9
Maximum	5.08	3.42	4.59	0.12	47.2	84.9

Note: $\frac{\Delta AuM_t}{AuM_{t-1}}$ is the total AuM growth rate, which can be further divided into the two sub-components: NNA growth rate ($\frac{NNA_t}{AuM_{t-1}}$) and financial market returns (R_t). All three growth rates are measured over the period February 2006 - August 2009 on a monthly frequency and are based on the empirical data reported in table 5.1 aggregated across all client segments. The three margins are the revenue margin (RM), profit margin (PM) and cash flow margin (CFM). RM and PM are measured from the fourth quarter of 2001 to the second quarter of 2009 and averaged over this period. RM is based on quarterly AuM levels and therefore divided by 3 in order to reflect the monthly AuM level frequency employed in this study. CFM is measured from the first quarter of 2004 to the second quarter of 2009. All figures are in %.

no significant trend over an extensive history of 31 quarters (i.e. almost 8 years)⁶, justifying our assumption of constant margins over time. This is especially true for the revenue and profit margin. The cash flow margin, on the other hand, which can only be estimated at the level of the Credit Suisse Group, exhibits higher variance that might, however, stem from activities unrelated to the Credit Suisse Wealth Management business unit. Despite the fact that the descriptives in table 5.2 indicate that assuming constant margins should not lead to significant measurement errors of future net cash flows at the firm-level, we cannot rule out the existence of bias completely. Regarding the levels of these margins, they appear to be in line with the findings of recent international industry studies. For example, the European Private Banking Survey by McKinsey&Company (2009) reports an average annual revenue margin of close to 100 bps over the past 6 years. Although our revenue margin estimate at 120 bps (the annualized monthly RM) is slightly higher, our estimate is well in the range of possible country- and firm-specific margin variations. According to the same study, the average cost-to-income ratio lies at about 60% within the PWM industry. Our estimate of the profit margin (i.e. 1 - cost/income ratio) of close to 40% is perfectly in line with this estimate. The cash flow margin cannot reliably be validated using international industry studies, because while the tax burden of PWM institutes as a percentage of net profit has been around 7% over the past 9 years (Swiss Banking Institute, 2009), minority interests vary widely across firms.

Owed to the devastating financial crisis that overshadows our sample period, the average firm-level financial market return, reported in table 5.2, is -0.22% per month with a volatility of 2.79%. Total AuM on average remained unchanged over the sample period (i.e. the mean total AuM growth is 0% with a volatility of 2.83%). Nevertheless, these growth rates still compare favorably to the average level and volatility of European equity returns (as measured by the MSCI Europe Index) over the same period, which yielded a significantly lower average return of -0.45% per month with a substantially higher volatility of 5.83%. This leads us to the conclusion that portfolio managers at Credit Suisse Wealth Management were able to protect their clients to some degree from the adverse effects of the

⁶In unreported results, we confirm that the slope of a regression of the empirical observations for all margins over time is insignificantly different from zero.

financial crisis by diversifying their portfolios to other asset classes, such as bonds, thereby lowering the correlation of the returns on the average financial portfolio of a PWM client and European equity market returns. We nevertheless assume in our theoretical model development that this correlation remains high enough to justify that the dynamics of both series are so similar that they can be captured by the same stochastic model and that the incidence of jumps in European equity market returns is a good proxy for the incidence of jumps in the financial market returns R_t process. The degree to which this is in fact the case is analyzed in the next section of this chapter.

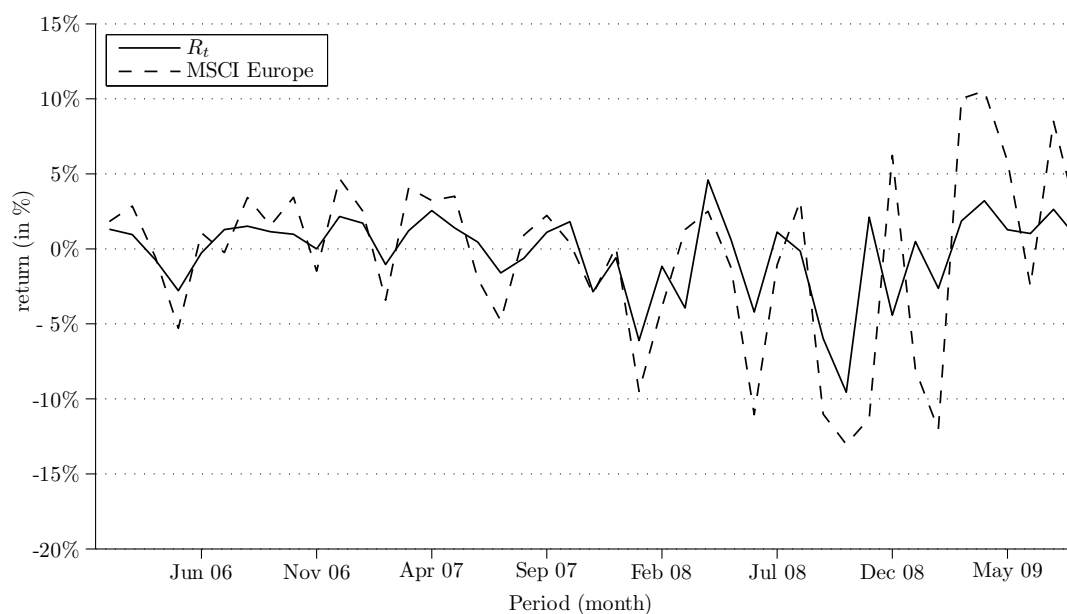
5.2.1 Equity return correlation

Overall, our analysis shows that, as expected, the average PWM client financial market return (R_t) process is highly correlated with European equity market returns. The comovement of both time series is illustrated by figure 5.4 that shows the development of average PWM client financial market returns and European equity market returns over time. While even the total AuM growth is highly correlated with European equity market returns (approximated by the MSCI Europe index returns)⁷, this correlation is even stronger when we isolate the R_t process from the total AuM growth process (using equation 4.9), which increases the correlation coefficient from 0.59 to 0.65.⁸ This is, because the development of NNA, the other component of total AuM growth, is not significantly related to financial market returns. This is in line with the findings of Horn (2009), who shows that the performance of PWM clients' financial portfolios (i.e. financial market returns) is only one of many factors determining clients' loyalty. The fact that the NNA growth rate ($\frac{NNA_t}{AuM_{t-1}}$) and financial market returns (R_t) are unrelated to each other justifies the assumption of stochastic independence of these two processes in our proposed model setup.

⁷As indicated in section 5.1.1 of this chapter, a well-diversified index of European equities is expected to closely mirror financial market returns of the average client portfolio in our sample (i.e. the R_t process). This is, because the portfolio composition of the average client in our sample of European client segments is expected to be biased towards European equities, due to the well documented home bias. In unreported results, we confirm that, in fact, the correlation with national equity indices is significantly lower.

⁸Both Pearson correlation coefficients are computed for the period February 2006 - August 2009 and are significant at the 1% confidence level.

Figure 5.4: Development of average PWM client financial market returns (R_t) and European equity market returns (MSCI Europe) over time

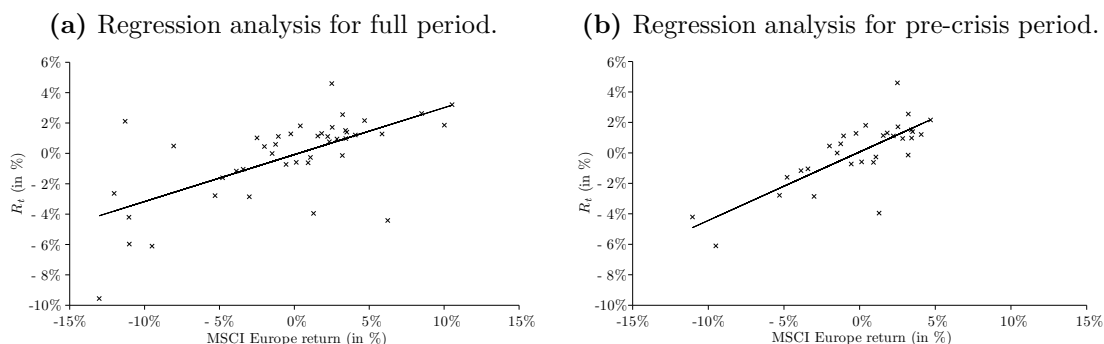


Note: Average PWM client financial market returns (R_t) are measured over the period February 2006 - August 2009 on a monthly frequency and are based on the empirical data reported in table 5.1 aggregated across all client segments. European equity market returns are approximated by the MSCI Europe index returns obtained from the Thomson Reuters Financial Datastream service with the same frequency and over the same time period.

Furthermore, it is interesting to note that the correlation between average PWM client financial market returns and European equity market returns changes over time. Although it is always high, the correlation is substantially higher prior to the start of the financial crisis (approximately September 2008), than for the full period. More specifically, the correlation reaches a level of 0.78 in the pre-crisis period (i.e. February 2006 - August 2008), compared to 0.65 over the full period (i.e. February 2006 - August 2009).⁹ Since we cannot observe the exact portfolio composition of the clients included in our sample, we can only conjecture that the reason for this phenomenon is the shift of AuM from equity to bond investments by portfolio managers at the time the financial crisis became apparent. This is supported by various PWM studies that document such a shift in the portfolio composition of PWM clients over the period in question (e.g. Capgemini and Merrill Lynch, 2009; McKinsey&Company, 2009). These findings

⁹Again, both Pearson correlation coefficients are significant at the 1% confidence level.

Figure 5.5: Regression of average PWM client financial market returns (R_t) on European equity market returns (MSCI Europe)



Note: Full period in (a) is from February 2006 to August 2009. Pre-crisis period in (b) is from February 2006 to August 2008. Average PWM client financial market returns (R_t) are measured on a monthly frequency and are based on the empirical data reported in table 5.1 aggregated across all client segments. European equity market returns are approximated by the MSCI Europe index returns obtained from the Thomson Reuters Financial Datastream service also on a monthly frequency.

are further substantiated by performing a simple regression analysis of average PWM client financial market returns on European equity market returns. While the R^2 (i.e. the explanatory power) of the regression for the full period is already high at 42%, as illustrated by figure 5.5a, figure 5.5b reveals that the explanatory power increases even further to as much as 60%, when restricting the regression to the pre-crisis sample period (i.e. before September 2008). Similarly, the slope of the regression line, which can be interpreted as the sensitivity of the financial portfolio of the average client in our sample to equity market returns, is equal to 0.31 for the full sample period compared to 0.45 for the pre-crisis sample period. This again indicates that the exposure to equity market developments of the average PWM client's financial portfolio is significantly higher before the crisis than in its aftermath.

5.2.2 Test of autocorrelation

The stochastic models for the development of NNA and financial market returns (i.e. equations 4.11 and 4.12) are based on the assumption that each new observation is independent from the last one. Stated differently, the stochastic models assume the absence of autocorrelation in the time-series of observations. We now

proceed to test whether this assumption can actually be validated by our empirical data. The presence of autocorrelation in a time-series of data is usually verified by determining a number of different test statistics, among them the regular and partial autocorrelation coefficients and the Ljung-Box Q-statistic (Ljung and Box, 1978).

Given the time-series of returns on the average financial portfolio of a PWM client across all segments (R_t), the sample autocorrelation coefficient φ for time lag k is calculated as:

$$\varphi_k = \frac{\sum_{t=k+1}^T (R_t - \bar{R})(R_{t-k} - \bar{R})}{\sum_{t=1}^T (R_t - \bar{R})^2} = \frac{\text{Cov}[R_t, R_{t-k}]}{\text{Var}[R_t]} \quad (5.3)$$

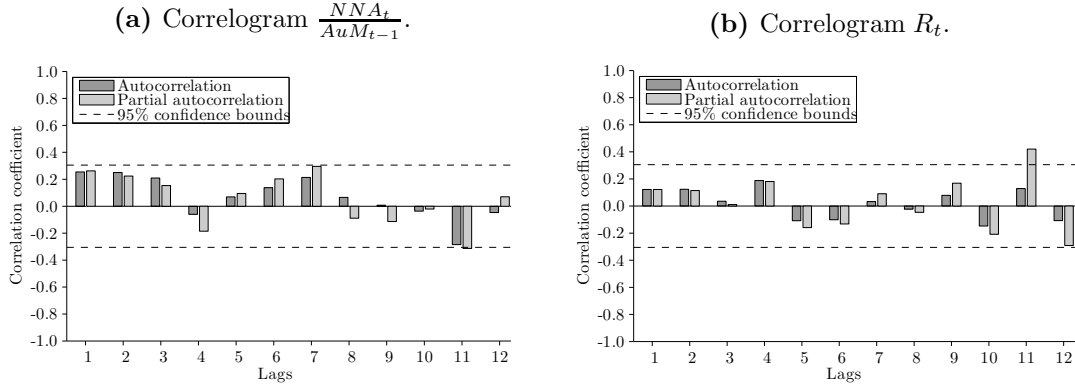
This sample autocorrelation coefficient represents the gross correlation of R_t and R_{t-k} . Nevertheless, it is also necessary to account for the possible effects of time lags that lie between 0 and k . Otherwise the true underlying serial relationship of the time-series of data could be masked. More specifically, it is necessary to examine the autocorrelation for a certain time lag net of any expected disturbing effects of any intervening time lags. This can be achieved by calculating the partial autocorrelation coefficient φ^* for time lag k , which can be expressed as:

$$\varphi_k^* = \frac{\sum_{t=k+1}^T R_t^* R_{t-k}^*}{\sum_{t=k+1}^T (R_{t-k}^*)^2} \quad (5.4)$$

where R_t^* and R_{t-k}^* are the residuals of the regressions of R_t and R_{t-k} on $\{1, R_{t-1}, R_{t-2}, \dots, R_{t-k+1}\}$, respectively. The same methodology is also applied to compute the regular and partial autocorrelation coefficients of the empirical development of NNA across all client segments ($\frac{NNA_t}{AuM_{t-1}}$).

The results for both time-series are reported in the correlograms shown in figure 5.6. Both, the regular and partial autocorrelation coefficients, are calculated and shown up to lag of 12 and their significance is tested at the 95% confidence level.¹⁰ As both panels of figure 5.6 indicate, neither the time series for the NNA process ($\frac{NNA_t}{AuM_{t-1}}$), nor the one for the financial market returns process (R_t), is

¹⁰Testing for autocorrelation up to a time lag of 12 observations and at a 95% confidence interval is widely accepted within the so-called Box-Jenkins methodology for large samples and is regarded as sufficient to capture any serial correlation.

Figure 5.6: Correlograms

Note: The empirical development of NNA across all client segments ($\frac{NNA_t}{AuM_{t-1}}$) and the returns on the average financial portfolio of a PWM client across all segments (R_t) are observed with monthly frequency over the period February 2006 - August 2008, i.e. 31 months. The (partial) autocorrelation coefficients are computed for lags 1 to 12. Whenever the correlation coefficients cross the dotted line, the coefficients are significant at the 5% confidence level

significantly autocorrelated. While the NNA process appears to exhibit a higher degree of autocorrelation than financial market returns, none of the coefficients is significant at the 5% confidence level for any of the 12 time lags. Although, the partial autocorrelation coefficients in figure 5.6a and 5.6b are both slightly above or below the 95% confidence bound at time lag 11, these results do not persist.

The absence of significant autocorrelation for both processes is further substantiated by table 5.3, which reports the Q-statistics and their corresponding p-values generated using the methodology proposed by Ljung and Box (1978). Instead of testing the randomness for each distinct time lag, the Ljung-Box Q-statistic tests the overall randomness, based on a total number of lags K . Given the time-series of returns on the average financial portfolio of a PWM client across all segments (R_t), it is calculated as:

$$Q = T(T + 2) \sum_{k=1}^K \frac{R_k^2}{T - k} \quad (5.5)$$

Again under the hypothesis that the time series is white noise, Q follows a χ^2 distribution with K degrees of freedom. This test is preferred over an alternative test proposed by Box and Pierce (1970), due to its better small- and medium-sized

Table 5.3: Ljung-Box Q-statistic test

Lag	$\frac{NNA_t}{AuM_{t-1}}$		R_t	
	Q-statistic	p-value	Q-statistic	p-value
1	2.977	0.084	0.685	0.408
2	5.549	0.062	1.403	0.496
3	7.613	0.055	1.463	0.691
4	8.218	0.084	3.214	0.523
5	8.461	0.133	3.813	0.577
6	9.456	0.150	4.349	0.630
7	11.913	0.104	4.407	0.732
8	12.149	0.145	4.435	0.816
9	12.152	0.205	4.792	0.852
10	12.230	0.270	6.066	0.810
11	17.125	0.104	7.064	0.794
12	17.261	0.140	7.788	0.802

Note: The empirical development of NNA across all client segments ($\frac{NNA_t}{AuM_{t-1}}$) and the returns on the average financial portfolio of a PWM client across all segments (R_t) are observed with monthly frequency over the period February 2006 - August 2008.

sample characteristics. Analogous to the test in figure 5.6, the Q-statistics are determined up to a time lag of 12. All p-values are above the 5% confidence level and are therefore insignificant. The results also confirm the finding from figure 5.6 that the degree of autocorrelation for the financial market return process is generally lower than for the NNA process.

To summarize, the results from the autocorrelation analysis confirm the hypothesis of randomness for both, the NNA and financial market return processes and justify the assumption of independent distributions that is required for the application of the proposed stochastic models in equations 4.11 and 4.12.

5.2.3 Stochastic model verification

Table 5.4 presents the results of the parameter calibration for the empirical time series aggregated across all segments (i.e. for the firm-level growth rates $\frac{NNA_t}{AuM_{t-1}}$ and R_t). While the parameters from this calibration are not actually used in the empirical application (because we are interested in the segment-level parameter

Table 5.4: Stochastic model comparison

Process	Model	Parameters (in %)					LL	JD-D
		μ	σ	λ	ϕ	δ		
$\frac{NNA_t}{AuM_{t-1}}$	D	0.22***	0.74***				149.8	
	JD	0.32***	0.71***	16.5***	-0.60***	0.00	132.2	-
R_t	D	-0.22***	2.76***				93.4	
	JD	0.25***	2.14***	16.7***	-2.78***	3.28***	160.6	0.000

Note: The empirical development of NNA across all client segments ($\frac{NNA_t}{AuM_{t-1}}$) and the returns on the average financial portfolio of a PWM client across all segments (R_t) are observed with monthly frequency over the period February 2006 - August 2009. The parameters are estimated by maximizing the log-likelihood (LL) of the following two stochastic processes:

$$\text{Diffusion model (D)} = \mu\Delta t + \sigma\varepsilon_t\sqrt{\Delta t}$$

$$\text{Jump-diffusion model (JD)} = \mu\Delta t + \sigma v_t\sqrt{\Delta t} + Y j_t$$

where μ and σ represent the diffusion drift and volatility parameters, ε_t and v_t are standard normal variables, the jump intensity is given by $j_t \sim Poisson(\lambda)$ and the jump size follows $\ln Y \sim N(\phi, \delta^2)$. For a more detailed description of the maximum likelihood estimation methodology refer to appendix A. JD-D shows the p-value for the log-likelihood ratio test of difference between the two proposed models. *, **, *** means significant at the 10%, 5%, 1% level, respectively.

estimates), the results enable us to compare the proposed stochastic models in equations 4.11 and 4.12 with their alternatives and to verify the consistency and validity regarding the interpretation of each parameter. In particular, the following analysis enables us to answer whether the proposed diffusion (D) model for the NNA process in equation 4.11 is able to capture the dynamics of the NNA process well or whether a jump component adds to the model fit. Similarly, we assess whether the inclusion of a jump component in the specification of the proposed model for the financial market return process in equation 4.12 significantly enhances the model fit compared to a simple diffusion model.

The parameters are calibrated using the log-likelihood maximization method and the estimated incidence of jumps over our sample period (see section 5.1.1). A detailed description of the calibration method and the log-likelihood functions used is provided in appendix A of this document. As a first preliminary test, we compare the empirical arithmetic mean and volatility in table 5.2 to the calibrated parameters of the diffusion model in table 5.4. This allows us to assess the

overall calibration accuracy, since theory suggests that both methods should yield exactly the same parameters. In fact, the deviations are only marginal. We therefore conclude that our sample is large enough to achieve a high degree of calibration accuracy. This result is further substantiated by the fact that nearly all parameters for both models are highly significant and the overall log-likelihood (LL) reported in table 5.4 is high.

On a more detailed level, the results of the stochastic model comparison in table 5.4 show that the diffusion (D) model is better able to capture the dynamics of the NNA process ($\frac{NNA_t}{AuM_{t-1}}$) than the jump-diffusion (JD) model. This is indicated by a higher log-likelihood of the former model compared to the latter for the NNA process. Accordingly, the addition of a jump component to the proposed stochastic model in equation 4.11 does not enhance the fit of the model to the empirical data. We conclude that the incidence of jumps (crisis events) in financial markets does not necessarily lead to extraordinary client asset acquisition and defection events in the PWM industry. While one could argue that the poor performance of clients' financial portfolios during times of financial crisis might lead to extraordinarily high client asset defections, two important factors counteract this effect. First, PWM clients often refrain from reducing their share-of-wallet or from ending the relationship altogether in order to avoid the realization of losses. Second, because all PWM institutions are faced with poor financial market returns during times of financial crisis to more or less the same degree, clients appear to realize that their assets would not necessarily be better off if invested elsewhere. Therefore, unless the financial returns on clients' financial portfolios of a particular PWM institution are significantly below the PWM market average or a particular PWM institution faces other idiosyncratic factors during times of financial turmoil, our results suggest that the incidence of financial market crisis events on its own does not have a significant impact on the NNA process of a PWM provider. As indicated in section 5.2.1, this result corroborates the findings of Horn (2009), who shows that the performance of PWM clients' financial portfolios is only one of many factors determining clients' loyalty.

With regard to the financial market returns process (R_t), the calibration results reported in table 5.4 demonstrate that the inclusion of a jump component in

the stochastic process specification significantly enhances the fit of the model to the empirical data. This is indicated by a substantially higher log-likelihood of the jump-diffusion (JD) model compared to the simple diffusion model. In fact, the log-likelihood test of difference reported in the last column of table 5.4 shows that the increase in log-likelihood from one model specification to the other is significant at the 1% level. We therefore conclude that the proposed stochastic model specification in equation 4.12 dominates the alternative of a simple diffusion model. With respect to the parameter estimates, it is interesting to observe that the significant negative diffusion drift (μ) of the financial market returns process turns positive once we account for jumps, due to the large negative and highly significant jump drift (ϕ). While this highlights the importance of accounting for jumps in the R_t process, the diffusion drift remains surprisingly low, considering that this parameter represents the monthly return on the average PWM client's financial portfolio. We assume that this is a direct consequence of the generally unfavorable financial market development over a large fraction of our sample period. Moreover, by comparing the estimates of the drift and volatility parameters across the NNA and financial market return processes, we conclude that while the NNA process mainly contributes to total AuM growth, the financial market return process mostly causes the development of total AuM to fluctuate. Therefore, economically speaking, the acquisition of new client assets constitutes the primary source of true long-term AuM growth (i.e. value), while financial market returns are the primary risk factor faced by the PWM industry, a fact that is propagated by many practitioners within the industry (Swiss Bankers Association, 2009).

Overall, the results reported in table 5.4 lend support to the models specified in equations 4.11 and 4.12, by illustrating their stochastic dominance over alternative stochastic model specifications as well as their consistency and validity with regard to the interpretation of each parameter.

5.3 Chapter summary

In summary, the first section of this chapter presents the various data sources and the measurement of the variables required for the empirical application of

the proposed CPM model. The main data source for this study is Credit Suisse Wealth Management of the Credit Suisse Group. Thanks to proprietary data on the segment-level development of AuM and NNA, this study is able to put the model assumptions to an empirical test and to calibrate the proposed stochastic models using a real world example. All other required data is from the financial reports of the Credit Suisse Group. The measurement of two specific variables, namely the incidence of jumps over the sample period and the discount rate, is discussed in depth, as it requires further data and analysis.

In a preliminary analysis the empirical data and the related descriptives are presented to the reader, while at the same time confirming the consistency and validity of all assumptions that are put to an empirical test. The test results show that, first, financial market returns on the financial portfolios of PWM clients determine the lion's share of total AuM growth. Nevertheless, the acquisition of new client assets is the primary source of sustainable long-term AuM growth, while financial market returns mainly contribute to the volatility of total AuM growth. Second, the assumption of constant margins is reasonable, considering the low volatility of margins over time, and the level of estimated margins is in line with industry studies. Third, the correlation of the returns on the average financial portfolio of PWM clients (i.e. the R_t process) and European equity market returns is very high, justifying that the dynamics of both time series can be captured by the same stochastic process and supporting the use of European equity market return data to identify the incidence of jumps. In spite of the high correlation with equity returns, portfolio managers at Credit Suisse were able to protect the average client to some degree from the adverse effects of the financial crisis by diversifying the average portfolio into other asset classes. While this finding holds for the entire sample period, it is even more visible when comparing the pre-crisis results to those of the full sample period. The results suggest that portfolio managers altered the composition of the average client portfolio substantially after the first effects of the financial crisis became apparent, significantly lowering the correlation of the average client portfolio with equity market returns. Fourth, while we find a very high correlation of equity market returns and the returns on the average financial portfolio of PWM clients, we find no correlation between equity market returns and the development of NNA, or sim-

ilarly between R_t and the NNA process. In line with our model setup, we can therefore conclude that the acquisition and defection of client assets is not related to the performance of clients' financial portfolios or equity market returns in general and that the dynamics of both subcomponents of total AuM growth are independent of each other. Fifth, we do not find evidence of autocorrelation in the time series of either the development of NNA or the returns on the average financial portfolio of PWM clients. This allows us to employ the proposed stochastic models specified in equations 4.11 and 4.12. Finally, by comparing the empirical calibration results of the proposed stochastic models with alternative specifications, we conclude that the inclusion of a jump component in the specification of the stochastic model for the financial market return process in equation 4.12 significantly enhances the empirical model fit. Moreover, we demonstrate that the incidence of financial market crisis events does not appear to have a significant impact on the client asset acquisition and defection process in the PWM industry, indicating that the performance of PWM clients' financial portfolios is only one of many factors determining clients' loyalty.

Many of these preliminary results are already interesting by themselves and contribute to our understanding of the PWM industry. More importantly, however, they set the stage for the empirical application of the proposed CPM model in the next chapter.

Chapter 6

Results

The last chapter was devoted to presenting the empirical data used in this study and to assess the consistency and validity of the proposed model setup. This chapter builds on the previous one and is dedicated to the actual application of the proposed Customer Portfolio Management (CPM) model to our empirical case. More specifically, we begin our analysis in section 6.1 with a segment-level correlation analysis and then proceed with the calibration of our proposed stochastic models for the NNA and financial market return processes. The calibration results together with the firm-level variables estimated in chapter 5 are employed in section 6.2 to value the portfolio of the empirically observed composition of client segments. Section 6.3 focuses on the application of the proposed optimization algorithm to the existing allocation of firm resources to client segments. A useful extension of the CPM model, namely its application to the problem of evaluating a strategic expansion of the existing customer portfolio into new segments is proposed in section 6.4. Finally, we point out managerial implications of the transition of the existing into the optimal customer portfolio in section 6.5. Section 6.6 concludes by providing a brief chapter summary.

6.1 Model calibration

The calibration of the proposed CPM model involves two separate steps. First, we need to estimate the correlation structure of the NNA and financial market return processes across our wealth and geographic PWM client segments, in order

to generate the required correlated random variables for our proposed stochastic models. Second, the stochastic parameters for the models specified in equations 4.11 and 4.12 need to be calibrated using the segment-level data presented in table 5.1b.

6.1.1 Correlation analysis

The results of the segment-level correlation analysis of the empirical data presented in table 5.1b are reported in table 6.1. The analysis reveals that, although the results for the total AuM growth in table 6.1a are mixed, a very different picture emerges, if the two subcomponents of total AuM growth are analyzed separately. In particular, we find that while the process of client asset acquisition and defection events (i.e. the NNA process) is entirely uncorrelated across segments (see table 6.1b), the opposite is true for the financial market return process as shown by table 6.1c. All the correlation coefficients reported in table 6.1c are positive and highly significant. This finding regarding the segment-level correlation structure of the financial market return process is in line with our expectations formulated in chapter 4. Accordingly, the empirical correlation matrix of table 6.1c is used to generate the correlated random variables required for the Monte Carlo simulation of our financial market return model in equation 4.12. In particular, the correlation matrix ρ^v is set equal to the empirical correlation matrix in table 6.1c. The correlated random variables are generated employing the technique of Cholesky decomposition. For a more detailed discussion of this technique refer to appendix B. Based on the results from our empirical correlation analysis in table 6.1b and the lack of theory indicating otherwise (see chapter 4), we assume that the random variables of the NNA process specified in equation 4.11 are uncorrelated across wealth and geographic PWM client segments.

6.1.2 Stochastic parameter calibration

The segment-level parameters for the models of the NNA and financial market return processes are again calibrated using the maximum likelihood method described in appendix A and the incidence of jumps estimated over our sample period in section 5.1.1. Table 6.2 reports the results. In contrast to the stochastic

Table 6.1: Segment-level correlation analysis

(a) Correlations of $\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}}$.			
Segment	1	2	3
1	1.00		
2	0.38***	1.00	
3	0.49***	0.11	1.00

(b) Correlations of $\frac{NNA_{s,t}}{AuM_{s,t-1}}$.				(c) Correlations of $R_{s,t}$.			
Segment	1	2	3	Segment	1	2	3
1	1.00			1	1.00		
2	-0.12	1.00		2	0.78***	1.00	
3	0.05	-0.12	1.00	3	0.95***	0.74***	1.00

Note: $\frac{\Delta AuM_{s,t}}{AuM_{s,t-1}}$ is the total segment-level AuM growth rate, which can be further divided into the two subcomponents: the segment-level NNA growth rate ($\frac{NNA_{s,t}}{AuM_{s,t-1}}$) and the segment-level financial market returns ($R_{s,t}$). All three growth rates are measured over the period February 2006 - August 2009 with monthly frequency and are based on the empirical data reported in table 5.1b. *, **, *** means significant at the 10%, 5%, 1% level, respectively.

model comparison in table 5.4, the parameter calibration in table 6.2 is performed using the *segment-level* empirical data presented in table 5.1b. Moreover, the calibration results are only reported for the proposed stochastic models, whose statistical dominance has already been demonstrated in the stochastic model comparison in section 5.2.3. The average log-likelihood (LL) of the segment-level model calibration reported in the last column of table 6.2 is high and suggests a good overall fit of our model to the empirical data.

The segment-level model calibration reveals systematic differences across the geographic and wealth segments. Especially the calibration results for the NNA process vary widely across segments and demonstrate the importance of segments 2 and 3 as drivers of the overall firm-level AuM growth. Both segments exhibit a high and significant positive drift parameter (μ) for the client asset acquisition and defection (NNA) process, suggesting average monthly asset growth rates (independent from financial market returns) of 0.66% and 1.21%, respectively. At the same time, both segments, but especially segment 2, exhibit very high volatility parameters (σ). At a first glance, these high volatilities are surprising, given

Table 6.2: Segment-level parameter calibration

Process	Segment	Parameters (in %)					LL
		μ	σ	λ	ϕ	δ	
$\frac{NNA_{s,t}}{AuM_{s,t-1}}$	1	-0.01	0.54***				92.2
	2	0.66***	9.66***				93.7
	3	1.21***	3.34***				95.3
$R_{s,t}$	1	0.30***	2.13***	16.7***	-2.86***	3.66***	160.0
	2	-0.12**	2.19***	16.5***	-1.58***	3.76***	157.6
	3	0.01	2.34***	16.8***	-2.56***	1.65***	158.6

Note: The empirical development of segment-level NNA ($\frac{NNA_{s,t}}{AuM_{s,t-1}}$) and segment-level financial market returns ($R_{s,t}$) are observed with monthly frequency over the period February 2006 - August 2009. The parameters are estimated by maximizing the log-likelihood (LL) of the following two stochastic processes for each segment s :

$$\frac{NNA_{s,t}}{AuM_{s,t-1}} = \mu_s^{NNA} \Delta t + \sigma_s^{NNA} \varepsilon_{s,t} \sqrt{\Delta t} \quad (4.11)$$

$$R_{s,t} = \mu_s^R \Delta t + \sigma_s^R v_{s,t} \sqrt{\Delta t} + Y_s j_t \quad (4.12)$$

where μ_s^{NNA} (μ_s^R) and σ_s^{NNA} (σ_s^R) represent the diffusion drift and volatility parameters of the NNA (financial market return) process for segment s , $\varepsilon_{s,t}$ and $v_{s,t}$ are standard normal variables, the jump intensity is given by $j_t \sim Poisson(\lambda)$ and the jump size follows $\ln Y_s \sim N(\phi_s, \delta_s^2)$. For a more detailed description of the maximum likelihood estimation methodology refer to appendix A. *, **, *** means significant at the 10%, 5%, 1% level, respectively.

that the volatility of the NNA process on the aggregate firm-level is comparably low (see table 5.4). However, because the NNA process is uncorrelated across segments (see table 6.1b) and the relative weights of segments 2 and 3 in the current customer portfolio are low (1.8% and 23%, respectively), the high diffusion volatilities of these segments almost disappear on the aggregate firm-level. Overall, the client asset acquisition and defection (NNA) dynamics of segments 2 and 3 stand in stark contrast to those of segment 1. While the parameters of the NNA process indicate that both segments 2 and 3 are growth segments, segment 1 appears to be a rather mature client segment, characterized by stagnating growth. In particular, segment 1 has a drift parameter insignificantly different from zero and a very low diffusion volatility.

Overall, the calibration results for the financial market return process also reported in table 6.2 are more similar across segments. Nevertheless, we still observe

some major differences in the parameters across segments, reflecting variations in client investment preferences and therefore differences in the portfolio exposure to financial market developments. While the general level of volatility (σ) and, not surprisingly, the intensity of jumps (λ) are very similar across segments, major differences can be observed regarding the diffusion drift (μ) and jump size drift (ϕ) parameters. With respect to these latter two parameters, segment 2 differs most from all other client segments, with a significantly negative diffusion drift parameter and the lowest negative jump size drift parameter. We conclude that this segment is the one most affected by the generally unfavorable financial market developments over a large fraction of the sample period, but at the same time the least affected by the actual crisis events. Overall, these relatively large differences in the financial market return dynamics of segment 2 compared to all other client segments are in line with the results of our segment-level correlation analysis reported in table 6.1c that also shows this segment to differ from the others. The parameters of segment 3 are more similar to the ones of segment 1, the largest difference, in terms of economic relevance, being the insignificant diffusion drift parameter of segment 3. This leads us to the conclusion that the average portfolio of a client belonging to segment 3 is more affected by the generally unfavorable financial market development over our sample period, than the average portfolio of a client belonging to segment 1. The jump parameters, in contrast, suggest that the exposure of segment 1 clients to crisis events is slightly higher compared to those of segment 3.

The segment-level calibration results enable us to assess the attractiveness of individual customer assets within the customer portfolio and illustrate the trade-offs between the different value-relevant characteristics. More specifically, while the various drift parameters allow us to draw conclusions on the ability of a particular client segment to accelerate and enhance cash flows, the various volatility parameters indicate the segment's contribution to the overall volatility of cash flows (Srivastava, Shervani and Fahey, 1998). However, the number of segment-level features and the complexity of their interaction is too high to draw any final conclusions at this point regarding a more optimal allocation of resources across customer assets. Again, this highlights the need for a comprehensive CPM model, like the one developed in this study.

6.2 Valuation of the customer portfolio

We now proceed to valuing the existing customer portfolio by generating the Customer Equity (CE) probability distribution of the empirically observed composition of the customer portfolio. This is done using the correlation structure of the financial market return process reported in table 6.1c and the parameter calibration results presented in table 6.2. In addition to these segment-level parameters that are used to specify equations 4.11 and 4.12, we require a number of inputs that have already been estimated from observable firm-level data in chapter 5 and are summarized in table 6.3. These firm-level parameters are required to transform the projected development of future segment-level AuM into future net cash flows and ultimately into an estimate of CE.

Apart from these empirical inputs, our proposed CPM model setup also requires two simulation parameters that are unobservable and hence cannot be estimated empirically, namely the number of simulations for our Monte Carlo analysis and the planning horizon (H) over which the actual path of cash flow development is modeled.

The number of simulations used to generate the CE probability distribution is set at 1,000 for two reasons: first, this number is regarded as large enough to produce stable and reliable distribution parameters; second, the time consumed by our numerical optimization increases substantially with a higher number of simulations. We also rerun our analysis using 10,000 simulations, but find no significant differences in our results. The planning horizon (H) is specified to be five years (or 60 months). Although, related studies most commonly employ a shorter planning horizon of three years, arguing that the majority of the clients' lifetime value will be captured in this period, these studies use a higher discount rate of 15% p.a. (e.g. Gupta and Lehmann, 2005; Kumar and Shah, 2009; Kumar, Luo and Rao, 2008; Venkatesan, Kumar and Bohling, 2007; Venkatesan and Kumar, 2004). Discounting implies that future cash flows contribute to the overall CE at a diminishing rate. More specifically, employing a discount rate of 15% p.a. implies that cash flows generated three years in the future are already discounted by one-third of their value (i.e. the discount factor reaches 0.66 after three years). Lowering the discount rate lowers the discount factor, suggesting

Table 6.3: Empirical firm-level parameters

Parameter	
Revenue margin (RM)	0.10%
Profit margin (PM)	39.20%
Cash flow margin (CFM)	60.40%
Discount rate (d) p.a.	11.06%
Long-term growth rate (g) p.a.	5.00%

Note: The revenue margin (RM) represents the average management fee earned on AuM over the period of one month, implying an annual management fee of 1.2%.

that a smaller percentage of cash flows is captured after only three years. Since our discount rate is estimated empirically at around 11% p.a., we increase the planning horizon to five years. This will ensure that we capture approximately the same percentage of cash flows as if we were to use a discount rate of 15% p.a. and a planning horizon of three years.

By generating a large number of possible valuation outcomes by means of a Monte Carlo simulation that employs the proposed stochastic models and empirically calibrated parameters, we are able to generate a probability distribution of CE (CE^0), given the currently observed composition of the client segment portfolio (w^0). The process of this Monte Carlo simulation is illustrated in table 6.4, which shows an excerpt of the actual data tables generated during the simulation. The table demonstrates how the projected future segment-level growth rates for the NNA and financial market return processes are transformed into future segment-level AuM estimates that are again used to derive future segment-level net cash flows. These future segment-level net cash flows are then aggregated across all client segments to obtain a stream of future firm-level cash flows that can be used to compute the present and terminal value necessary to derive the final CE estimate. By simulating a large number of possible future growth rate realizations, we are thus able to generate a probability distribution of CE realizations from which we can ultimately infer an expected value and the lower partial moment (LPM). These estimates represent our measures of value and risk for the existing customer portfolio. The equations that are employed in each of these simulation steps are summarized in table 4.1. The full CE probability distribu-

Table 6.4: Monte Carlo simulation

Simulation	Period	Growth rates (in %)						Levels (in million CHF)					
		Segment $\frac{NNA_{s,t}}{ANM_{s,t-1}}$		Segment $R_{s,t}$		Segment $ANM_{s,t}$		Segment $CF_{s,t}$		CF_t		CE	
		1	2	1	2	1	2	1	2	3	3	3	
1	1	1.00	4.87	-2.42	-0.73	2.10	-1.40	14,354	371	4,215	3.40	0.09	1.00
	2	0.35	-6.66	3.02	-0.84	-3.19	-1.42	14,283	334	4,283	3.38	0.08	1.01
	3	-0.04	15.22	-3.32	1.22	-1.38	1.07	14,452	381	4,186	3.42	0.09	0.99
	:	:	:	:	:	:	:	:	:	:	:	:	:
	61	-0.14	-20.10	1.41	-6.49	-5.97	-2.73	20,016	181	8,895	4.74	0.04	2.11
	61	0.37	-4.27	1.07	-0.96	-2.80	-1.18	14,230	322	4,378	3.37	0.08	1.04
2	1	0.70	-6.95	1.02	-3.31	-2.71	-4.93	13,859	291	4,206	3.28	0.07	1.00
	2	0.12	-9.96	2.26	0.50	-0.25	1.47	13,945	261	4,363	3.30	0.06	1.03
	3	0.12	-9.96	2.26	0.50	-0.25	1.47	13,945	261	4,363	3.30	0.06	1.03
	:	:	:	:	:	:	:	:	:	:	:	:	:
	61	-0.21	-4.42	9.39	-0.48	-0.81	-1.53	9,456	83	7,085	2.24	0.02	1.68
	61	:	:	:	:	:	:	:	:	:	:	:	3.94
1000	1	0.01	1.12	1.55	2.68	-0.03	2.55	14,699	351	4,562	3.48	0.08	1.08
	2	-0.19	12.80	5.69	2.37	1.92	2.29	15,020	402	4,926	3.56	0.10	1.17
	3	-0.30	7.59	-1.00	-0.19	0.60	-1.25	14,946	435	4,815	3.54	0.10	1.14
	:	:	:	:	:	:	:	:	:	:	:	:	4.82
	61	-0.37	7.46	4.11	-0.97	0.44	-0.66	11,243	221	4,407	2.66	0.05	1.04
	61	:	:	:	:	:	:	:	:	:	:	:	3.76
		Expected value (in million CHF)						Lower partial moment (in million CHF)					
		260.94						7.45					

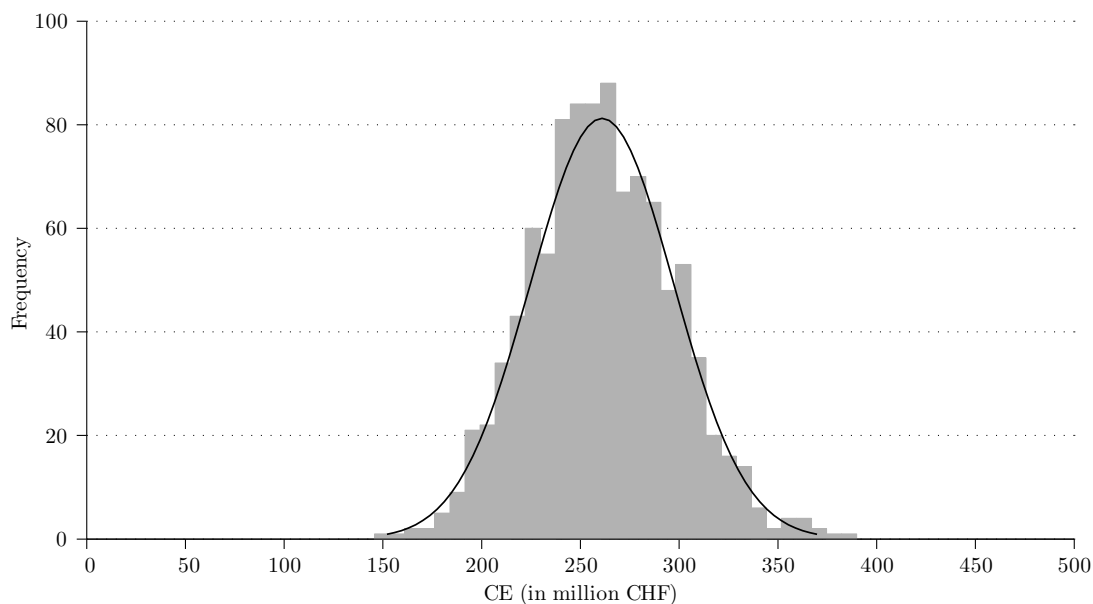
Note: This table illustrates how the probability distribution of CE for the empirically observed customer portfolio composition is generated using simulations. In particular, in each simulation, we generate a time-series of forecasts for the segment-level growth rates $\frac{NNA_{s,t}}{ANM_{s,t-1}}$ and $R_{s,t}$ for the next 61 periods (months) across client segments 1 to 3. The time-series of segment-level growth rates are then transformed into segment-level AuM and net cash flow forecasts. Finally, the segment-level cash flows are aggregated on the firm-level and then discounted and summed over the forecasting horizon in order to arrive at an estimate of CE. By simulating a large number of possible cash flow realizations, we are thus able to infer the expected value and LPM from the probability distribution of CE.

tion of the existing customer portfolio (CE^0) derived from the simulation in table 6.4 is presented in figure 6.1. The corresponding sample distribution parameters are reported in table 6.5a.

The mean of this CE probability distribution can be interpreted as the expected value of the customer portfolio, given its empirically observed client segment composition. Assuming, as pointed out above, that these client segments represent the entire universe of client segments for the firm in question, this value is a good approximation of firm value (Bauer and Hammerschmidt, 2005; Gupta, Lehmann and Stuart, 2004; Kumar and Shah, 2009; Libai, Muller and Peres, 2009; Skiera, Wiesel and Schulze, 2009). Nevertheless, we are unable to assess whether the expected value of CE is in fact a good approximation of firm value for our empirical case study for three reasons. First, the three client segments in our sample only represent a subsample of the firm's customer portfolio. Second, the private wealth management activity is only one business unit within a large group of business units and we are only able to estimate the market value for the entire group. Third, the true level of AuM for each client segment is distorted by an unknown factor.

As pointed out in section 4.2.3 and in contrast to Kumar and Shah (2009), we opt for the LPM instead of the volatility as our measure of risk. This is, because we expect the CE probability distribution to be non-normal and hence non-symmetrical due to the presence of jumps (i.e. downside events) in the valuation model. By visually assessing figure 6.1, we can draw the conclusion that at least minor differences exist between the shaded grey area that represents the probability density of the simulated distribution and the black line, which depicts the probability density of a normal distribution with equal mean and variance. However, the evidence reported in table 6.5 does not support our visual conclusion. More specifically, the sample distribution parameters reported in table 6.5a show that both, the skewness and excess kurtosis of the CE probability distribution of the existing customer portfolio are close to zero, as expected under the assumption of a normal distribution.¹ Moreover, the mean and median of the distribution are almost identical, again indicating normality of the underlying

¹While we expect a sample kurtosis of three for a normal distribution, the excess kurtosis is expected to be zero, because the excess kurtosis equals the sample kurtosis minus three.

Figure 6.1: CE probability distribution for the existing customer portfolio

Note: The shaded grey area represents the probability density of the simulated distribution. The black line depicts the probability density of a normal distribution with mean and variance equal to the one of the simulated distribution.

Table 6.5: Characteristics of the CE probability distribution for the existing customer portfolio**(a)** Distribution parameters.

Distribution parameter	
Mean (in million CHF)	260.94
Median (in million CHF)	259.66
Volatility (in % of mean)	13.91
Skewness	0.16
Excess kurtosis	0.07

(b) Distribution tests of normality.

Test	Statistic	p-value
Jarque-Bera	4.55	0.096
Lilliefors	0.02	0.391
Anderson-Darling	0.44	0.295
χ^2 goodness-of-fit	4.58	0.599

probability distribution. In light of this inconsistency, we conduct a number of formal distribution tests to assess whether and to what extent the empirical distribution departs from normality. The results of these distribution tests (four in total) are reported in table 6.5b. The methodology behind each of them is described in more detail in appendix C. Overall, the results are mixed. On the one hand, the Jarque-Bera test, as the most widely used parametric test of distribution normality, suggests that the hypothesis of normality for the CE probability distribution depicted in figure 6.1 must be rejected at the 10% significance level. On the other hand, the non-parametric tests point in the opposite direction. We therefore conclude that, against our expectations, the departure from normality for the existing portfolio of customer segments is only minor. A possible explanation for this unexpected result is the fact that, while the jump size parameters reported in table 6.2 are both high and significant, the jump frequency is comparably low. This means that over the planning horizon of 5 years, the incidence of jumps is relatively low. Despite the ambiguous evidence for our empirical case at hand, non-normality of the distribution cannot be ruled out. In light of this and because from a theoretical point of view the use of the LPM as a measure of risk is more appropriate in the context of customer portfolios and in the presence of jump events, it remains our risk measure of choice.²

6.3 Optimization of the customer portfolio

After having generated the probability distribution of the value of the *existing* customer portfolio (CE^0), we now turn to applying the optimization algorithm developed in section 4.2 in order to find the composition of client segments (\mathbf{w}^*) that maximizes expression 4.23 and is therefore in line with the preferences of the firm as the risk-averse investor in the customer portfolio. Before proceeding with the actual optimization, the proposed portfolio optimization algorithm requires the specification of five further parameters. These parameters, together with their respective specification, are reported in table 6.6. Because they are unobservable

²The adequacy of LPM as our risk measure of choice is later confirmed in sections 6.3 and 6.4, where we present strong evidence for the absence of normality of the CE probability distribution for portfolio compositions different from the empirically observed one.

Table 6.6: Portfolio optimization parameters

Parameter	
Segment weight tolerance (ξ)	40%
Global minimum segment weight (w^{min})	1%
Global maximum segment weight (w^{max})	98%
Transaction cost factor (c)	15%

and hence cannot be estimated empirically, we discuss their specification in the following.

The segment weight tolerance (ξ) is set at 40%, implying that the optimization algorithm is restricted to search for more optimal client segment portfolio weights within an interval of 40% around the empirically observed segment weights (\mathbf{w}^0). This weight tolerance can be regarded as the maximum possible shift of a segment weight in the context of a one-period portfolio optimization. The global minimum and maximum segment weights (w^{min} and w^{max}) are set at 1% and 98%, respectively. This is deemed to be a reasonable value for the lowest and highest possible segment weights, considering the empirically observed weighting within the customer portfolio. Generally speaking, these parameters are not expected to have a large influence on the results, but for technical reasons their specification is nevertheless a necessity. Using equation 4.18, the resulting lower and upper bounds that restrict the optimization algorithm to search for optimal solutions only in the constructed interval around the empirically observed client segment weights are reported in table 6.7. While these bounds are chosen for illustrative purposes, decision makers at PWM institutions should be able to set meaningful intervals by drawing on their experience and business judgement.

The specification of the transaction cost parameter (c) is substantially more difficult, because in addition to being unobservable, the interpretation of its absolute value is difficult, if not altogether impossible. Moreover, the literature hardly provides any guidance on how to find a reasonable value for it. For illustrative purposes, we specify the transaction cost parameter to be 15%. This means that transaction costs amount to 15% of the sum of total client segment weight shifts and overall CE is reduced by the resulting percentage (e.g. if the sum of segment weight shifts is 20%, 3% of total CE is lost due to transaction costs).

Table 6.7: Client segment weight bounds (in %)

Client Segment	lb	w^0	ub
Segment 1	35.2	75.2	98.0
Segment 2	1.0	1.8	41.8
Segment 3	1.0	23.0	63.0

Note: w^0 is the vector of empirically observed customer portfolio weights. lb and ub represent the vector of lower and upper segment weight bounds, respectively. All figures are in %.

Employing the parameter specifications of table 6.6, the numerical solution to expression 4.23 suggests that the optimal customer portfolio requires a shift of resources among client segments, as reported in table 6.8. This table contrasts the empirically observed and optimal allocation of firm resources to client segments in terms of portfolio weights. Overall, we find that while the weight of segment 1 is substantially reduced by the optimization algorithm, the weight of segment 3 is increased, making the customer portfolio as a whole more balanced. Given the results from the segment-level analysis performed in section 6.1.2, this finding is not surprising. Contrary to segment 1, segment 3 is a growth segment, whose NNA-related AuM growth dominates the one of segment 1 as well as the one of segment 2. Although, segment 1 exhibits a much lower volatility of the NNA process, this fact appears to be less important on the portfolio-level. The reason is that the NNA process is uncorrelated across segments, lowering the impact of the segment-level NNA volatility at the aggregate firm-level substantially, due to large diversification effects for this component of total AuM growth (see results in table 6.1). For the financial market return process, the effect is the opposite. Although, segment 1 clearly exhibits the most favorable return drift, this is relatively less important compared to its high overall contribution to volatility and therefore risk at the portfolio-level. Because, unlike the NNA process, the financial market return process is highly correlated across segments, it is central to identify a combination of client segments whose aggregate volatility is lower. Therefore, the optimization algorithm favors segments with a low return correlation and a low jump size.³ Both of these features are common to segments 2 and

³Since the correlation of jumps across segments is one, a lower jump size is the only way to reduce the cash flow volatility stemming from crisis jumps.

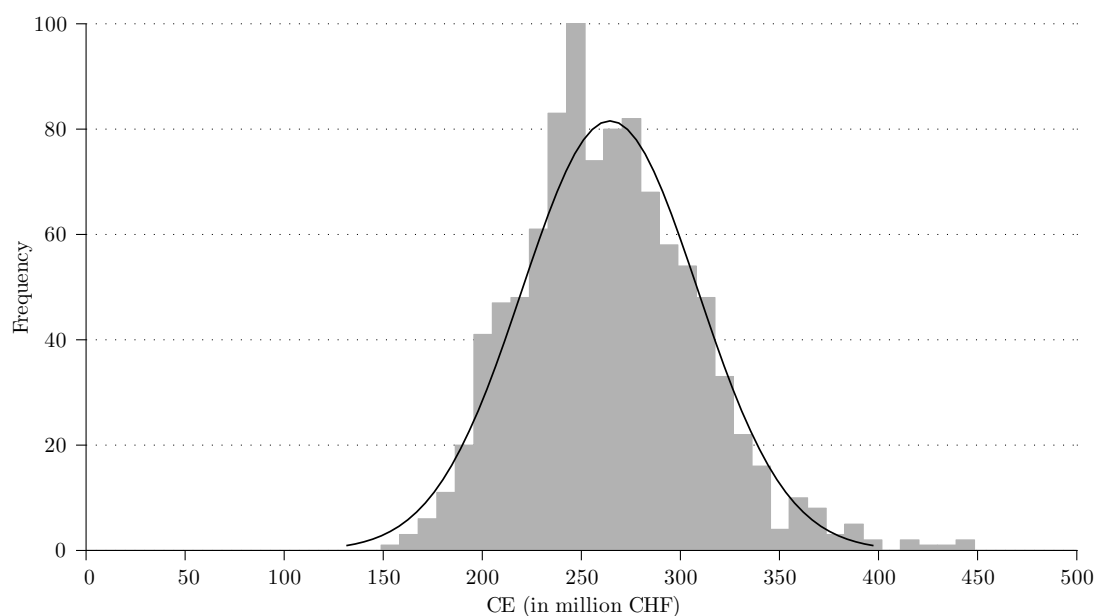
Table 6.8: Client segment weights (in %)

Client Segment	w^0	w^*
Segment 1	75.2	44.2
Segment 2	1.8	1.8
Segment 3	23.0	54.0
Total	100.0	100.0

Note: w^0 and w^* represent empirically observed and optimal customer portfolio weights, respectively. All figures are in %.

3. The overall direction of weight shifting within the portfolio of client segments is therefore consistent with our expectations. Apparently, the very low financial market return correlation of segment 2 with the other two segments and the comparatively low jump size are not sufficient to outweigh the low (or even negative) NNA and return drifts and the very high NNA volatility. Consequently, no additional resources are allocated to segment 2 for the benefit of balancing the overall portfolio. Finally, it is interesting to note that none of the segment weight bounds are reached in the optimization. This result suggests that either the transaction costs of a further shift in segment weights are prohibitive or the level of risk aversion restricts the optimization algorithm in its ability to chose a customer portfolio with higher CE, but also higher risk.

Employing these optimized client segment weights w^* to value the optimal customer portfolio, results in the CE probability distribution (\widehat{CE}^*) shown in figure 6.2. The corresponding distribution parameters are reported in table 6.9a and reveal that compared to the CE distribution for the existing customer portfolio (CE^0), the distribution for the optimal portfolio is shifted to the right. This increases the expected value (net of transaction costs) by 3.5 million CHF or 1.3%. This increase in value already includes a provision for transaction costs of 27 million CHF or 9.3% of the optimized portfolio value. At the same time the dispersion around the expected value of the optimal CE distribution (i.e. the volatility) is higher. This suggests an increase in portfolio risk as measured by the LPM. More specifically, the LPM of the CE probability distribution for the optimal customer portfolio is 7.83 million CHF. Compared to the empirically ob-

Figure 6.2: CE probability distribution for the optimal customer portfolio

Note: The shaded grey area represents the probability density of the simulated distribution. The black line depicts the probability density of a normal distribution with mean and variance equal to the one of the simulated distribution.

Table 6.9: Characteristics of the CE probability distribution for the optimal customer portfolio**(a)** Distribution parameters.

Distribution parameter	
Mean (in million CHF)	264.42
Median (in million CHF)	261.12
Volatility (in % of mean)	16.77
Skewness	0.53
Excess kurtosis	0.69

(b) Distribution tests of normality.

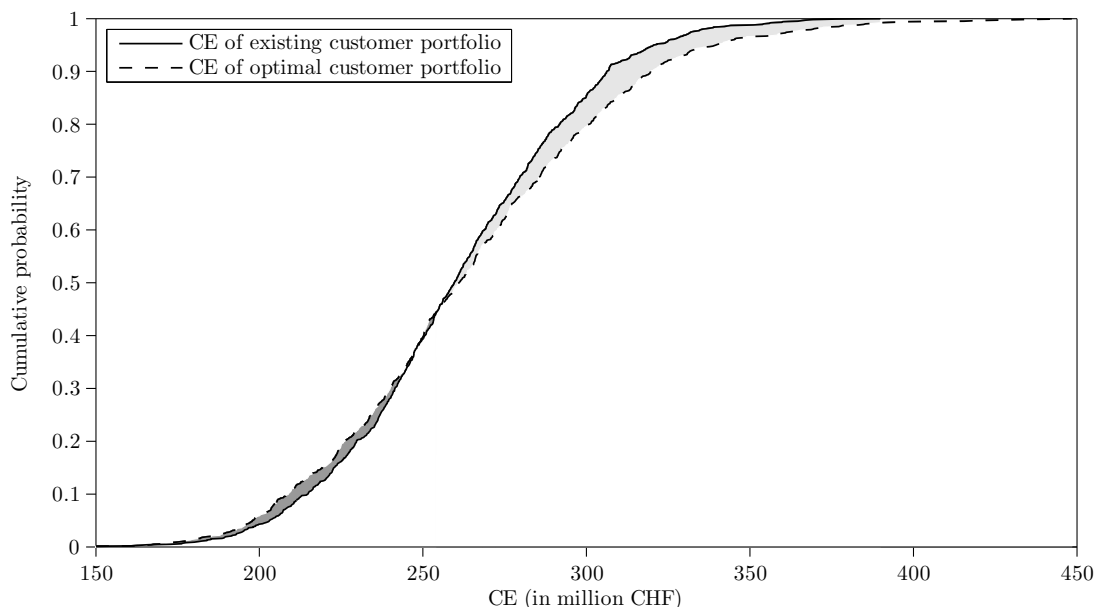
Test	Statistic	p-value
Jarque-Bera	66.61	0.001
Lilliefors	0.04	0.001
Anderson-Darling	2.32	0.000
χ^2 goodness-of-fit	28.93	0.000

served customer portfolio, this is an increase of 0.38 million CHF or 5.1%. The substantial increase in the skewness and excess kurtosis as well as the increase in the difference between the mean and median of the CE distribution are an indication for a more significant departure from normality. The results of all four distribution tests of normality are reported in table 6.9b. As expected, we find that the null hypothesis of distribution normality for the CE probability distribution for the optimal customer portfolio can be rejected at the 1% significance level for all parametric and non-parametric tests. Despite the fact that we were unable to obtain equally consistent results for the empirically observed customer portfolio in table 6.5b, this evidence clearly underlines the need for an alternative, non-parametric measure of portfolio risk such as the LPM in the chosen model setup.

Figure 6.3 presents a direct comparison of the cumulative CE probability distributions of both the existing and the optimal customer portfolios. The figure clearly shows that the optimization of the customer portfolio not only leads to a substantial shift of the cumulative CE probability distribution to the right, but also to a distribution whose increase is less steep due to a higher volatility. Taken together, both effects cause the cumulative CE probability distribution of the optimal customer portfolio to lie above the one of the existing portfolio towards the left tail of the distribution (i.e. the downside) and vice versa towards the right tail of the distribution (i.e. the upside). This implies that both curves cross at a certain CE level, where the cumulative probability of both CE distributions is equal. The areas thus created between the curves of the cumulative distribution for the existing and optimal customer portfolios are dark (light) shaded to the left (right) of the crossing point in figure 6.3. The dark (light) shaded area can be interpreted as the additional losses (gains) of the optimal customer portfolio relative to the existing one, with the area of the gains being approximately 4 times larger than the area of the losses.⁴ Therefore, a substantial increase in the value of the customer portfolio is achieved without a proportional increase in the attached cash flow risk, resulting in higher shareholder value. This lends

⁴By applying trapezoidal numerical integration, we are able to approximate the area under the empirical cumulative probability distribution functions in figure 6.3. This in turn enables us to quantify and compare the areas between the two curves to the left and right of the crossing point.

Figure 6.3: Comparison of the empirical cumulative CE probability distribution for the existing and optimal customer portfolio



Note: The figure compares the cumulative probability distribution of the CE for the existing portfolio of client segments (\mathbf{CE}^0) with the one for the optimal customer portfolio ($\widehat{\mathbf{CE}}^*$). The dark (light) shaded area represents the additional losses (gains) of the optimal customer portfolio relative to the existing one.

further support to the appropriateness of the optimization algorithm as specified in expression 4.23.

While we have established that the difference between the two empirical distributions is economically significant, we would also like to assess the statistical significance of their difference. The parametric t -test, one of the most widely used methods for this purpose, is not appropriate in the case at hand, since it assumes normality of the probability distributions. As the results in tables 6.9b show, normality for both distributions does not hold for the case at hand. Hence, we rely on the Kolmogorov-Smirnov test instead. This test has been proposed by Massey (1951) as a non-parametric alternative to the t -test, which compares the empirical distributions directly without assuming a theoretical probability distribution function. Assuming that the empirical cumulative probability functions of our two sample vectors \mathbf{CE}^0 and $\widehat{\mathbf{CE}}^*$ are given by $F_{\mathbf{CE}^0}(\cdot)$ and $F_{\widehat{\mathbf{CE}}^*}(\cdot)$,

respectively, the Kolmogorov-Smirnov (KS) test statistic for level $x = CE$ can be expressed as:

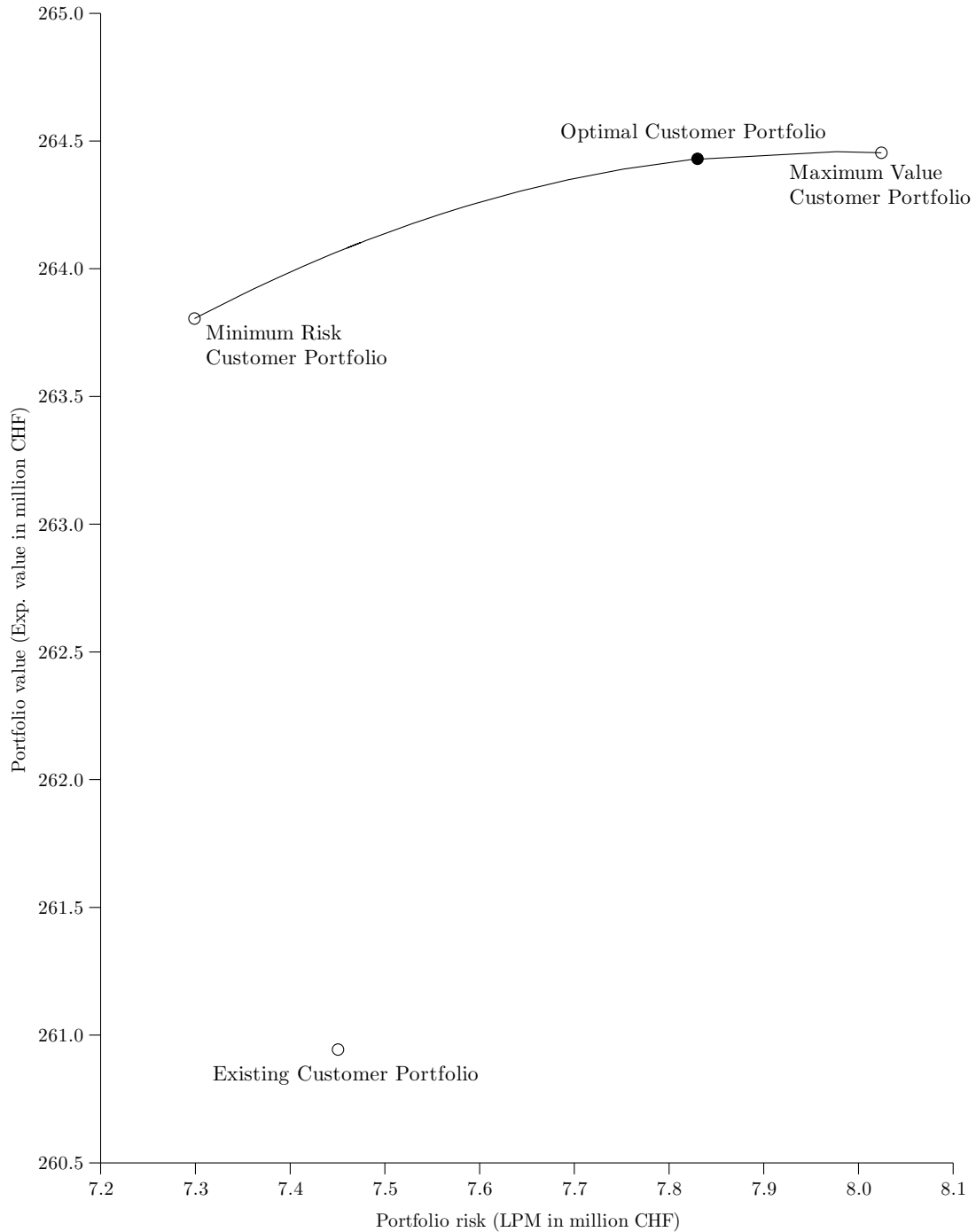
$$KS = \sup_x |F_{CE^0}(x) - F_{\widehat{CE}^*}(x)| \quad (6.1)$$

We find that the CE distributions for the empirically observed and optimal customer portfolios differ significantly, as indicated by a KS test statistic of 0.07, significant at the 1% level. This result can be interpreted as meaning that the largest absolute difference between the cumulative probability of the two distributions is 7% for a given level of CE. We are therefore able to reject the null hypothesis of distribution equality at the 1% level and conclude that the difference between the two empirical distributions is statistically significant. The methodology for inferring the level of significance from a given value of KS is described in appendix C.

Next, we derive the efficient frontier of customer portfolios in the value/risk (M-LPM) space depicted in figure 6.4. In order to generate the M-LPM efficient frontier, we compute the minimum portfolio risk for a given range of customer portfolio values. Similar to Jarrow and Zhao (2006), we implement the following optimization algorithm for this purpose:

$$\begin{aligned} \min_{\mathbf{w}} \quad & \text{LPM}_1^{\text{E}[CE^0]}[\widehat{CE}(\mathbf{w})] \\ \text{s.t.} \quad & \text{E}[\widehat{CE}(\mathbf{w})] \geq \psi \\ & \mathbf{w}'\mathbf{1} = 1 \\ & \mathbf{w} \geq 0 \\ & \mathbf{lb} \leq \mathbf{w} \leq \mathbf{ub} \end{aligned} \quad (6.2)$$

From the universe of all customer portfolios, whose expected values $\text{E}[\widehat{CE}(\mathbf{w})]$ are at least in excess of a given reference level ψ , the optimization algorithm in expression 6.2 selects the minimum LPM customer portfolio. The range of possible reference levels depends on the expected value of the customer portfolio at the lower and upper bound of the efficient frontier. The lower (upper) bound of the efficient frontier is the minimum risk (maximum value) portfolio. The minimum risk portfolio is determined by minimizing the LPM irrespective of

Figure 6.4: M-LPM efficient frontier of customer portfolios

Note: The figure shows the M-LPM efficient frontier of customer portfolios as well as the exact locations of the existing and optimal customer portfolio and the minimum risk and maximum value customer portfolio in the value-risk (M-LPM) space.

the reference level. The maximum risk portfolio is generated by maximizing the expected value of the customer portfolio regardless of the level of risk (i.e. LPM). Expression 6.2 is applied to a range of 100 equally-spaced reference levels that lie between the expected values of the minimum risk and maximum value portfolios in order to generate the efficient frontier in figure 6.4.

Apart from showing the position of the minimum risk and the maximum value customer portfolios that mark the bounds of the efficient frontier, figure 6.4 also indicates the exact locations of the existing and the optimal customer portfolios in the value-risk (M-LPM) space. Not surprisingly, we find that while the optimal customer portfolio is located on the efficient frontier, the existing customer portfolio is positioned far below the frontier. In fact, without increasing the level of portfolio risk relative to the existing customer portfolio, the optimization algorithm is able to find a customer portfolio whose expected value net of transaction costs is substantially higher than that of the existing portfolio.

Analogous to portfolios of financial assets the efficient frontier of customer portfolios shown in figure 6.4 is upward sloping and concave underlining two important characteristics. First, the relationship between risk and value is positive resulting in a true trade-off between risk and value considerations in the optimization. More specifically, the portfolio optimization algorithm is only able to achieve a decrease in the level of portfolio risk by sacrificing a certain amount of expected portfolio value. Similarly, a higher expected value of the customer portfolio can only be reached, if the investor is willing to bear the higher level of attached portfolio risk. Second, the concavity of the efficient frontier indicates the presence of diversification effects in the portfolio optimization. However, the degree of concavity is relatively low. The reason is that segment 2, which promises the largest diversification effects due to its low correlation with segments 1 and 3 (see table 6.1), never reaches a substantial weight in the customer portfolio, because of its otherwise unfavorable risk and value characteristics (see table 6.2).

Given the objective function of the portfolio optimization algorithm specified in expression 4.23, the optimal customer portfolio is located at the exact point on the efficient frontier where the marginal gain in value relative to the marginal increase in risk of the customer portfolio is highest. While this portfolio is generally preferred by the firm as the risk-averse investor in the customer portfolio, the firm

might still choose to invest in a customer portfolio that lies to the left or right of the optimal portfolio along the efficient frontier. Which portfolio is ultimately selected therefore also depends on the level of risk aversion of the particular firm in question.

6.4 Expansion of the customer portfolio

This section shows that, apart from the optimization of the customer portfolio with regard to existing client segments, the proposed CPM model can be extended to also consider the addition of a new client segment to the existing portfolio. In the PWM industry, the growth of institutions into new client segments is an important strategic issue. If, for example, a PWM provider were to expand its operations to a new geographical region or into a new wealth segment, managers would like to assess the potential effect on firm value, the degree to which resources should be dedicated to the expansion plan and the strategic consequences with respect to existing clients. Our CPM model is able to provide managers with answers to these vital questions. More specifically, given a relatively small set of parameters, it is not only able to estimate the value-increasing effect of adding a new segment to the existing portfolio, but also determines the optimal weighting of the new segment and the respective effects on the optimal allocation of resources among existing client segments. This section therefore extends the portfolio selection problem from three to four client segments. This enables us to further illustrate the advantages of our stochastic and dynamic CPM model over conventional, deterministic and static models. The reason is that diversification effects it accounts for become more visible, when the complexity of the resource allocation problem and hence the number of customer assets within the customer portfolio, is higher.

Although this section provides managers with a useful tool to support their decision making regarding the strategic development of firm operations into new client segments, it is important to note that the results are sensitive to the parameter specifications chosen for the new client segment. Because the historic development of AuM is usually unavailable for new client segments, these parameters have to be set to certain levels based on the managers' experience and

business judgement. Because the interpretation of the stochastic parameters for the NNA and financial market return processes are economically straightforward, we believe that it is possible for experienced managers to find a meaningful model specification. Managers are nevertheless cautioned to perform a scenario analysis using a set of parameters that ranges from very pessimistic to very optimistic. This approach effectively generates confidence bounds around the results and enables managers to assess the sensitivity of the results to their parameter choices. In the analysis below, we do not perform such a scenario analysis, as the purpose of this section is to provide the reader with an illustration of potential applications and extensions of the developed CPM model. A more detailed analysis of the issue would only add little value and is outside the scope of this study.

The stochastic parameters for the new client segment for both, the stochastic processes as well as the financial market return correlation structure, are reported in table 6.10. For comparison, we also report the parameters for all existing client segments. In order to illustrate the effect of adding a new client segment to the existing portfolio, we choose a new segment from an emerging market, because our study deals with geographic segments and because an expansion to emerging markets is currently deemed to be a realistic scenario within the PWM industry. Accordingly, the chosen set of parameters is relatively extreme, but still reasonable considering the empirically calibrated parameters for the existing segments. In particular, we specify the NNA process as reflecting a client segment that is characterized by strong growth, but also high growth volatility. This is typical for rather young client segments, whose demand for PWM services is not yet satisfied, as is the case for many emerging markets. Our specification of the financial market return process has a relatively high diffusion drift and volatility term. This reflects the fact that in emerging countries financial markets usually exhibit high expected returns coupled with an exceptionally high volatility. The jump intensity is set equal to the empirically calibrated parameter for the existing segments. The reason is that we assume jumps to affect all client segments at the same time. This assumption is reasonable considering the high degree of integration of today's global financial markets. Nevertheless, while we assume synchrony of the incidence of jumps across client segments, the degree to which segments are affected by jumps is expected to vary substantially cross-sectionally.

Table 6.10: Stochastic parameters of new client segment**(a)** Stochastic process parameters.

Process	Segment	Parameters (in %)				
		μ	σ	λ	ϕ	δ
$\frac{NNA_{s,t}}{AuM_{s,t-1}}$	1	-0.01	0.54			
	2	0.66	9.66			
	3	1.21	3.34			
	new	1.00	6.00			
$R_{s,t}$	1	0.30	2.13	16.7	-2.86	3.66
	2	-0.12	2.19	16.7	-1.58	3.76
	3	0.01	2.34	16.7	-2.56	1.65
	new	0.45	3.00	16.7	-3.70	3.00

Note: $\frac{NNA_{s,t}}{AuM_{s,t-1}}$ and $R_{s,t}$ denote the segment-level NNA and financial market return processes, respectively. The diffusion process component has drift μ and volatility σ . Jumps occur with intensity λ . The average jump size is given by ϕ with volatility δ .

(b) Correlation structure of $v_{s,t}$.

Segment	1	2	3	new
1	1.00			
2	0.78	1.00		
3	0.95	0.74	1.00	
new	0.65	0.75	0.75	1.00

Note: $v_{s,t}$ is the correlated random variable of the diffusion process for the financial market returns $R_{s,t}$.

In the case of the new client segment, we specify a high negative jump size coupled with an average jump size volatility, as crisis events are known to affect the financial markets of emerging nations to an even higher degree than those from developed countries. Finally, we add the new segment to the empirical correlation structure for the diffusion process of $R_{s,t}$ in table 6.10b. We choose relatively moderate correlation coefficients, since returns in emerging markets are expected to be less correlated with developed financial markets (due to the home bias) and the investment styles inherent to the portfolios of PWM client segments from emerging markets are likely to be fundamentally different from the ones of

Table 6.11: Moment-matching results for $v_{s,t}$

Client Segment	RMSE (in %)		
	θ_c	θ_m	θ
Segment 1	2.26	9.89	6.16
Segment 2	3.26	10.03	6.64
Segment 3	2.61	9.95	6.33
New Segment	0.77	0.09	0.63

Note: RMSE=Root-Mean-Squared-Error. θ represents the entire set of matched parameters for the random variable $v_{s,t}$ that can be further subdivided into θ_c and θ_m , which only represent the collection of correlations and distribution moments, respectively. All figures are in %.

developed European markets. All firm-level and optimization parameters are kept constant to ensure comparability of the results to those of the existing customer portfolio optimization in section 6.3.

In order to achieve comparability of the results of the existing and expanded customer portfolio, we cannot rely on the Cholesky decomposition method described in appendix B for generating the required series of correlated random variables for the financial market return process $v_{s,t}$. The reason is that the Cholesky decomposition of the correlation matrix reported in table 6.10b also differs regarding the factor decomposition of existing client segments. As a result, the simulated valuation paths differ from the ones used for the valuation of the existing customer portfolio in section 6.2, producing slight differences in the CE distribution parameters even for a large number of simulations. To overcome these shortcomings, we have to find a series of standard normal random variables that is correlated with the existing segments as specified by the correlation matrix in table 6.10b, without changing the simulated valuation paths of our existing customer assets. This can be achieved by moment-matching, which represents a numerical alternative to the Cholesky decomposition for generating correlated random numbers. In particular, this approach involves the numerical minimization of the distance between the moments (and correlations) of the simulated random numbers and the desired target moments (and correlations). For the purpose of minimization, these distances are typically summarized in a Root-

Mean-Squared-Error (RMSE). Following Hoyland, Kaut and Wallace (2003), the function of the RMSE of these distances can be written as:

$$RMSE = \sqrt{\frac{1}{N_\theta}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)^2} \quad (6.3)$$

where N_θ is the number of parameters to be matched (i.e. the number of distribution moments and correlations) and $\boldsymbol{\theta}$ and $\boldsymbol{\theta}_0$ are the actual and target value of the parameters, respectively. In our case, the number of parameters to be matched (N_θ) is five. More specifically, since we would like to generate a series of standard normal variables for the diffusion process $v_{new,t}$ that satisfies the correlation structure of table 6.10b, we have to match the first and second moment of the distribution (i.e. mean equal to zero and variance equal to one) and three correlation coefficients. The minimization of the RMSE is performed for each simulated valuation path individually and, depending on the desired level of precision, is very time-consuming.⁵ The results of the moment-matching are reported in the last row of table 6.11. For the purpose of comparison, we also report the RMSE of the correlated standard normal random series of the existing client segments that were generated using Cholesky decomposition. The results show that, while the numerical moment-matching algorithm is much less efficient, it is able to match the actual to the desired target parameters with higher precision. This is especially the case when looking at the RMSE of the distribution moments only, but is also true for the RMSE of the correlation coefficients. The RMSE of $v_{s,t}$ of the new client segment calculated over all matched parameters is on average ten times lower than the one for any of the existing segments.

The optimal allocation of resources after the addition of the new segment (\boldsymbol{w}^* new) is reported in the last column of table 6.12. For comparison, we also show the empirically observed segment weights of the existing customer portfolio prior to the optimization (\boldsymbol{w}^0), as well as the optimal resource allocation without the addition of the new segment but after the optimization performed in section 6.3 (\boldsymbol{w}^* old). Overall, we find the general direction and size of the resource shifting activity among the existing client segments to be relatively similar, regardless

⁵We allow the minimization algorithm a maximum of 50,000 iterations to converge to the lowest possible RMSE. The minimization algorithm is stopped, if the speed of conversion of the RMSE falls below a value of 10^{-6} .

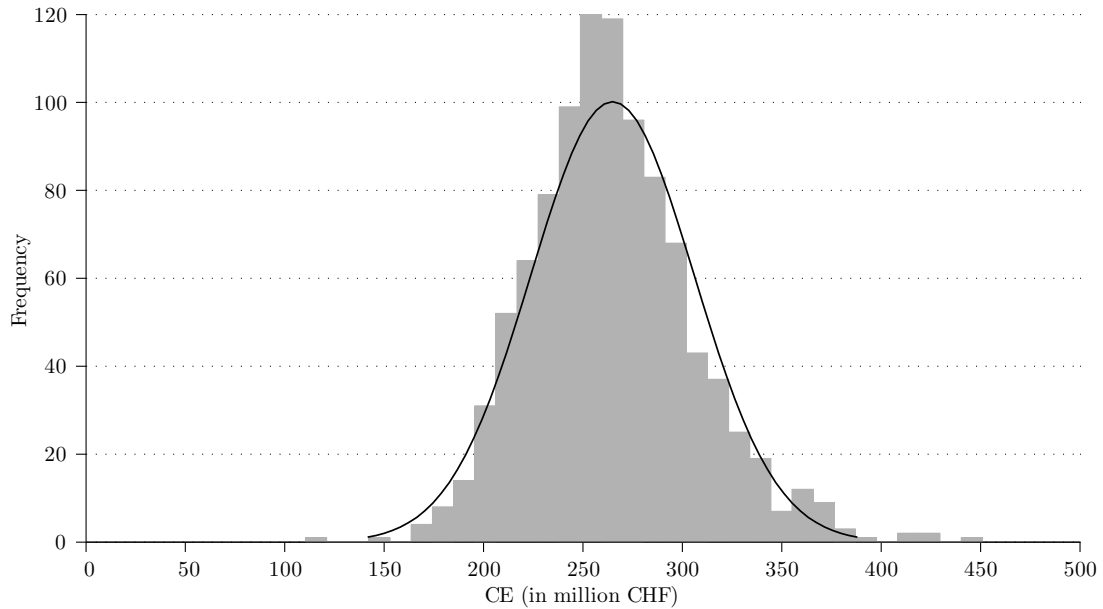
Table 6.12: New client segment weights (in %)

Client Segment	w^0	w^*	
		old	new
Segment 1	75.2	44.2	42.6
Segment 2	1.8	1.8	1.8
Segment 3	23.0	54.0	34.8
New Segment	0.0	0.0	20.8
Total	100.0	100.0	100.0

Note: w^0 and w^* represent empirically observed and optimal customer portfolio weights, respectively. All figures are in %.

of whether the new segment is added or not, underlining the robustness of the optimization results of the proposed CPM model. Moreover, the last column of table 6.12 suggests that a weight of 20.8% for the new segment within the expanded customer portfolio is optimal. To achieve this weighting, the optimization algorithm reduces the weight of segment 1 even further than for the optimal portfolio of existing customer segments. At the same time, the increase in the weight of segment 3 is substantially lower compared to the optimal portfolio of existing customer assets. As pointed out above, the weight of segment 2 remains unchanged due to its overall unfavorable value and risk characteristics.

The CE probability distribution for the optimal composition of the expanded customer portfolio is depicted in figure 6.5 along with its respective characteristics in table 6.13. It is interesting to note that the addition of the new client segment hardly contributes to an increase in overall portfolio value compared to the optimal portfolio of existing customer segments. In particular, relative to the optimal existing customer portfolio, the expected value of the expanded customer portfolio is only higher by approximately 0.5 million CHF. At a first glance, this result is unexpected given the high drift parameters of both the NNA and the financial market return processes for the new customer segment reported in table 6.10a. However, at closer inspection the only modest increase in portfolio value can be explained by the following reasons. First, the increase in the weight of the new customer segment is mainly achieved at the expense of segment 3, which is the portfolio's main source of NNA growth. Second, the provision for transaction

Figure 6.5: CE probability distribution for the optimal expanded customer portfolio

Note: The shaded grey area represents the probability density of the simulated distribution. The black line depicts the probability density of a normal distribution with mean and variance equal to the one of the simulated distribution.

Table 6.13: Characteristics of the CE probability distribution for the optimal expanded customer portfolio**(a)** Distribution parameters.

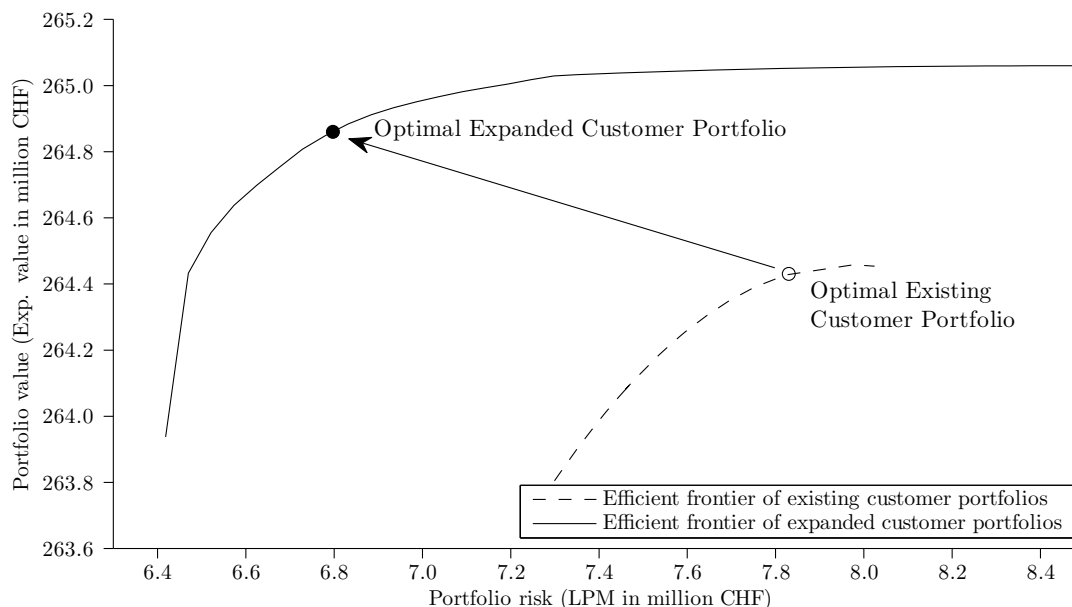
Distribution parameter	
Mean (in million CHF)	264.86
Median (in million CHF)	261.41
Volatility (in % of mean)	15.50
Skewness	0.52
Excess kurtosis	1.05

(b) Distribution tests of normality.

Test	Statistic	p-value
Jarque-Bera	90.39	0.001
Lilliefors	0.05	0.001
Anderson-Darling	3.21	0.000
χ^2 goodness-of-fit	29.14	0.000

costs is substantial with more than 28 million CHF (almost 10% of the expected portfolio value). Finally, the high drift parameters of the new segment are partly compensated by its large negative jump size parameter. Hence, the lack of additional portfolio value generated by the expansion of the customer portfolio does not come as a surprise. Nevertheless, while the addition of the new client segment adds little to the expected value of the overall customer portfolio, it does contribute significantly to lowering overall portfolio risk. More specifically, compared to the optimal portfolio of existing customer segments the LPM of the optimal expanded customer portfolio is lower by more than 1 million CHF or by more than 13%. Despite the high volatility parameters for both the NNA and financial market return processes of the new client segment (see table 6.10a), the low correlation of the financial market return process with existing client segments, as specified for the new segment in table 6.10b, is able to significantly lower overall portfolio risk. This finding highlights the importance of accounting for customer dynamics in the valuation and optimization of customer portfolios. Moreover, it demonstrates that substantial diversification effects can be realized from holding a balanced portfolio of customer assets.

The extent to which the optimal expanded customer portfolio dominates the optimal existing customer portfolio can best be demonstrated by figure 6.6, which shows the position of both portfolios in the value-risk (M-LPM) space. The arrow indicates that relative to the optimal existing customer portfolio, the optimal expanded customer portfolio is significantly shifted to the left (towards lower portfolio risk) and lies slightly higher (towards higher portfolio value). The same is also true for the entire frontiers of efficient customer portfolios that are also depicted in figure 6.6. Consequently, the firm, as the risk-averse investor in the customer portfolio, is able to select an expanded customer portfolio that achieves significantly lower overall risk for a given level of portfolio value. More importantly, with the addition of the new client segment, the concavity of the efficient frontier of expanded customer portfolios is substantially higher compared to the one of existing customer portfolios. Again, this demonstrates that the firm is generally able to realize much higher diversification effects when investing in the expanded customer portfolio rather than in the portfolio of existing client segments. Therefore, we conclude that the firm would prefer the optimal customer

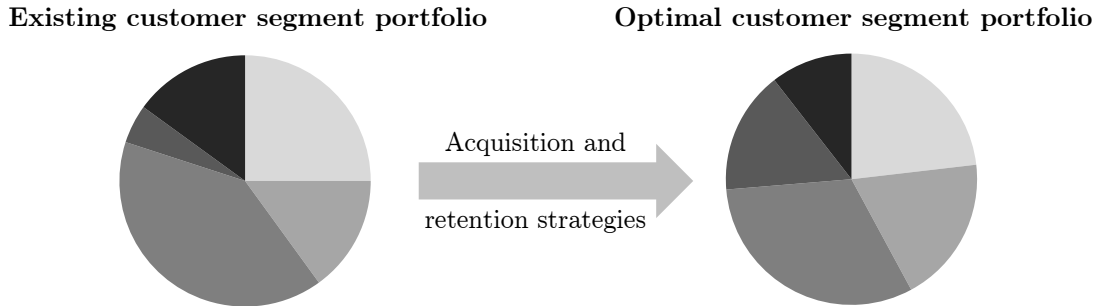
Figure 6.6: Comparison of M-LPM efficient frontier of customer portfolios

Note: The figure shows the position of the M-LPM efficient frontier of expanded customer portfolios relative to the one of portfolios of existing client segments. The figure also indicates the exact locations of the optimal existing and expanded customer portfolio in the value-risk (M-LPM) space.

portfolio with the expansion into the new client segment over the optimized composition of existing client segments, in order to maximize shareholder value.

6.5 Managerial implications

Once the optimal customer segment portfolio weights \mathbf{w}^* are determined, managers have to formulate resource allocation strategies regarding the firm's customer acquisition and retention efforts to transform the existing portfolio of customers into the optimal one, as visualized by figure 6.7. The problem here is that, unlike financial assets, customer assets are not very liquid and the achievement of optimal customer weights in the short-term is hardly possible. This is especially true in the PWM industry that relies on relatively few, long-lasting, trustful and personal relationships. As a medium- to long-term goal, however, the achievement of these optimal client segment weights is very desirable for PWM providers, because it gives them a strategic direction for growth and promotes

Figure 6.7: Customer segment portfolio transition (schematic)

a structured and analytical approach to the management of client relationships. Because the time horizon of the customer portfolio transition is expected to be long, it is important to reevaluate the CPM model continuously. This enables managers to consider unexpected changes in the operational environment that are relevant for the valuation of customer assets.

Although, it is beyond the scope of this study to provide an extensive overview of possible acquisition and retention strategies developed by the marketing discipline, we now turn to a brief discussion of recent findings in the related literature that can be viewed as a rough guide for managers.

In the customer valuation and management literature, the problem of transferring the empirically observed (i.e. the existing) into the optimal customer portfolio is usually addressed with so called customer prioritization and selective resource allocation strategies that consist of concentrating the firm's customer acquisition and retention efforts on those customers that are most valuable. Besides targeting the right customers, the focus of these resource allocation models is to provide guidance to decision makers in order to achieve the optimal blend of marketing mix elements and the optimal balance between acquisition and retention expenditures. Prominent examples within this literature are Reinartz, Thomas and Kumar (2005), Venkatesan and Kumar (2004), Pfeifer (2005) and Bhatnagar, Maryott and Bejou (2007). As Homburg, Droll and Totzek (2008) and Kumar and Shah (2009) show, such prioritization strategies can significantly increase the value of a firm, even without considering potential value dynamics. In a very recent article, Homburg, Steiner and Totzek (2009) find that explicitly

accounting for the dynamics between segments can increase the positive impact of such prioritization strategies even further.

However, it is important to note that while such strategies might lead to the preferential treatment of some particularly valuable customers or customer segments, they also automatically lead to a reduction of resources available for and committed to less valuable segments. The latter often respond with substantial dissatisfaction that can have significant adverse effects for the firm. Hence, prioritization strategies always have to be implemented carefully. More specifically, managers should attempt to achieve the customer portfolio transition by increasing the weight of the most valuable segments, rather than actively trying to reduce the weight of the less valuable ones. This, of course, implies growth in the overall capacity to service customers and is not always a feasible option depending on the particular industry. In the case of the PWM industry, the capacity to service clients is generally very flexible, as the product offering is easily scalable and providers are mostly only constrained by their number of relationship managers that usually service a certain amount of AuM. Nevertheless, whenever an increase in the firm's capacity is infeasible or undesirable, one can still resort to the option of active relationship dissolution strategies (also called customer divestment), in order to achieve the desired customer portfolio weighting. Although only few studies have examined the effect of these strategies, the results point in the same direction. In particular, Mittal, Sarkees and Murshed (2008), Mittal and Sarkees (2006) and Helm (2004) find that while such strategies are certainly viable, the required processes are often very costly and can only be implemented over long time horizons. Furthermore, the literature on word-of-mouth effects has established that depending on the size of the personal networks and the degree of opinion leadership of dissatisfied customers, substantial adverse effects can arise for the firm via negative word-of-mouth (e.g. Anderson, 1998; Richins, 1983). In spite of the fact that we have already anticipated these effects to some degree in our optimization algorithm by provisioning for transaction costs, the size of these effects might still be larger than expected. If the discontinuation of some customer relationships cannot be avoided, Haenlein and Kaplan (2009) provide a number of useful recommendations on how to break up with customers in the least painful way.

6.6 Chapter summary

This chapter demonstrates the actual application of the proposed Customer Portfolio Management (CPM) model to our empirical case. In particular, the model calibration performed in the first section of this chapter illustrates how the proposed stochastic processes for the valuation of the customer portfolio are calibrated employing our segment-level empirical sample data. The empirical segment-level correlations are in line with our expectations expressed in chapter 4 and show that while the client asset acquisition and defection process is uncorrelated across segments, the returns on the average financial portfolio of PWM clients within one segment are highly correlated across segments, with the level of correlation differing across segment pairs. Furthermore, the calibration of the stochastic parameters indicates that the proposed stochastic models fit the empirical data well and are thus by and large able to capture the process dynamics of the two components of total AuM growth. Besides this, the parameter values reveal systematic differences across the geographic and wealth segments regarding both, growth from new asset acquisitions and financial market returns.

Employing the calibrated stochastic processes, we are able to value the empirically observed customer portfolio by generating a probability distribution of Customer Equity (CE) by means of Monte Carlo simulation. Given the probability distribution of the existing customer portfolio, we then turn to the application of our proposed optimization algorithm to find the composition of client segments that maximizes shareholder value. The optimization results show that by holding a more balanced portfolio of client segments, a substantial increase in the value of the customer portfolio can be achieved without a proportional increase in the attached cash flow risk, resulting in higher shareholder value. Moreover, the analysis of the derived CE probability distributions corroborates our choice of a non-parametric measure of portfolio risk in order to account for the significant departures from distribution symmetry. We are also able to demonstrate that the efficient frontier of customer portfolios is upward sloping and concave. The former characteristic indicates that the relationship between risk and value is positive, resulting in a true trade-off between risk and value considerations in

the optimization of customer portfolios. The concavity of the efficient frontier, on the other hand, indicates the presence of diversification effects.

Next, we illustrate a potential application or extension of the proposed CPM model, namely the evaluation of a strategic expansion of the operations of a PWM provider into a new client segment. Given a relatively small set of parameters, we demonstrate that the model is not only able to estimate the value-increasing (or risk-reducing) effect of adding a new segment to the existing customer portfolio, but also determines the optimal weighting of the new segment within the existing portfolio and the respective effect on the optimal allocation of resources among existing client segments. Moreover, the results demonstrate that substantial diversification effects can be realized by expanding the portfolio into new client segments, whose financial market return correlations with existing client segments are low. Again, this highlights the importance of accounting for customer dynamics in the valuation and optimization of customer portfolios and further illustrates the advantages of our stochastic and dynamic CPM model over conventional, deterministic and static models.

We devote the last section of this chapter to the discussion of managerial implications regarding the transition of the existing into the optimal customer portfolio. Although, an extensive review of the literature is out of the scope of this study, we briefly introduce the reader to different customer acquisition and retention strategies that have been proposed throughout the academic literature. These strategies should guide decision makers in the formulation of resource allocation strategies in order to make the transition less costly for the firm.

Chapter 7

Conclusion

In summary, our study develops a comprehensive Customer Portfolio Management (CPM) model that enables a firm to identify the shareholder value-maximizing customer portfolio and guides managers in their resource allocation decisions regarding customer acquisition and retention strategies. The theoretical model development draws on the most recent findings throughout the related literature, in order to extend the concept of customer-based firm *valuation* to customer-based firm value *optimization*. This is achieved by applying reduced-form stochastic models to capture the dynamics of the customer value generation process, as well as by applying financial portfolio selection theory to the problem of managing customer portfolios. Since the customer value generation process is very industry-specific, the study chooses to develop the CPM model in the context of the private wealth management (PWM) industry. The model is not only highly relevant to decision makers within this industry as a tool to guide marketing strategy, but also for risk management purposes.

Employing a set of proprietary client segment-level data from one of the world's largest PWM institutions, the study is able to apply the proposed theoretical CPM model to an empirical case. In a preliminary analysis of the data and in the course of our empirical application, we are able to validate all assumptions made during our theoretical model development. The results from our empirical application confirm that the proposed CPM model is able to identify the customer portfolio that maximizes value and at the same time accounts for the risk preferences of the firm as the investor in the customer portfolio. Furthermore, our

results demonstrate that the firm can realize substantial diversification effects, arising from the value dynamics across different customer assets, by holding a balanced customer portfolio. This allows the firm to increase the expected value of the customer portfolio with a lower than proportional increase in the attached cash flow risks. We conclude that managers can realize substantial benefits in terms of shareholder value by basing their resource allocation decisions regarding customer acquisition and retention strategies on the results of the proposed CPM model. Finally, our study shows that the proposed CPM model cannot only be employed to optimize the existing portfolio of customer assets, but can also be used to support the strategic decision-making process regarding the expansion of the customer portfolio.

Our results suggest that marketing strategy is more closely related to a firm's risk management than is often realized by managers in practice. This has long been well understood in the retail banking business, where customer acquisition and retention decisions are often based on credit scoring models (i.e. risk assessments). The PWM industry along with most other consumer industries, on the other hand, lacks appropriate mechanisms to ensure that marketing efforts are not only driven by value considerations, but equally by the overall level of risk attached to the realization of future cash flows. Furthermore, the results of our study imply that it is not optimal to make these value and risk considerations on the level of the individual customer or customer segment. Instead, the firm is better off by evaluating the contribution of each customer or customer segment to the overall value and risk of the customer portfolio at the firm-level. Only then do potential diversification effects from holding a balanced portfolio of customer assets become visible.

Our results should be interpreted with caution. First and foremost, the case study approach limits the generalizability of the results of the empirical application to other firms. Second, for confidentiality reasons, we are unable to disclose the true composition of the client portfolio in our empirical case study, as well as the exact wealth and geographic segmentation criteria used to derive client segments. This limits our ability to interpret the results and validate their economic intuition. Moreover, due to the sensitivity of the data, we have to refrain from employing segment-specific revenue and profit margins in the empirical applica-

tion of our CPM model. Finally, the model calibration results are influenced by the effects of the financial crisis over our sample period, implying that slightly different calibration results may be obtained in the absence of financial turmoil.

Besides addressing some of the limitations of this study, more research is warranted to help us better understand and tackle the problem of valuing and optimizing portfolios of customer assets. Future research efforts should be directed towards the development of a similar CPM model in the context of a different, preferably nonfinancial services industry. This would require the adaptation of the dynamic customer-based firm valuation model to capture the characteristics of the customer value generation process of that particular industry. By doing this, researchers could demonstrate whether the applicability of financial portfolio selection theory is restricted to industries, where customer value is largely dependent on financial market developments. Another avenue for future research is the refinement of the portfolio optimization algorithm itself, such as the development of a dynamic optimization framework that explicitly provides for a stochastic investment opportunity set. Although, this extension would substantially increase the complexity of the CPM model, it would also allow for the inclusion of time-varying customer value parameters that, depending on the specific context, could better reflect the true underlying value dynamics within the customer portfolio.

Part III

Appendix

Appendix A

Maximum Likelihood Estimation

The model parameters of this study are calibrated using the maximum likelihood estimation method, employing the log-likelihood functions proposed by Jorion (1988). Let us assume that the probability density function of a vector of observations $\mathbf{x} = \{x_1, \dots, x_T\}$ (which in our case is equal to the observations of either $NNA_{s,t}/AuM_{s,t-1}$ or $R_{s,t}$), conditioned on a set of parameters $\boldsymbol{\theta}$, is denoted by $f(\mathbf{x} | \boldsymbol{\theta})$. This function not only identifies the data generation process behind an observed sample of data, it also provides a mathematical description of the data the process will produce. Assuming that \mathbf{x} is independently and identically distributed (i.i.d.), the joint density is equal to the product of the individual densities and can be expressed as:

$$f(x_1, \dots, x_T | \boldsymbol{\theta}) = \prod_{t=1}^T f(x_t | \boldsymbol{\theta}) = L(\boldsymbol{\theta} | \mathbf{x}) \quad (\text{A.1})$$

This joint density is the likelihood function $L(\cdot)$, defined as a function of the unknown parameter vector $\boldsymbol{\theta}$, conditional on the vector of sample observations \mathbf{x} . For simplicity reasons, it is common to work with the logarithm of the likelihood function. The reason is that while the likelihood function $L(\cdot)$ is equal to the repeated product of densities, the log-likelihood function $\ln L(\cdot)$ is equal to its sum and can thus be written as:

$$\ln L(\boldsymbol{\theta} | \mathbf{x}) = \ln f(x_1, \dots, x_T | \boldsymbol{\theta}) = \sum_{t=1}^T \ln f(x_t | \boldsymbol{\theta}) \quad (\text{A.2})$$

If we assume that the time series of observations in the vector \mathbf{x} follows a diffusion process (D) and is therefore normally distributed with constant mean μ and constant variance σ^2 , the log-likelihood function $\ln L_D(\boldsymbol{\theta} \mid \mathbf{x})$, viewed as a function of the parameter vector $\boldsymbol{\theta} = \{\mu, \sigma^2\}$, can be written as:

$$\ln L_D(\boldsymbol{\theta} \mid \mathbf{x}) = -\frac{T}{2} \ln(2\pi) + \sum_{t=1}^T \ln \left[\frac{1}{\sqrt{\sigma^2}} \exp \left(\frac{-(x_t - \mu)^2}{2\sigma^2} \right) \right] \quad (\text{A.3})$$

We now turn to the case when the observation vector \mathbf{x} is assumed to follow a mixed jump-diffusion process (JD). In that case, Jorion (1988) proposes to add a Poisson process to the log-likelihood function above, where the jump intensity is λ (i.e. the mean number of jumps per period t) and the jump size Y has a posited distribution of $\ln Y \sim N(\phi, \delta^2)$. The parameter vector is therefore extended to $\boldsymbol{\theta} = \{\mu, \sigma^2, \lambda, \phi, \delta^2\}$ and the log-likelihood function $\ln L_{JD}(\boldsymbol{\theta} \mid \mathbf{x})$ becomes:

$$\begin{aligned} \ln L_{JD}(\boldsymbol{\theta} \mid \mathbf{x}) = & -T\lambda - \frac{T}{2} \ln(2\pi) \\ & + \sum_{t=1}^T \ln \left[\sum_{j=0}^{\infty} \frac{\lambda^j}{j!} \frac{1}{\sqrt{\sigma^2 + \delta^2 j}} \exp \left(\frac{-(x_t - \mu - \phi j)^2}{2(\sigma^2 + \delta^2 j)} \right) \right] \end{aligned} \quad (\text{A.4})$$

Because we collect weekly equity returns to create the time series of jumps and the unit of time in this study is monthly, the maximum number of jumps that can occur per unit of time is 4. Hence, the infinity sum is truncated at that value in order to be able to numerically optimize the above function.

The maximum likelihood method estimates the true parameter vector $\boldsymbol{\theta}_0$ by finding the value of $\boldsymbol{\theta}$ from the parameter space Θ that maximizes $\ln L(\boldsymbol{\theta} \mid \mathbf{x})$. This value of $\boldsymbol{\theta}$ is the maximum likelihood estimator (MLE) of $\boldsymbol{\theta}_0$ and is denoted by $\hat{\boldsymbol{\theta}}$:

$$\hat{\boldsymbol{\theta}} = \arg \max_{\boldsymbol{\theta} \in \Theta} \ln L(\boldsymbol{\theta} \mid \mathbf{x}) \quad (\text{A.5})$$

The covariance matrix of the MLE is estimated from the inverse of the information matrix \mathbf{I} . The information matrix contains the expected values of

the second-order derivatives of the log-likelihood function evaluated at the true parameter vector $\boldsymbol{\theta}_0$ and is given by:

$$[\mathbf{I}(\boldsymbol{\theta}_0)]^{-1} = \left\{ -E_0 \left[\frac{\partial^2 \ln L(\boldsymbol{\theta}_0)}{\partial \boldsymbol{\theta}_0 \partial \boldsymbol{\theta}'_0} \right] \right\}^{-1} \quad (\text{A.6})$$

As $\boldsymbol{\theta}_0$ is usually unknown, it can be approximated by $\hat{\boldsymbol{\theta}}$, which should be equivalent asymptotically. However, the second-order derivatives of the log-likelihood function, also known as the Hessian matrix \mathbf{H} , are almost always complicated nonlinear functions of the observations, whose exact expected values are also unknown. Therefore, a second estimator is computed using the actual (not the expected) Hessian matrix, yielding:

$$[\hat{\mathbf{I}}(\hat{\boldsymbol{\theta}})]^{-1} = \left(-\frac{\partial^2 \ln L(\hat{\boldsymbol{\theta}})}{\partial \hat{\boldsymbol{\theta}} \partial \hat{\boldsymbol{\theta}}'} \right)^{-1} \quad (\text{A.7})$$

Because the Hessian matrix and its inverse are symmetric, the variances and therefore also the standard errors of the MLE can be found on the main diagonal. There even exists a third method for estimating the covariance matrix of the MLE.¹ However, it tends to be less reliable for small and moderate sized finite samples as is the case in our study and is hence not employed.

¹This estimator is known as the BHHH estimator (named after the authors Berndt, Hall, Hall and Hausman, who developed the estimator in 1974) or the outer product of gradients (OPG) estimator.

Appendix B

Generating Correlated Random Variables

Suppose that $\mathbf{V} = \{V_1, \dots, V_N\}$ is a random vector. Then Σ , the covariance matrix of \mathbf{V} , is the $(N \times N)$ matrix, whose $(i, j)^{th}$ element is given by $\Sigma_{i,j} = \text{Cov}(V_i, V_j)$.

The problem of generating a vector of random normal variables with mean zero and specified correlation structure Σ can then be formulated as generating \mathbf{V} , such that $\mathbf{V} \sim MN(0, \Sigma)$, where MN is the multivariate normal distribution.

Now suppose that we generate a set of random variables Z_i that are independently and identically distributed with $Z_i \sim N(0, 1)$ for $i = 1, \dots, N$. Then it can be easily shown that:

$$C_1 Z_1 + \dots + C_N Z_N \sim N(0, \sigma^2) \quad (\text{B.1})$$

where $\sigma^2 = C_1^2 + \dots + C_N^2$. That is, a linear combination of normal random variables is again normal. More generally, let \mathbf{C} be an $(N \times N)$ matrix and let $\mathbf{Z} = \{Z_1 \ Z_2 \ \dots \ Z_N\}'$. Then:

$$\mathbf{C}'\mathbf{Z} \sim MN(0, \mathbf{C}'\mathbf{C}) \quad (\text{B.2})$$

so that the problem reduces to finding \mathbf{C} , such that:

$$\mathbf{C}'\mathbf{C} = \Sigma \quad (\text{B.3})$$

If the covariance matrix Σ is symmetric so that $\Sigma' = \Sigma$, the diagonal elements satisfy the condition $\Sigma_{i,i} \geq 0$ and the matrix is positive definite implying that $V'\Sigma V > 0$ for all $V \in \mathbb{R}^n \neq 0$, it may be written as:

$$\begin{aligned}\Sigma &= U'DU \\ &= (U'\sqrt{D})(\sqrt{D}U) \\ &= (\sqrt{D}U)'(\sqrt{D}U)\end{aligned}\tag{B.4}$$

where U is an upper triangular matrix and D is a diagonal matrix. The matrix $C = \sqrt{D}U$ therefore satisfies $C'C = \Sigma$ and is called the Cholesky decomposition of Σ .

Appendix C

Distribution Tests of Normality

The most popular test for the normality of a probability distribution is a test developed by Bera and Jarque (1980). The Jarque-Bera test statistic (JB) is a parametric goodness-of-fit measure of departure from normality, based on the standardized sample skewness (γ) and kurtosis (κ) of a distribution. For an empirical distribution of $\mathbf{x} = \{x_1, \dots, x_N\}$, it can be written as:

$$JB = \frac{N}{6} \left(\gamma^2 + \frac{(\kappa - 3)^2}{4} \right) \quad (\text{C.1})$$

where the standardized sample skewness (γ) and kurtosis (κ) are calculated as:

$$\gamma = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^3}{\left[\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \right]^{3/2}} \quad ; \quad \kappa = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^4}{\left[\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \right]^2} \quad (\text{C.2})$$

The JB test statistic has an asymptotic χ^2 distribution with two degrees of freedom and can be used to test the null hypothesis that the data is drawn from a normal distribution.

Although the Jarque-Bera test statistic is the most widely used test for the normality of a given probability distribution, it has often been criticized for its dependence on parametric assumptions. Therefore, we also implement a number of nonparametric normality tests in our study.

The Kolmogorov-Smirnov test is the most common among the non-parametric tests of normality. We implement a variation of this test proposed by Lilliefors

(1967) in our study. The main difference between the two tests is that unlike the Lilliefors test, the Kolmogorov-Smirnov test requires the cumulative distribution function of the normal distribution to be predetermined. If it has to be determined from the data, the Kolmogorov-Smirnov test is not accurate. Since we would like to test the probability distribution of CE against a normal distribution without specifying the parameters, we opt for the Lilliefors test. Nevertheless, the test statistic (KS) is equal for both tests and is calculated as:

$$KS = \sup_x |F_e(x) - F_n(x)| \quad (C.3)$$

where $F_e(\cdot)$ is the empirical cumulative distribution function and $F_n(\cdot)$ is the normal cumulative distribution function. The null hypothesis of distribution equality is rejected at significance level α , if $\sqrt{\frac{N^2}{2N}}KS > \Upsilon_\alpha$, where Υ is the Kolmogorov distribution, whose cumulative probability distribution function is given by:

$$F_\Upsilon(x) = 1 - 2 \sum_{i=1}^{\infty} (-1)^{i-1} \exp^{-2i^2x^2} = \frac{\sqrt{2\pi}}{x} \sum_{i=1}^{\infty} \exp^{-(2i-1)^2\pi^2/8x^2} \quad (C.4)$$

From this cumulative probability distribution function we can find Υ_α so that $F_\Upsilon(\Upsilon_\alpha) = 1 - \alpha$.

Besides the Lilliefors test, we implement a test developed by Anderson and Darling (1952), because Stephens (1974) found the Anderson-Darling test statistic to be substantially more powerful than either the Kolmogorov-Smirnov or the Lilliefors test. If the Anderson-Darling test is used to assess the goodness-of-fit of both, an empirical distribution of observations and the normal distribution, and supposed that the standard normal cumulative distribution function is given by $F_{sn}(\cdot)$, the Anderson-Darling test statistic (AD) can be expressed as follows:

$$AD = -N - \sum_{i=1}^N \frac{2i-1}{N} [\ln F_{sn}(y_i) + \ln F_{sn}(y_{N+1-i})] \quad (C.5)$$

where \mathbf{y} is the vector of \mathbf{x} that is sorted by size and standardized by its mean and standard deviation. The AD test statistic is then adjusted for sample size

and compared to a set of critical values to determine the significance of the test statistic. These critical values are specific to the small sample size adjustment formula. In our study, the adjustment formula as well as the corresponding critical values are from Stephens (1976).

Finally, we implement the χ^2 goodness-of-fit test in our study. This test is chosen over the alternative Shapiro-Wilk test, because it is particularly suitable for large sample sizes (as is the case in our study with $N=1000$ for the probability distribution of CE), while the Shapiro-Wilk test has its strength with small samples. The χ^2 goodness-of-fit test is performed by grouping the data into m bins, calculating the observed and expected counts for those bins (o and e , respectively) and computing the following test statistic:

$$\chi_{test}^2 = \sum_{i=1}^m \frac{(o_i - e_i)^2}{e_i} \quad (\text{C.6})$$

The statistic has an approximate χ^2 distribution with $m - 1$ degrees of freedom, when the counts are sufficiently large. Consequently, the null hypothesis of distribution normality is rejected at significance level α , if $\chi_{test}^2 > \chi_{1-\alpha, m-1}^2$, or stated differently, if the test statistic χ_{test}^2 is larger than the $1 - \alpha$ quantile of a χ^2 distribution with $m - 1$ degrees of freedom.

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