

SELECTED PERSPECTIVES ON INSTITUTIONAL INVESTMENT OBJECTIVES

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List of Acronyms

AAM	Aggregated active management
AC	Asset class
ACT	Current total assets
ADR	American Depositary Receipt
Agri, For	Agriculture, forestry, fishing firms, SIC 0100-0999
AI	Alternative Investments
ALM	Amihud (2002) liquidity measure
AMEX	American Stock Exchange
AMF	'Master-KAG', Formal Asset Management Firm
ANR	Abnormal returns
APE	Average partial effect
AR	Absolute return investments
AR(1)	Autoregressive model of order 1
Ask	Ask price of stock
ASY	Information asymmetry index based on measures of liquidity
at	Total assets
AuM	Assets under Management
AV	Asset volatility
B	Bond mandate
BE	Book equity
BHB86	Brinson et al. (1986)
Bid	Bid price of stock
BP	Basis points

BVI	'Bundesverband Investments und Asset Management e.V.', German asset management association
CH	Switzerland
Coll	Collaterals
Cov	Covariance
CRSP	Center for Research in Security Prices
CUSIP	Committee on Uniform Security Identification Procedures alphanumeric code
DP	Depreciation and amortization
DT	Total debt
DW	Durban-Watson test statistic
E	Equity mandate
E.g.	For example, <i>exempli gratia</i>
EBIT	Earnings before interest and tax
EC	European Commission
EONIA	Euro OverNight Index Average
et al.	and others, ' <i>et alii</i> '
EX	Exchange code
exNASDAQ	.	Sample which excludes all NASDAQ firms
FE	Fixed Effects
FM	Fama and MacBeth (1973) estimation
F-p	Probability of the Wald F-test statistic
GDP	Gross Domestic Product
GER	Germany
HM81	Henriksson and Merton (1981)
IFRS	International Financial Reporting Standards
IK00	Ibbotson and Kaplan (2000)
Ind	Industry effect
InvG	'Investmentgesetz', German Investment Act
INVT	Inventories - total
IPO	Initial public offering
IT	Information Technology
ITCB	Investment tax credit

KAG	'Kapitalanlagegesellschaft', Asset Management Firm
KAGG	'Gesetz über Kapitalanlagegesellschaften', German Investment Trust Act
Kurt	Kurtosis
LCT	Current liabilities - total
Lev	Leverage
LL	Value of the log-likelihood function
LM-p	Heteroscedasticity robust Lagrange-Multiplier statistic probability
Logit	Logistic regression, Logit model
LOT	Proportion of zero returns by Lesmond et al. (1999)
LPM	Linear probability model
LR	Log-likelihood ratio
LR-p	Probability of the log-likelihood ratio
LSDV	Least squares dummy variable
M2B	Market-to-book ratio
Main	Main Mandate Sample
Manu1	Manufacturing firms, SIC 2000-2999
Manu2	Manufacturing firms, SIC 3000-3999
ME	Market Equity
Min, Cons	..	Resources, mining and construction firms, SIC 1000-1999
MMA	Multi-Manager Account
N	Newly added mandate
NASDAQ	...	National Association of Securities Dealers Automated Quotations
noAR	Sample which excludes absolute return mandates
NYSE	New York Stock Exchange
O	Other mandate
Obs	Observations
OECD	Organisation for Economic Co-operation and Development
OIBDP	Operating income before depreciations
OL	Overlay mandate
Old	Old Mandate Sample

OLS	Ordinary least squares
Outperf	Outperformance
p.	page
P	Price
p-Val	p-value of test statistic
p.a.	per annum
p.m.	per month
pp.	pages
P/L	profit and loss account
PCA	Principal component analysis
PERMCO ..	Permanent company identification number by CRSP
PFS	Preferred stock
PI	Pretax income
POLS	Pooled ordinary least squares
PPENT	property, plant and equipment net
Probit	Probit maximum-likelihood regression, probit model
Profit	Profitability
PSTK	Preferred stock - par value
PSTKL	Preferred stock - Liquidating value
PSTKRV ...	Preferred stock - Redemption value
Quant	Quantile
R&D	Research and Development
RE	Retained earnings
Restr	Restricted model
ROLL	Roll (1984) liquidity measure
RTC	round-trip transaction costs
S	Relative bid-ask spread
S&P	Standard & Poor's Financial Services LLC
SAA	Strategic Asset Allocation
SALE	Sales (net)
SC	Share code
SEQ	Stockholders equity
SER	Standard error of regression

Ser1	Services firms, SIC 7000-7999
Ser2	Services firms, SIC 8000-8999
SES	Security Selection
Shrout	Shares outstanding
SIC	Standard Industrial Classification
Skew	Skewness
Std	Standard deviation
TAA	Tactical Asset Allocation
Tax	Tax rate
TE	Tracking Error, active risk
TM66	Treynor and Mazuy (1966)
Trade	Wholesale and retail trade firms, SIC 5000-5999
TV	Trading volume
TXDB	Deferred taxes
TXT	Income taxes - total
UCITS	Undertakings for Collective Investment in Transferable Securities
U.S.	United States of America
U.S. GAAP	United States Generally Accepted Accounting Principles
UK	United Kingdom
Uni	Uniqueness
Utility	Transportation, telecommunication and utility firms, SIC 4000-4999
V	Volatility
VarEx	Variation explained by PCA in %
Vol	Volume total
vs.	versus
XRD	Research and development expense
Z"	Altman and Saunders (1998) Z"-score

List of Symbols

Symbols in Essay 1

$\#$	Number
$\#M$	Number of mandates in a MMA
$\#M_{avail}$	Number of mandates available for a MMA in the dataset
$\#M_{cons}$	Ratio of mandates considered to calculate MMA return
$\#MMA$	Number of MMAs
$\#OL$	Number of overlay mandates in a MMA
α_i	Intercept in cross sectional regression for MMAs (i)
α_i^t	Alpha of MMA (i), intercept of time series regression
α_j^t	Alpha of mandate (j), intercept of time series regression
β_i	Slope in cross sectional regression for MMAs (i)
β_i^t	Systematic risk of MMA (i), slope of time series regression
β_j^t	Systematic risk of mandate (j), slope of time series regression
γ_i	Slope in timing capability regression for mandates (i)
γ_j	Slope in timing capability regression for MMAs (j)
Δc	Transaction costs
D	Dummy variable in timing capability regression of Henriksson and Merton (1981)
ϵ_i	Error term in cross sectional regression for MMA (i)
$\epsilon_{i,t}$	Unsystematic risk of MMA (i), error term of time series regression
ϵ_j	Error term in cross sectional regression for mandates (j)

$\epsilon_{j,t}$	Unsystematic risk of mandate (j), error term of time series regression
H_0	Null hypothesis
H_A	Alternative hypothesis
i	Index for MMA
j	Index for mandate
M_{cons}	Ratio of considered to all available mandates to calculate MMA returns
n	Number of mandates within a MMA
Obs	Number of Observations
p	Confidence level in statistical tests
r_f	Risk free rate
R^2	Goodness-of-fit, R-squared of regression
R_i^{MMA}	Annualized return of MMA (i)
$R_{i,t}^{MMA}$	Return of MMA (i) in period (t)
R_i^{SAA}	Annualized return of strategic asset allocation of MMA (i)
$R_{i,t}^{SAA}$	Annualized return of strategic asset allocation of MMA (i)
R_i^{TAA}	Annualized return of tactical asset allocation of MMA (i)
$R_{i,t}^{TAA}$	Timing return of MMA (i) in period (t)
R_j^{BM}	Annualized benchmark return of mandate (j)
$R_{j,i,t}^{BM}$	Benchmark return of mandate (j) in MMA (i) in period (t)
R_j^M	Annualized return of mandate (j)
$R_{j,i,t}^M$	Return of mandate (j) in MMA (i) in period (t)
R_j^{SES}	Annualized return of security selection of mandate (j)
$R_{j,i,t}^{SES}$	Return of security selection of mandate (j) in MMA (j) in period t
R_j^{TAA}	Annualized return of tactical asset allocation of mandate (j)
$R_{j,i,t}^{TAA}$	Return of tactical asset allocation of mandate (j) in MMA (j) in period t
$\sum_{i=1}^n x_i$	Sum of variables x_i for $i = 1, \dots, n$
$std(x)$	Standard deviation of variable x
TE_i^{AAM}	Tracking error of MMA (i) from aggregated active management

TE_i^{TAA}	Tracking error of MMA (i) from tactical asset allocation
TE_i^{Total}	Total tracking error of MMA (i)
TE_j^{TAA}	Tracking error of mandate (j) from tactical asset allocation
TE_j^{Total}	Total tracking error of mandate (j)
TE_j^{SES}	Tracking error of mandate (j) from security selection
$w_{i,j,t}$	Weight of a mandate (j) in MMA (i) in period (t)
$\bar{w}_{i,j}$	Strategic weight of a mandate (j) in MMA (i) in period (t)

Symbols in Essay 2

#	Number
# AR_j	Number of absolute return mandates of MMA (j)
# M	Total number of mandates
# M_j	Number of mandates of MMA (j)
# MMA	Total number of MMAs
# OL_j	Number of overlay mandates of MMA (j)
α_i	Alpha (intercept) of mandate (i) from market model
$\hat{\alpha}_i$	Estimated alpha of mandate (i) from market model
Age_i	Age in months of mandate (i) in the dataset
Age_{MMA_j} ...	Age in months of MMA (j) in the dataset
AC_i^j	Remaining mandates summed by asset class for mandate (i) and MMA (j)
ANR_i	Abnormal return of mandate (i)
$A\hat{N}R_i$	Estimated abnormal return of mandate (i) from market model
β_C	Slope coefficient for control variables (C)
β_i	Slope coefficient of return of mandate (i)
$\hat{\beta}_i$	Estimated systematic risk of mandate (i) from market model
B_i	Dummy for bond mandate
γ_0	Coefficient of intercept of regression
γ_B	Coefficient of bond intercept of regression
γ_{MMA}	Coefficient of MMA intercept of regression
γ_Y	Coefficient of year intercept of regression

C_i	Control variable of mandate (i)
\check{C}_i	Within transformed (time series demeaned) control variable of mandate (i)
\bar{C}_i	Time series mean of control variable of mandate (i)
$cf_{i,t}$	Active cash flow to mandate (i) in period (t) in % of the MMA
$cf_{MMA_j,t}$	Active cash flow to MMA (j) in period (t) in % of the MMA
$\Delta\#M_j$	Change of number of mandates of MMA (j)
ΔAC_i^j	Change in asset classes for mandate (i) in MMA (j), equal to $(\Delta B, \Delta E_i^j, \Delta O_i^j, \Delta N_i^j)$ in calendar year
ΔB_i^j	Change in the sum of bond mandates for mandate (i) in MMA (j) in calendar year
ΔE_i^j	Change in the sum of equity mandates for mandate (i) in MMA (j) in calendar year
ΔN_i^j	Change in newly launched mandates for mandate (i) in MMA (j) in calendar year
ΔO_i^j	Change in the sum of other mandates (including money market, absolute return, alternative investment, unspecified) for mandate (i) in MMA (j) in calendar year
$\Delta\sigma_i$	Change in volatility of a mandate from period ($t1$) to period ($t2$)
$\Delta\check{\sigma}_i$	Within transformed (time series demeaned) change in volatility of a mandate from period ($t1$) to period ($t2$)
$\Delta\sigma_{BM}$	Change in volatility of a mandate benchmark from period ($t1$) to period ($t2$)
ΔTE_i	Change in active risk (tracking error) of a mandate from period ($t1$) to period ($t2$)
$\Delta\check{TE}_i$	Within transformed (time series demeaned) change in active risk (tracking error) of a mandate from period ($t1$) to period ($t2$)
Δx_i	Change in weight of mandate (i) in a MMA in calendar year
$\Delta x_{i,t}$	Change in weight of mandate (i) in a MMA from in period (t)

$\Delta\ddot{x}_i$	Within transformed (time series demeaned) changes in weight of mandate (i)
δ_R	Slope coefficient of performance rank
$\delta_{B,R}$	Slope coefficient of performance rank with bond interaction term
E_i	Dummy for equity mandate
$ExTE_i$	Excess tracking error of mandate (i) in a period
FE_{MMA}	Fixed effects for MMA
$FE_{Y,MMA}$	Fixed effects for year and MMA
FE_Y	Fixed effects for year
$FE_{M,Y,MMA}$	Fixed effects for mandate, year and MMA
FE_M	Fixed effects for mandate
φ_i	Autocorrelation of mandate returns (R_i)
$\bar{\varphi}$	Mean of autocorrelation of mandate returns over all periods
ϵ_i	Error term for mandate (i) in regression model
$\ddot{\epsilon}_i$	Within transformed (time series demeaned) error term of mandate (i)
i	Index of mandate
$isAR_i$	Dummy variable for absolute return mandate of mandate (i)
j	Index of MMA
$\lambda_{\Delta AC}$	Slope coefficient of change in asset class
$\lambda_{\Delta B}$	Slope coefficient of change in sum of bond mandates
$\lambda_{\Delta E}$	Slope coefficient of change in sum of equity mandates
$\lambda_{\Delta N}$	Slope coefficient of change in sum of new mandates
$\lambda_{\Delta O}$	Slope coefficient of change in sum of other mandates
$\lambda_{B,\Delta AC}$	Slope coefficient of change in asset class for bond interaction term
$\lambda_{B,\Delta B}$	Slope coefficient of change in sum of bond mandates for bond interaction term
$\lambda_{B,\Delta E}$	Slope coefficient of change in sum of equity mandates for bond interaction term
$\lambda_{B,\Delta N}$	Slope coefficient of change in sum of new mandates for bond interaction term

$\lambda_{B,\Delta O}$	Slope coefficient of change in sum of other mandates for bond interaction term
m	Counter for mandates in a MMA
M	Number of mandates in a MMA
MMA_j	Least squares dummy variable (LSDV) for MMA (j)
N	Newly launched mandates
O	Other mandates
ρ	Pearson correlation
R^2	Goodness-of-fit
\tilde{R}^2	Adj. goodness-of-fit
$R_{BM,t}$	Benchmark return of mandate in period (t)
R_{BM}	Benchmark return of mandate
$R_{i,t}$	Return of a mandate (i) in period (t)
R_i	Return of a mandate (i)
\ddot{R}_i	Within transformed (time series demeaned) return of mandate (i)
\hat{R}_i	Estimated return of mandate (i) from market model
$R_{MMA_j,t}$	Return of MMA (j) in period (t)
R_{MMA_j}	Return of MMA
$Rank_i$	Rank of mandate (i) based on performance measure
σ_i	Volatility of mandate (i)
$\ddot{\sigma}_i$	Within transformed (time series demeaned) change in volatility of mandate (i)
σ_{MMA_j}	Volatility of MMA (j)
$\sum z_i$	Sum of variables z_i
$t1$	First period in the calendar year
$t2$	Second period in the calendar year
TE_i	Full period tracking error of mandate (i)
$TE_{i,t}$	Tracking error of mandate (i) in year (t)
\ddot{TE}_i	Within transformed (time series demeaned) change in active risk (tracking error) of mandate (i)
χ^2	Chi-squared test statistic

x_i	Weight of mandate (i) in a MMA on its first observation in January
y_i	dependent variable of mandate (i)
Y_t	Least squares dummy variable (LSDV) for year (t)

Symbols in Essay 3

$\alpha_{i,t}^d$	Coefficient of intercept of yearly regression of negative observed stock returns of firm (i) on market returns in period (t)
$\alpha_{i,t}^u$	Coefficient of intercept of yearly regression of positive observed stock returns of firm (i) on market returns in period (t)
$ALM_{i,t}$	Adjusted Amihud (2002) liquidity measure of firm (i) in period (t)
$ASY_{i,t}$	Information asymmetry index of firm (i) in period (t)
$\ddot{A}SY_{i,t}$	Time demeaned information asymmetry index of firm (i) in period (t)
$AV_{i,t}$	Asset Volatility of firm (i) in period (t)
β	Slope coefficient in market regression
β_0	Coefficient of intercept of regression
β_{ASY,Lev^B} ...	Slope coefficient of information asymmetry index for book leverage
β_{ASY,Lev^M} ...	Slope coefficient of information asymmetry index for market leverage
β_{ASY}	Slope coefficient of information asymmetry index
β_C	Slope coefficient of control variable (X)
β_Y	Coefficient of intercept of year effects
$BE_{i,t}$	Book Equity of firm (i) in period (t)
c	Transaction costs, half bid-ask spread
$d_{i,t}$	Dummy variable indicating a buy or sell transaction in stock of firm (i) in period (t)
$C_{i,t}$	Control variable of firm (i) in period (t)

$\ddot{C}_{i,t}$	Time demeaned control variable of firm (i) in period (t)
$Coll_{i,t}$	Collateral of firm (i) in period (t)
$Cov(x_{i,t}; x_{j,t})$	Covariance between variables $x_{i,t}$ and $x_{j,t}$
δ_0	Coefficient of intercept of regression
δ_{Lev^*}	Speed of leverage adjustment
$\Delta ASY_{i,t}$	Change in the information asymmetry index in period (t)
$\Delta \ddot{A}SY_{i,t}$	Time series demeaned change in the information asymmetry index $ASY_{i,t}$
$\Delta C_{i,t}$	Change in control variable C of firm (i) in period (t)
$\Delta Lev_{i,t}$	Change in leverage from period ($t - 1$) to (t)
$\Delta Lev_{i,t}^*$	Target leverage change from period ($t - 1$) to (t)
$\Delta \ddot{Lev}_{i,t}^*$	Time demeaned target leverage change from period ($t - 1$) to (t)
$\Delta P_{i,t}$	Change in stock price of firm (i) in period (t)
D	Dummy variable for structural shocks in leverage
$\epsilon_{i,t}$	Error term of firm (i) in period (t)
$\ddot{\epsilon}_{i,t}$	Time demeaned error term of firm (i) in period (t)
$f_{i,t,k}$	Factor (k) in principal component analysis (PCA) explaining set of variable for firm (i) in period (t)
FE_F	Firm fixed effect
FE_Y	Year fixed effect
γ_0	Coefficient of intercept of regression
γ_C	Slope coefficient of change in control variable (ΔC)
γ_{Lev^*}	Slope coefficient of target leverage change
$\gamma_{Lev^*}^{All}$	Slope coefficient of target leverage change in 'All' sample
$\beta_{Lev^*}^{Survivor}$	Slope coefficient of target leverage change in 'Survivor' sample
γ_Y	Coefficient of intercept of year effects
i	Index of firm
$Ind_{i,t}$	Industry median leverage of firm (i) in period (t)
j	Index of firm
k	Index of explanatory factors in PCA
K	Number of explanatory factors in PCA

λ	(Kyle, 1985) liquidity measure
$Lev_{i,t}^*$	Leverage target of firm (i) in period (t)
$Lev_{i,t}$	Leverage of firm (i) in period (t)
$\ddot{Lev}_{i,t}$	Time demeaned leverage of firm (i) in period (t)
$Lev_{i,t}^B$	Book Leverage of firm (i) in period (t)
$Lev_{i,t}^M$	Market Leverage of firm (i) in period (t)
$LOT_{i,t}$	Lesmond et al. (1999) ratio of zero returns of firm (i) in period (t)
$M2B_{i,t}$	Market-to-Book of firm (i) in period (t)
$ME_{i,t}$	Market Equity of firm (i) in period (t)
n	Number of realizations of a liquidity variable
$n_{\#P_{i,t}}$	Number of days with CRSP estimated stock price of firm (i) in period (t)
$n_{R_{i,t}=0}$	Number of days with zero return in stock price of firm (i) in period (t)
OLS_Y	Year fixed effect in POLS
p	p-Value of significance
$P_{i,t}$	Stock price of firm (i) in period (t)
$P_{i,t}^*$	Stock price of firm (i) in period (t) in efficient markets
$P_{i,t}^{Ask}$	Ask stock price of firm (i) in period (t)
$P_{i,t}^{Bid}$	Bid stock price of firm (i) in period (t)
$P_{i,t}^{Mid}$	Mid stock price of firm (i) in period (t)
$PFS_{i,t}$	Preferred Stock of firm (i) in period (t)
$Profit_{i,t}$	Profitability of firm (i) in period (t)
ρ	Correlation coefficient
R^2	Goodness-of-fit
\tilde{R}^2	Adjusted goodness-of-fit
$R_{i,t}$	Return p.a. of firm (i) in period (t)
$R_{BM,i,t}$	Benchmark return p.a. of firm (i) in period (t)
$ROLL_{i,t}$	Roll (1984) liquidity measure of firm (i) in period (t)
$RTC_{i,t}$	Lesmond et al. (1999) round trip transaction costs of firm (i) in period (t)
$\sigma_{ALM_{i,t}}$	Amihud (2002) liquidity risk of firm (i) in period (t)

$\sigma_{ASY_{i,t}}$	Information asymmetry index based on measures of liquidity risk of firm (i) in period (t)
$\sigma_{LOT_{i,t}}$	Lesmond et al. (1999) ratio of zero returns risk measure of firm (i) in period (t)
$\sigma_{ROLL_{i,t}}$	Roll (1984) liquidity risk measure of firm (i) in period (t)
$\sigma_{RTC_{i,t}}$	Round trip transaction cost risk measure of firm (i) in period (t)
$\sigma_{S_{i,t}}$	Spread liquidity risk measure of firm (i) in period (t)
$\sigma_{TV_{i,t}}$	Trading volume liquidity risk measure of firm (i) in period (t)
$\sum x_{i,t}$	Sum of variables $x_{i,t}$
$S_{i,t}$	Relative spread of firm (i) in period (t)
$Size_{i,t}$	Size of firm (i) in period (t)
$\theta_{t,k}$	Factor loading in principal component analysis in period (t)
t	Index of period (year)
T	Number of yearly observations
$Tax_{i,t}$	Tax Rate of firm (i) in period (t)
$TV_{i,t}$	Trading Volume of firm (i) in period (t)
$u_{i,t}$	Random shocks to stock price of firm (i) in period (t)
$Uni_{i,t}$	Uniqueness of firm (i) in period (t)
$V_{i,t}$	Volatility p.a. of firm (i) in period (t)
$x_{i,t}$	Empirical liquidity measures for firm (i) in period (t)
\bar{x}_i	Time series mean of a variable $x_{i,t}$
$\ddot{x}_{i,t}$	Time series demeaned (within transformed) variable $x_{i,t}$
\bar{x}_t	Mean of variables x_i over all firms in period (t)
$x_{j,t}$	Empirical liquidity measure for firm (j) in period (t)
$Y_{i,t}$	Least square dummy variable for years
$Z''_{i,t}$	Altman and Saunders (1998) Z'' -Score of firm (i) in period (t)
$z_{i,t}$	Error term in period (t)
Z_1, \dots, Z_4	Weighting coefficients to calculate citeAltman1998 Z'' score

Chapter 1

Introduction

1.1 Institutional Investments

Institutional investments are of major economic relevance. In accordance with OECD statistics, in 2009 insurance corporations and pension funds accounted for more than U.S. \$15.9 trillion in financial assets under management (AuM). Roughly 60% of these were held by autonomous pension funds. Regulated investment companies – mutual and closed-end funds – accounted for U.S. \$11.2 trillion. In sum these assets correspond to more than 190% of the U.S. GDP.¹ In Germany institutional investors are less active in capital markets compared to the U.S. (Nürk, 1998). However, they still

¹The Bureau of Economic Analysis at the U.S. Department of Commerce states the gross domestic product (GDP) at current prices to be U.S. \$14.1 trillion (see <http://www.bea.gov/national/index.htm#gdp>).

account for roughly 110% of the GDP.² Mutual funds manage about €1.1 trillion, insurance corporations and pension funds roughly €1.6 trillion.

Since the seminal work of Lakonishok et al. (1992) on "The Structure and Performance of the Money Management Industry", academia has become aware of the need to study institutional investments in more detail. Among others the above mentioned authors address detrimental incentive structures and agency problems. Two other prominent fields of research are performance and its persistence (see, e.g., Bogle and Twardowski, 1980; Carhart, 1997; Busse et al., 2010) and institutional investors' relevance for asset prices and capital markets (see, e.g., Gompers and Metrick, 2001; Barber and Odean, 2006).

Research is inevitable, as institutional investment services are intended to facilitate investments, guarantee access to various assets and markets, realize economies of scale and offer improved skills and monitoring to their beneficiaries – in most cases smaller public investors. However, compared to regulated investment companies less is known on their features and factors of success, probably due to limited data access.

This doctoral thesis contributes to this field of financial research from an empirical perspective. It therefore assists public investors to come to a solution for the "make or buy" decision regarding the investment process, which consists of the following five cyclical steps (see Bruns and Meyer-Bullerdiek, 2008; Fabozzi, 2009):

²The German Federal Statistical Office states the GDP at current prices to be €2.4 trillion (see Statistisches Bundesamt, 2010).

1. Determination of the investment objectives
2. Data collection and research
3. Investment strategy and asset allocation
4. Portfolio construction and trading
5. Performance analysis

In other words, any public investor has to carry out the previous tasks either independently or by relying on e.g. insurance corporations and pension funds. The results in this work offer the former and members of the industry insights of how these single steps are turned into life in the institutional investment setting. Furthermore, this research reveals which factors might be potential drivers of success with regard to key investment objectives, namely *"performance"*, *"investment risk"* and *"liquidity"*.

Disclosed findings support to identify and demand value creating tasks, if investment services are needed. From an industry perspective, service providers have to demonstrate their unique value and selling proposition to their customers on an ongoing basis. Insights might enable asset managers, investment consultants, banks, and insurance corporations to improve their services.

The posed and answered questions in this thesis are the following: *Which investment choice – strategic asset allocation, tactical allocation or security selection – is the main driver of investment performance?* Which one yields the most opportunities for outperformance? An answer indicates

which services customers should demand and how the industry should apply scarce resources optimally. *Do institutional investors offer a reduction of harmful risk-taking conducted by investment managers as shown for mutual funds?* If they can, this yields an argument why to rely on e.g. insurance companies. However, any individual investor must deliberate over her or his willingness to pay for this service. Finally, *do firm characteristics, which drive capital structure decisions, drive equity liquidity as well?* This is particularly relevant for institutional investors which have to meet liabilities vis-à-vis their beneficiaries at all times. The financial crises in 2007/08 has demonstrated that a deterioration of the liquidity of assets hits large market participants considerably and may even imperil economic sustainability.

An analysis of institutional investments is also of high relevance for regulatory authorities. Commonly legal bodies have access to specific investment vehicles which are less regulated compared to e.g. mutual funds, available in the retail segment. In Germany for example 65% of all non-regulated investment companies' AuM are managed in roughly 3,900 so-called "special funds" ("Spezialfonds") as stated by the German asset management association (BVI, 2010a). Research on institutional investors' ability to achieve classical investment objectives under a diverging regulatory regime may provide evidence on the need to improve regulation. Therefore a large fraction of this thesis explicitly deals with this type of investments.

Institutional investments have not been clearly defined until now. Following classical finance text books such as Reilly and Brown (2006) and Bodie et al. (2008), these are a commitment of a cash amount, e.g. in € or U.S. \$, by

a corporate body for a specified period to receive future payments. Albeit the following list is not exclusive, in accordance with Fabozzi (2009) the main *institutional investors* are: insurance corporations, depository institutions, (corporate) pension funds, regulated investment companies, corporates, as well as endowments and foundations.

1.2 Liquidity as Investment Objective

Previously three different investment objectives – performance, investment risk, and liquidity – have been listed. The first two are commonly accepted in financial research, as an investment is equivalent to a trade of an ex ante known cash amount for future expected and thus insecure pay-offs (Reilly and Brown, 2006). Since the seminal works of Bernoulli, various famous authors have contributed to the consideration of return and risk in utility functions, the portfolio optimization problem and asset pricing (see, e.g., Markowitz, 1952; Sharpe, 1964; Lintner, 1965; Fama and MacBeth, 1973; Ross, 1976).³

For liquidity the situation is somewhat different. But to discuss liquidity as an investment objective in more detail, it is necessary to provide a basic understanding of this elusive concept. Although its clear definition is subject to theoretical models (Hasbrouck, 2007), it is supposed that "an asset is said to be liquid if it can be sold in a short time, at a price not too much below the price the seller would get if he took plenty of time to

³For a comprehensive overview see Ingersoll (1987).

sell the asset.” (Black, 1971, pp. 29-30)⁴ By the previous definition, the two dimensions of liquidity as market friction – price and opportunity costs of waiting – become obvious.⁵

But, if we study the theoretical literature on the inclusion of liquidity in preference functions, we find only few publications. Some first theoretical approaches are contributed by Tobin (1958), Longstaff (1995), Vayanos and Vila (1999), Longstaff (2001) and Faig and Shum (2002). A preference for liquidity is motivated either by transaction imbalances or portfolio considerations. In the first case individuals do not have perfectly matching in- and outflows. In the latter case fears of losses in assets within the portfolio constitute the need to re-balance the portfolio. Indeed, public investors consider liquidity in their investment decisions, depending on their socio-economic background and their life cycle stages (see, e.g., Baker and Haslem, 1974; Ramaswami, 1992). Therefore several authors have proposed methods to include liquidity in the portfolio context (see, e.g., Davis and Norman, 1990; Dumas and Luciano, 1991; Longstaff, 2001; Browne et al., 2003; Lo et al., 2003; Vath et al., 2007).

Importantly, the target of this doctoral thesis is neither a theoretical deduction of utility functions including liquidity nor a discussion of the underlying assumptions in financial decision making and portfolio optimization. This work rather aims at improving the understanding of factors which drive objectives in institutional investments from a practical view. The need to ex-

⁴Amihud et al. (2006) define liquidity as ”the ease of trading a security.” [p. 1]

⁵Bernstein (1987) rather distinguishes between market depth, breadth and resiliency. Standard financial models (such as those of Sharpe, 1964; Black and Scholes, 1973; Cox et al., 1985) assume frictionless markets and perfect liquidity (see Kempf, 1999).

PLICITLY consider asset liquidity can be motivated by three related arguments: 1) the empirically observed link between return and liquidity, 2) regulatory and risk management requirements, and 3) its informational content.

First, price effects lead to the well-known significant negative relation of liquidity and returns. Long-term investors such as insurances may be willing to bear market frictions which constrain their discretion to earn a compensation (Amihud et al., 2006). Among others (e.g. Amihud and Mendelson, 1989; Brennan and Subrahmanyam, 1996; Baker and Wurgler, 2002; Baker and Stein, 2004) Amihud and Mendelson (1986) show for U.S. stocks from 1961 through 1980 that the average risk-adjusted portfolio returns for the subsequent period ($t + 1$) increases by 0.21% if bid-ask spreads of included firms rise by 1% in the actual period.

Other authors analyze liquidity risk (see, e.g. Chordia et al., 2000, 2001; Hasbrouck, 2001; Huberman and Halka, 2001; Amihud, 2002). Finally, Acharya and Pedersen (2005) are the first to develop and test a liquidity adjusted CAPM to reflect liquidity risk components explicitly. They find a significant risk premium of 1.1% p.a. for U.S. stock portfolios from 1963 through 1999.

Second, the financial crisis in 2007/08, also called "liquidity crisis" proved that the dictum "Cash is King" becomes a matter of substance. In strongly bearish markets institutional investors search for safe and more liquid assets (Longstaff et al., 2005). Various sources, from journal articles to newspapers report such behavior in the aftermath of the credit crunch and the LTCM collapse (see, e.g., Acharya and Pedersen, 2005; Agarwal et al., 2010;

Chung, 2008; Goyenko and Sarkissian, 2008; Acharya et al., 2010; Ablan, 2010). Consequently, the liquidity of specific markets decreases sharply or disrupts systematically, as for asset backed securities in the latest crisis. Here banks had to disclose write-downs of about U.S. \$2.2 trillion (IMF, 2010).

Fair value accounting as well as banking and insurance regulation are assumed to be among the main reasons for institutional investors' behavior (see Franke and Krahnert, 2008; Laux and Leuz, 2009; Claessens et al., 2011). The two leading international accounting standards, U.S. GAAP and IFRS, both require listed companies to apply a three level framework for disclosing financial instruments. From top to bottom these are: observable market prices (mark-to-market), market prices of similar items and if none of the former exists financial modeling (mark-to-model)

In the latter case, asset liquidity must be considered explicitly. Therefore, commonly the work of Silber (1991) and Emory (1997) is used, which legitimate discounts of 30% to 40%. Adjusted discount rates could apply the liquidity adjusted CAPM of Acharya and Pedersen (2005). An option valuation approach may use the work of Longstaff (1995). Finally, Koeplin (2000) determines multiples which represents the external view.

Risk management regulation also demands financial institutions to consider liquidity in their investment decisions. German minimum requirements for risk management explicitly define liquidity risks and require financial in-

stitutes to monitor and manage their assets' liquidity and to provide highly liquid assets especially in stressed market environments.⁶

Overall, a reduction of liquidity to the point of no trading puts the ability to meet liabilities at risk. Thus institutional investors need to account for liquidity in the investment process – at least as a side condition. It is essential to develop an understanding of how liquidity may develop over time and which factors drive a single asset's liquidity.

Third, Kyle (1985), Easley and O'Hara (1987), and Glosten (1989) discuss asymmetric information as source for illiquidity although sources are manifold.⁷ They argue that the size of a buy (sell) order reveals information on the buyer's (seller's) information advantage to the counterpart. The probability to trade with an insider increases with the order size. Therefore, institutional investors need to consider that large trades, which they often conduct and are often faced with, reveal information about insiders.

⁶See Rundschreiben 11/2010 (BA) Mindestanforderungen an das Risikomanagement (MaRisk), from the 15th of December 2010, BTR 3.1., http://www.bafin.de/cln_152/nn_722754/SharedDocs/Veroeffentlichungen/DE/Service/Rundschreiben/2010/rs__1011__ba__marisk.html#doc2028716bodyText24.

⁷Exogenous transaction costs, such as brokerage fees or order-processing costs and inventory costs of market makers, are highlighted by Stoll (1978), Ho and Stoll (1981), and O'Hara and Oldfield (1986). For a comprehensive overview on theoretical concepts, see e.g. O'Hara (1995) and Hasbrouck (2007).

1.3 Structure

The previous motivation gives a first intuition for the starting point of my research. The target is to improve our understanding of which factors affect the achievement of objectives in the institutional investment process. Besides, academic relevance results are of particular interest for public investors, the asset management industry, and regulatory authorities.

Hence, this doctoral thesis comprises three selected essays (see chapters 2 to 4). The first two essays conduct empirical research employing data on German institutional investments from a non-publicly available but audited data source. Both analyze multi-manager accounts in which an investor appoints multiple investment managers, a state-of-the-art investment vehicle, accessible to legal bodies only. The third essay uses a large set of U.S. stock market and balance sheet data. Despite differences in either research focus or employed data, all three essays contribute to various challenges which institutional investors face in the investment process to achieve their objectives. Chapter 5 summarizes the main findings in the three essays and gives a brief outlook for further research.

1.3.1 Essay 1: Investment Choice in Multi-Manager Accounts

The first essay (chapter 2) studies in detail the success of investment choices in terms of outperformance and risk.⁸ It therefore contributes to the understanding of steps 3 to 5 of the investment process.

Using an audited German institutional dataset of multi-manager accounts (MMA),⁹ this study contributes to the discussion on the importance of investment activities for institutional investors. We analyze the effects of strategic and tactical asset allocation as well as security selection in the diverging spheres of activity of institutional investors and subordinate managers. The research gap for this type of investment vehicle and the financial sophistication of institutional investors demand a detailed analysis.

Our main findings are: The high explanatory power between 75% and 90% of the strategic allocation in the cross section and in the time series underpins the importance of this investment choice. The underperformance of -0.21% p.a. is in comparison to the average U.S. investor remarkably low. Assigned managers offer slightly positive alpha with a positive skew, which shows the attractiveness of active management. The avoidance of market timing by investors and managers may improve investment performance.

⁸The original essay, entitled "Investment Choice in Multi-Manager Accounts – Empirical Evidence from the German Market", is joint research work of Lars Helge Haß, Lutz Johanning and Timur Karabiber. Parts of an early German version were used in Johanning and Flöck (2009).

⁹We thank Universal-Investment-Gesellschaft mbH, Frankfurt am Main, Germany, for providing this dataset.

1.3.2 Essay 2: Risk-Taking in Institutional Investments

The second essay (chapter 3), concentrates on MMAs, alike.¹⁰ Institutional investments differ in several key aspects, including financial sophistication and frequency of monitoring from retail mutual funds. This paper analyzes how this "effective governance" impedes tournament behavior. For mutual funds, it has been shown that relative "loser" managers tend to increase risk as a means to improve their performance, while "winners" can lock in their returns. The second essay therefore deals with the intersection of managers' portfolio construction and trading behavior (Step 4) and investors' performance analysis (Step 5) in the investment process.

We study German multi-manager accounts (MMAs),¹¹ which are not accessible to the general investing public and are similar in structure to U.S. vehicles. We show that performance measures such as alpha are frequently used to conduct reallocations between managers in MMAs. This constitutes an even more pronounced instrument of "effective governance" for bond mandates. However, the potential for asset loss due to poor performance can act as a deterrent for harmful risk-taking. Instead, risk management requirements imposed by institutional investors drive the risk in mandates, and highlight their governance abilities.

¹⁰The original essay, entitled "Effective Governance in Institutional Investments – Reallocations and Tournament Behavior in German Multi-Manager Accounts", is joint research work of Lutz Johanning, Timur Karabiber, Denis Schweizer and Maximilian Trossbach.

¹¹We thank Universal-Investment-Gesellschaft mbH, Frankfurt am Main, Germany, for providing this dataset.

1.3.3 Essay 3: Anticipated Capital Structure and Equity Liquidity

Completing the former two, the third essay (chapter 4) demonstrates how investors collect and process data (Step 2) in the investment process which ultimately impacts equity liquidity.¹²

This paper uses a new perspective to analyze information obtained from capital structure decisions. Most previous studies either separately tested how firms adjust to leverage targets, or observed how financial policy changes convey information such as balance sheet items. However, we analyze the impact of expected (targeted) capital structure decisions, which can be build on firms' fundamental data, on information asymmetries. We measure the latter by using equity liquidity. The effect is based on the assumption that one of the main drivers of liquidity is the information asymmetry that exists between managers (insiders) and owners (outsiders).

For our empirical analysis, we use an information asymmetry index based on six measures that capture trading activity, trading costs, and the price impact of order flow. Under the assumption of joint determination of leverage and liquidity, we find that expected increases in leverage (target leverage changes) decrease our information asymmetry index. This is consistent with the signalling hypothesis of Ross (1977), and is equivalent to increases in equity liquidity.

¹²The original essay, entitled "Do Markets Anticipate Capital Structure Decisions? – Feedback Effects in Equity Liquidity" is joint research work of Timur Karabiber and Denis Schweizer.

Chapter 2

Investment Choice in Multi-Manager Accounts

2.1 Introduction

It is widely accepted that the performance of investment portfolios has three main sources:¹ *long-term strategic asset allocation (SAA)*, *tactical asset allocation (TAA)* and *security selection (SES)*. Contrary to the long-term and passive nature of the SAA, the TAA and the SES both represent active management in portfolio choice. For a long time the main result in literature was that the SAA holds very high explanatory power over time for returns. But on the contrary it only has medium relevance in the cross section. Late

¹The original essay, entitled "Investment Choice in Multi-Manager Accounts – Empirical Evidence from the German Market", is joint research work of Lars Helge Haß, Lutz Johanning and Timur Karabiber. Parts of an early version were used in Johanning and Flöck (2009).

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research based on bootstrapping simulations has proven that return potential can equally be created by the SAA or the SES.

In this paper we analyze investment choices in German multi-manager accounts (MMA), where institutional investors (denoted as "*investors*" in the following) appoint multiple investment managers (denoted as "*managers*").² The latter are pooled investment vehicles for legal bodies only, such as insurance corporations, (corporate) pension funds, corporates, foundations, or endowments. An investigation is valuable for four main reasons: 1) The ongoing debate on the relevance of active management, 2) diverging spheres of activity in multi-manager accounts, 3) the financial sophistication of institutional investors, and 4) the high risk aversion of German investors.

First, the impact of the SAA vis-a-vis active management for explaining returns and risk is discussed lively in literature. The first strand includes mainly descriptive studies. Brinson et al. (1986), BHB86 in the following, were among the first to analyze the performance of U.S. pension funds. They find that active management has a negative value proposition of -1.1%. Time series regressions of yearly SAA returns on fund performance show a goodness-of-fit of 93.6% on average. In a successional article they conclude: "Clearly the contribution of active management is not statistically different from zero" (Brinson et al., 1991, p. 44). By simulating portfolios Hoernemann et al. (2005) back these findings.

But Hood (2005) shows that active management yields a return contributions between -2.9% and +3.6% p.a. Therefore he argues that it is neither

²For more details on the multi-manager concept see Stein and McIntire (2003).

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irrelevant nor to omit. Ibbotson and Kaplan (2000), denoted as IK00, investigate return variability of mutual and pension funds within the cross section and find much lower explanatory power of up to 40%. Further, authors such as Heston and Rouwenhorst (1994), Baca et al. (2000), Cavaglia and Moroz (2002), or Vardharaj and Fabozzi (2007) discuss the relevance of industry effects on strategic allocation.

Bootstrap simulations of portfolio returns make up the second strand of literature and are done e.g. by Kritzman and Page (2003). The authors draw returns of several securities from a large universe to generate portfolios. The security selection is similar to a bottom-up investment approach. They also top-down draw returns of benchmark indexes to simulate strategic portfolios. With 2.5% p.a. compared to 0.8% p.a. the SES offers a considerably higher return potential than the SAA. Assoé et al. (2004) and Assoé et al. (2006) use a more realistic value-weighting scheme in their simulations. They pinpoint, that the return potential is not achieved by higher risk. Hence they argue that strategic allocation, sector allocation and security selection are equally important.

Summarizing, descriptive studies support the importance of strategic asset allocation, while simulations underpin the relevance of security selection for financial success by their high return potentials.

Second, previous literature on investment choice has not paid any attention to diverging spheres of activity. It is implicitly assumed that all investment choices are concentrated at the investor's hands. For MMAs this is not the case. While investors define the SAA, and the TAA as rebalanc-

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ing between asset classes, appointed managers conduct TAA in systematic risk factors and SES. If not pleased by their managers' performance, institutional investors rather terminate a mandate (and appoint a new manager) than conducting it on their own. To the best of our knowledge, this study is the first which addresses spheres of activity for investors and fund managers separately. Hereby we can draw practically highly relevant conclusions for the allocation of resources in the investment process, manager selection, and performance measurement.

Further we avoid several difficulties of simulation studies, for which a comparison of the SES and the SAA must be conducted very carefully. Any portfolio constructed by a top-down simulation which consists of several benchmarks (as done by Kritzman and Page, 2003; Assoé et al., 2004) mandatory leads to a specific SES. Assume, that two equally weighted benchmarks such as the S&P 500 and the EURO STOXX 50 build the strategic portfolio. In this case, the security selection is equal to the value-weighting scheme employed to construct the two indexes.

In our example any simulation of security selection needs to include as many securities as the SAA portfolios, here 550. However, commonly fewer securities are used. This must lead to more extreme results. Moreover, if the SES is simulated within only one asset class, e.g. equities, a comparison with results from multi-asset class portfolios (SAA) seems inadequate.

Thirdly, retail investors differ considerably from institutional investors in terms of financial sophistication and information. For example in- and outflows to retail mutual funds exhibit a convex relationship to past perfor-

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mance (Sirri and Tufano, 1998). Further, the low sophistication and a lack of efficient control leads to principal agent problems. Brown et al. (1996) or more recently Chen and Pennacchi (2009) and Kempf et al. (2009) analyze the so-called "tournament behavior", where mutual fund managers adjust the risk structure of the fund to the disadvantage of their investors.

In contrast, institutional investors are characterized by systematic data collection, performance evaluation, manager selection (Bank for International Settlements, 2003), and professional risk management strategies (Sharpe, 2002b). Institutional investors also prosecute inferior performance similarly as they reward superior performance (see Del Guercio and Tkac, 2002). We therefore expect institutional investors' performance to diverge considerably from the results in the mutual fund research.

Fourth, an investigation of solely German institutional investors can contribute on the discussion of their relatively high risk aversion compared to international standards (Funke et al., 2006). But the sole study for Germany, done by Drobetz and Köhler (2002), analyzes mutual funds only. They find a relatively high underperformance of active management amounting to -2.37% p.a. Besides lower financial sophistication, this may be traced back to their dataset. They analyze a small sample for Germany and Switzerland for a short observation period of six years, including the boom and bust of the dotcom bubble.

The remaining of the article is structured as follows: Section 2.2 describes the structure of the data and displays summary statistics. Section 2.3 examines the performance and risk data of the institutional investments

at hand. The institutional investor's sphere of activity is analyzed in section 2.3.1, while fund managers' role is explored in section 2.3.2. Concluding remarks complete the article.

2.2 Data

2.2.1 Investment Choice and Dataset

Commonly investors follow a top-down investment approach within multi-manager accounts (MMA), as depicted in figure 2.1. First they decide on the strategic asset allocation (SAA) – the long-term and binding selection and subdivision of financial resources to asset classes. Portfolio weights are usually determined using portfolio optimization models (Markowitz, 1952; Tobin, 1958, see). The asset classes and the country assortment are later implemented via mandates for single managers. The sole active management decisions taken in this sphere of activity is a medium-term deviation from a previously determined asset class weighting scheme (Rudolph, 2003). The TAA is conducted by deferring required re-balancing, non-proportional cash-inflows and cash-outflows, and active reallocations. As a consequence single asset classes within the MMA are over- or under-weighted.

Mandate managers can also engage in timing. They may change their exposure to systematic risk factors, such as their benchmarks or the well known value, size and momentum factors, proposed by Fama and French (1993) and Carhart (1997). Both TAA types (investors' and managers') are

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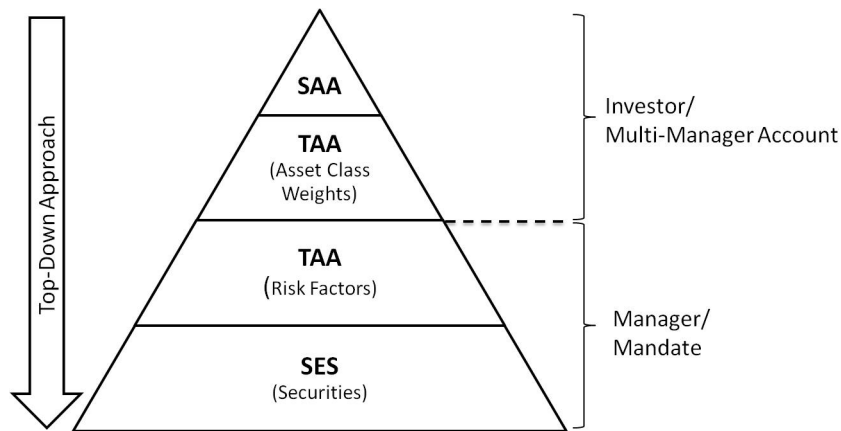


Figure 2.1: Spheres of Activity in Multi-Manager Accounts

based on forecasts (MacBeth and Emanuel, 1993) or rule-based historic data (Black and Perold, 1992). In the following, we consider the market risk factor to map market timing only. Our dataset forecloses any inference on other risk factors. Finally, managers allot financial resources to single securities constituting the security selection. According to the "fundamental law of active management" the SES explicitly offers a higher chance of success, due to the high number of single "bets" (Grinold and Kahn, 2000).

The audited dataset we use for the analysis was provided by Universal-Investment-Gesellschaft mbH, one of the three largest German asset management firms ("Kapitalanlagegesellschaft", KAG) for institutional investments. Our data provider offers passive portfolio management, data provision and reporting, as well as risk management systems to its customers. The dataset contains 429 mandates and 52 MMAs, with a total volume of more than €111 bn. in funds under administration as of December 2008. The German asset management association (BVI, 2010b) estimates the AuM in 2009 to

be roughly €640 bn.³ Our data thus represents roughly 17% of the market in terms of total outstanding amounts.

The multi-manager account data consists of three sources: benchmark, performance and weights data. This results in unique mandate and MMA identifiers, observation dates, benchmark names, standardized monthly portfolio values of mandates and related benchmarks, weights of every mandate within the multi-manager account and overlay mandate identifiers. Some mandates' data is available on higher frequency, e.g. on a weekly basis. To guarantee comparability of performance and risk measures, single mandates' data is harmonized on month's end. The general time horizon of our analysis covers exactly 20 years or 240 months from August 1989 to July 2008. We distinguished the following asset classes by static benchmark information: money market, bonds, equities, alternative investments (AI), absolute return (AR), and non-specified (Other).

2.2.2 Mandates' Data

Next we describe sample construction rules and show some descriptions. Contrary to the top-down approach, depicted in figure 2.1, we employ a bottom-up approach and start with the 429 mandates and 21,432 monthly observations at hand. In subsection 2.2.3 we subsequently aggregate the data to the MMA level. Owing the fact that our dataset stems from a non-

³In terms of size, it amounts to 5% of the national German GDP and to little less in terms of AuM of the total investment industry (see Gonnard et al., 2008).

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publicly available source, it is essential to conduct a mandate-by-mandate data review.

To do so we employ a four-step procedure, see Table 2.1: 1) we exclude non-relevant mandates, 2) we review the dataset for data errors and define the data which is used to construct the MMA data, 3) we exclude mandates with too less observations resulting in our main mandate sample, and 4) we define subsamples. Table 2.2 shows cross sectional descriptions of mandates (j) in the resulting (sub)samples.

In the first step, we exclude two types of mandates: overlay and virtual absolute return mandates. In recent years formal asset management firms (as our data provider) conduct risk management in so-called "overlays" on the MMA level for net positions. Here e.g. currency or interest risks are hedged with financial derivatives (see, e.g., Jorion, 1985; Heidorn and Siragusano, 2006). But we are interested in analyzing investment choices of investors and appointed managers. Therefore, we exclude 13 overlays with 483 observations.

Moreover, we exclude mandates which feature many zero benchmark returns and thus impede otherwise sound performance attribution techniques employed in this study (see, e.g., market model regressions as in Equation 2.9 in subsection 2.3.2). We identify 80 of these virtual absolute return mandates, with 4,404 monthly observations in total. A mandate is classified as virtual absolute return if a) no benchmark returns exist b) a ratio of zero benchmark returns to its total observations of 5% is exceeded. This holds throughout the whole analysis and all mandate and MMA samples.

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Table 2.1: Sample Construction

Step	Obs	#M	Specification
	21,432	429	Total
1	20,949	416	No Overlays
1	16,545	336	No 'Virtual Absolute Return'
2	1	1	Negative Fund Value
2	16	7	Winsorizing R_{BM} (0.05%)
2	16	10	Winsorizing R_M (0.05%)
	16,545	336	<i>MMA Construction</i>
3	13,583	193	Minimum of 3 Years of Obs / 'Main' Sample
4	12,239	180	'noSuspects' Subsample
4	7,188	79	'Old' Subsample

The data consists of all institutional mandates from August 1988 through July 2007. The first column indicates the four steps in the sample construction procedure. Columns 2 to 3 show the total number of monthly observations (Obs) and the number of included mandates (#M). The last column specifies the operation within each step.

In the second step, we identify data errors, which could probably drive our empirical results. We identify one mandate where the fund value drops below zero, which may represent short selling. We set this return to zero. Some mandates and their benchmarks show extreme returns in single months, which could probably drive any performance attribution. Therefore we winsorize 16 returns in 7 benchmarks and 10 mandates at the 0.05% and 99.95% level.⁴ Note here that the resulting mandate data is employed to construct the MMA data in subsection 2.2.3.

As third step we limit all samples to mandates with at least three full years, 36 months respectively, of available observations. This is done to allow for statistical inference. To derive the final "Main" mandate sample we exclude another 143 mandates with 2,962 monthly observations.

⁴The return quantiles for mandates and benchmarks are -17.4%/ 17.1% and -16.2%/19.2%.

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Table 2.2: Cross Sectional Data for Mandates

Sample	Main		noSuspects		Old	
	Mean	Std	Mean	Std	Mean	Std
	(Median)		(Median)		(Median)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Descriptions						
$\#M$	193		180		79	
Age	70.4 (59.0)	36.9	68.0 (59.0)	34.6	91.0 (75.0)	41.5
$w_{i,j,t}$	23.7% (16.2%)	23.6%	24.7% (17.6%)	24.0%	32.3% (23.5%)	26.8%
$R_{j,t}^M$ p.m.	0.45% (0.49%)	3.29%	0.43% (0.47%)	2.99%	0.41% (0.49%)	3.10%
Obs	13,583		12,239		7,188	
Panel B: Asset Class Weights						
Money	0.7%		0.7%		0.7%	
Bonds	43.3%		46.6%		49.6%	
Equity	50.7%		48.1%		47.3%	
AI	1.5%		1.6%		0.6%	
AR	1.1%		1.1%		1.7%	
Other	2.8%		1.8%		0.1%	

The data consists of institutional mandates from August 1988 through July 2008. Panel A shows cross sectional yearly data including means, medians in parentheses below, and standard deviations for variables by rows and (sub)samples by columns. These include the "Main", "noSuspects", and "Old" samples. Depicted variables are the number of mandates, their age in months, monthly arithmetic returns, mandate weights within MMAs ($\#M$, Age , $R_{j,t}^M$, $w_{i,j,t}$). Panel B gives mandates per asset classes, which include money market, bonds, equity, AI, AR, and other indicated by rows and (sub)samples by columns.

In the fourth step we define two subsamples, to control for the robustness of our results. The subsample "noSuspects" excludes any mandates, where we identified potential data errors. The subsample, denoted as "Old", is the most restrictive one. Here we additionally require mandates to have at least five years (from August 2003 to June 2008) of observations.⁵

⁵However, for the sake of brevity, we mostly do not show the details for these subsamples. All respective tables are available from the authors upon request.

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Table 2.2 shows cross sectional descriptions for the three (sub)samples. Panel A discloses that our largest sample "Main" contains 193 mandates with 13,583 observations, while the "noSuspects" include 180 mandates. The number of monthly observations drops by roughly 10% to 12,239. In the most restrictive subsample "Old" only 79 remain, while total observations are cut back by about half to 7,188. Weights within MMAs are roughly 24% (in the following medians are disclosed in parentheses, 16%) but higher for the older mandates. Monthly arithmetic returns range from 0.41% to 0.45%. The average age is 70.4 months, which is close to 6 years.

Noteworthy, equity and bond mandates build the major stake, see panel B of Table 2.2. The previous account for more than 90% of all observations on average. Money, alternative (AI) and absolute return (AR) investments are only of minor relevance. Some mandates (Other) lack static benchmark information, e.g. in case of no agreements with investors. Note, that we excluded most of those in the construction process of the "Main" sample. The time series of our mandates in Table 2.13 in the Appendix indicates that bonds lost strongly in relevance for investors within our observation period (see panel A).

The unease of German institutional investors with new types of asset classes (AI, AR) has diminished slightly since the new millennium. In January 2000 the number of mandates (#M) is limited to only 23, but has increased strongly since. The main regional focus in 2008 of mandates' is Europe with 58% (see the last row of panel B). Only 11% of all managers

compete with a North American, mostly U.S. American, benchmark. This is in line with the home bias findings of French and Poterba (1991).

2.2.3 Multi-Manager Accounts' Data

To construct the MMA datasets, consistent with our available mandates information, we use the mandate data from the second step of the previous subsection. The time series of an MMA (i) return ($R_{i,t}^{MMA}$) is calculated as weighted ($w_{j,i,t}$) average of their mandate ($j = 1, \dots$) returns ($R_{j,i,t}^M$) (see Equation (2.1)). Table 2.3 shows descriptions for MMAs, where we again require a observation length of 36 months. In the largest of three multi-manager account samples we have 44 MMAs and 3,944 monthly observations (see the first two columns in panel A).

$$R_{i,t}^{MMA} = \sum_{j=1}^n w_{j,i,t} * R_{j,i,t}^M \quad (2.1)$$

MMAs have an average age of 89.6 months or slightly above seven years and earn (arithmetic) returns of 0.45% p.m. (0.51% p.m.) which is slightly higher than mandate returns, stemming from the weighting scheme. MMAs consist of roughly 5 mandates on average ($\#M_{avail}$), of which we consider 83% (M_{cons}) in our data construction.⁶ Although not common, overlay mandates where used in 27% of all MMA months. On average all investor assigned more than one absolute return manager (not reported in the table).

⁶Virtual AR mandates are excluded from calculations.

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Table 2.3: Cross Sectional Data for MMAs

	Main		NoSuspects		Old	
	Mean	Std	Mean	Std	Mean	Std
	(Median)		(Median)		(Median)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Descriptions						
<i>#MMA</i>	44		43		29	
<i>Age</i>	89.6	48.0	89.7	48.4	106.7	50.8
	(74.0)		(73.0)		(88.0)	
<i>R_{MMA}</i> p.m.	0.45%	2.47%	0.45%	2.37%	0.45%	2.52%
	(0.51%)		(0.50%)		(0.50%)	
<i>#M_{avail}</i>	5.08	4.57	5.08	4.61	4.52	3.81
	(4)		(4)		(3)	
<i>M_{cons}</i>	83.2%	24.0%	80.9%	26.8%	83.4%	25.9%
	(100.0%)		(100.0%)		(100.0%)	
<i>#OL</i>	0.27	0.60	0.27	0.60	0.28	0.61
	(0)		(0)		(0)	
Obs	3,944		3,858		3,094	
Panel B: Asset Class						
Money	0.5%	2.5%	0.4%	2.3%	0.5%	2.5%
Bonds	55.1%	32.4%	57.0%	32.0%	58.0%	32.5%
Equity	39.9%	31.2%	40.1%	31.3%	40.2%	32.2%
AI	0.5%	2.1%	0.5%	2.2%	0.4%	2.0%
AR	1.2%	7.5%	1.2%	7.6%	0.7%	5.2%
Other	2.9%	14.9%	0.7%	4.7%	0.2%	3.7%

The sample consists of institutional MMAs from August 1988 through July 2008. Panel A shows cross sectional yearly data including means, medians in parentheses below, and standard deviations for variables by rows and (sub)samples by columns. These include the "Main", "noSuspects", and "Old" samples, where MMA returns were calculated based on mandates which belong to specific samples. Depicted variables are the number of MMAs, their age in months, monthly arithmetic returns, the number of available and considered mandates, the number of overlay mandates per MMA, and the number of monthly observations (*#MMA*, *Age*, *R_{MMA}*, *#M_{avail}*, *M_{cons}*, *#OL*) Panel B gives weights of asset classes in MMA portfolios and include money market, bonds, equity, alternative investments (AI), absolute return (AR) and non-specified (other).

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For robustness we calculate two further subsamples. In the first case we exclude "suspect" mandates, where we identified data errors. But descriptions do not change in a structural manner, see columns 3 to 4. In the most restrictive subsample, we require MMAs to have at least five years of return history. Monthly observations are reduced to 3,094 in 29 MMAs (see the last two columns).

As denoted earlier, investors split up their assets to asset classes when determining the SAA. In panel B of Table 2.3 we notice that bond investments with 55% build the heart of institutional holdings. However, they became less relevant over time (see Table 2.14). Equities are second most important and represent roughly 40% of the portfolio. Again money market, alternative and absolute return investments are of minor importance.

If we compare asset class weights within MMAs (panel B of Table 2.3) with benchmark asset classes of mandates (panel B of Table 2.2), we find that investors assign less bond managers, 43%, but with higher fractions of their portfolio (55%). Equity as well as money market and alternative investments are thus smaller in size. Similar to mandates, the number of MMAs increases over time from only 3 in January 1990 to 44 MMAs in 2006.

2.3 Investment Choices

2.3.1 Investors' Investment Choice

In this section we analyze the investment decisions of investors on the MMA level. At first we analyze the importance of the strategic asset allocation (SAA) to explain variations in returns. Secondly, we elaborate on the value of active management for performance and risk measures.

Investors select different asset classes and contract out mandates to pursue their investment targets. Per definition the SAA is a long-term decision which demands to keep asset class weights constant. To capture this idea, we use strategic asset class weights ($\bar{w}_{i,j,t}$). These are specified at month's end in August 1988 or at the MMAs' first emergence in our dataset. Changes are only introduced for two reasons: a) a launch of new mandates, and b) a change of a mandates benchmark. The SAA return ($R_{i,t}^{SAA}$) of MMA (i) in period t , is then calculated as the sum of weighted benchmark returns ($R_{j,i,t}^{BM}$) of subsequent mandates (j) (see Equation (2.2)).

$$R_{i,t}^{SAA} = \sum_{j=1}^n \bar{w}_{i,j} * R_{j,i,t}^{BM} \quad (2.2)$$

With strategic returns at hand we investigate to which extent the return variation among MMAs is explained by differences in the SAA. Annualized MMA returns (see Equation (2.1)) and SAA returns (see Equation (2.2)) over the whole period as well as the last five years are used to carry out cross

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sectional regressions proposed by Ibbotson and Kaplan (2000) (IK00) in the following form:

$$R_i^{MMA} = \alpha_i + \beta_i * R_i^{SAA} + \epsilon_i \quad (2.3)$$

The values in column 2 of Table 2.4 indicate a goodness-of-fit of 75.8% to 88.8% for the full time series and even slightly higher values for the last five years (see column 3). The R^2 is roughly double as high as in other studies. If a "low R^2 of 40 percent must be the result of a large degree of active management", (Ibbotson and Kaplan, 2000, pp. 30-31), German MMAs on the contrary are very passive in nature. Our findings support the previous authors' prediction (generated by simulations) that reducing the TE in their sample by 50% leads to a doubling of the R^2 to the levels observed in our study.

Table 2.4: Regression Results for MMAs

	#MMA (1)	IK00 Cross Sectional R^2		BHB86 Time Series Mean R^2	
		Full (2)	5 Years (3)	Full (4)	5 Years (5)
<i>Main</i>	44	0.758	0.792	0.863	0.886
<i>noSuspects</i>	43	0.814	0.828	0.860	0.884
<i>Old</i>	29	0.888	0.889	0.867	0.909

The samples consist of the "Main", "noSuspects", "Old" institutional MMA (sub)samples from August 1988 through July 2008. The first column indicates the number of available MMAs (#MMA). Columns 2 to 3 show the goodness-of-fit of estimating Equations (2.3), proposed by Ibbotson and Kaplan (2000) (IK00), while columns 4 to 5 show results for Equation (2.4), proposed by Brinson et al. (1986) (BHB86). For each method results are depicted for the full period (Full) and the last five years (5 Years).

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To shed light on the importance of the SAA for the average MMA over time we employ the methodology of BHB86. Here we use SAA returns as explanatory variables in time series regressions (see Equation (2.4)). The mean R^2 s of 86.3% for the full period and 88.6% for the last five years for the "Main" sample (first row column 4 to 5),⁷ are consistent with previous research of BHB86, Brinson et al. (1991), Drobetz and Köhler (2002), and Hoernemann et al. (2005).

The results hereto suggest, that about 75% to 90% of the differences in returns between MMAs and of their returns over time can be ascribed to the strategic asset allocation. Hence, active management contributes 10% to 25% at a maximum to the overall performance.

$$R_{i,t}^{MMA} = \alpha_i^t + \beta_i^t * R_{i,t}^{SAA} + \epsilon_{i,t} \quad (2.4)$$

However, these analyses do not reveal any information on investors' capabilities to conduct tactical allocation. Treynor and Mazuy (1966), hereafter TM66, argue that investors, who are able to predict market developments, should earn higher returns than their benchmark in bearish markets, as they will reduce the systematic risk exposure. This return advantage should even increase the higher market losses are. In bullish markets investors rather increase their exposure. A non-linear relationship, as in Equation (2.5), between the benchmark excess returns and the MMA excess return results.

⁷Full descriptions can be provided by the authors upon request. Results for subsamples are structurally very similar and are available from the authors upon request.

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Henriksson and Merton (1981), HM81 in the following, also use a return-based approach. But they argue in favor of a less sophisticated timing approach. In their eyes investors rather forecast whether excess returns of the SAA will be above or below the risk-free rate (r_f).⁸ In this case the tactical strategy comprises of switching between two specified risk exposures, namely β_i and $\beta_i - \gamma_i$ (see Equation (2.6)). D is a dummy variable, that takes the value of (-1) if the risk-free rate exceeds strategic returns ($r_f > R_{i,t}^{SAA}$). For both methods, TM66 and HM81, a positive γ_i indicates timing capabilities.

$$R_{i,t}^{MMA} - r_f = \alpha_i + \beta_i * (R_{i,t}^{SAA} - r_f) + \gamma_i * (R_{i,t}^{SAA} - r_f)^2 + \epsilon_i \quad (2.5)$$

$$R_{i,t}^{MMA} - r_f = \alpha_i + \beta_i * (R_{i,t}^{SAA} - r_f) + \gamma_i * D * (R_{i,t}^{SAA} - r_f) + \epsilon_i \quad (2.6)$$

Table 2.5 depicts estimation results. We find negative timing capabilities on average and for the median, independent from the estimation method in the full time series (see models (1) and (3) in Panel A). The average negative coefficient of γ_i in Equation (2.5) of -1.31 (-0.46) indicates that losses in comparison to the SAA return increase the larger market movements are.

Applying HM81's method, we observe that on average investors increase their systematic exposure by 0.09 (0.04) instead of reducing it. We also depict results for all MMAs observed over the last five years, a bullish stock market environment, which excludes the youngest MMAs. Models (2) and (4) show

⁸The 1 month Euribor and the 1 month U.S.-Treasury Bill rate from June 2003 to May 2008 average 2.90% p.a. and 3.05% p.a. respectively. Bearing the dominance of the European and the U.S. market investments in our sample ($> 80\%$) in mind, Table 2.2, we think this is a good basis for calculations. Neither beta estimates nor goodness-of-fit are impacted by a variation in the risk-free rate.

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Table 2.5: Timing Capabilities in MMAs

Method	TM66				HM81				
Observation Model	Full		5 Years		Full		5 Years		
	(1)		(2)		(3)		(4)		
Panel A: Descriptions of γ_i									
Mean / Std	-1.31	4.93	-0.31	3.47	-0.09	0.24	-0.01	0.16	
(Median)	(-0.46)		(-0.11)		(-0.04)		(0.00)		
#MMA	44		35		44		35		
Panel B: Significant Timing Capabilities (γ_i) with $p = 0.95$									
Positive (#Sig)	10	(3)	17	(2)	14	(2)	19	(2)	
Negative (#Sig)	34	(11)	18	(8)	30	(11)	16	(5)	

The sample consists of the "Main" institutional MMA sample from August 1988 through July 2008. Panel A shows cross sectional descriptions including means, medians in parentheses below, and standard deviations for timing capabilities (γ_i) derived by estimating Equations (2.5) in columns 1 to 2, proposed by Treynor and Mazuy (1966) (TM66), and Equation (2.6) in columns 3 to 4, proposed by Henriksson and Merton (1981) (HM81). Panel B gives the number of positive / negative timing coefficients (γ_i) and the number of significant coefficients (#Sig) at the 95% confidence level (in one-sided t-tests) in parentheses.

negative timing capabilities as well. For the timing analysis of HM81, the average beta is increased by a mere 0.01 (0.0) in decreasing markets. TM66 coefficients are also less in size. We suggest that older investors rather abstain from an explicit switching between two levels of risk exposure.

Panel B shows the number of MMAs where γ_i is positive (negative) and significant. Evidently, 3 out of 44 investors show a significantly positive curvature (TM66) for the full period, while 11 exhibit negative timing capabilities (see the last two rows of the first column). For the HM81 model the situation is similar. Only 2 significantly increase systematic risk in up markets, which corresponds to the probability of error, while 11 decrease their risk exposure. The gap gets closer for the five year period. Regarding timing capabilities we may conclude, that the majority of investors failed in forecasting market trends and in adjusting their market exposure. Noteworthy,

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older investors have engaged less in timing in the last five years or improved skills respectively.

The previous results are based on the assumption, that investors shift between a risk-free rate and their strategic portfolio, rather than shifting among their asset classes. Hence, in contrast to TM66 and HM81, we propose an alternative approach to analyze timing activities. The structure of our dataset allows to consider time variant mandate weights within MMAs to calculate TAA returns ($R_{i,t}^{TAA}$) as weighted sum of consisting benchmark returns of mandates (see Equation (2.7)). This allows to compare SAA, TAA and investors' final MMA returns as well as their risk.

$$R_{i,t}^{TAA} = \sum_{j=1}^n w_{i,j,t} * R_{j,i,t}^{BM} \quad (2.7)$$

On the MMAs' level we calculated an strategic return of 5.14% p.a. (4.59%), while overall investors earned 4.92% p.a. (4.53%) (see columns 1 and 3 in Table 2.6).⁹ The accompanying total underperformance amounts to -0.21% p.a. (-0.17%) (see column 4), compared to a benchmark where no transaction costs are considered.

The existence of an average underperformance is in line with findings from previous literature. Sharpe (1991) emphasized the costs of active management, arguing that all investors build up the market. Therefore the market performance has to equal the average of all investors before costs. BHB86

⁹Results for subsamples are structurally very similar and are available from the authors upon request.

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Table 2.6: Performance and Risk Data of MMAs

$\#MMA = 44$	Investors		Managers	Total	Investors	AAM
	R_i^{SAA}	R_i^{TAA}	R_i^{MMA}	$R_i^{MMA} - R_i^{SAA}$	ΔR_i^{TAA}	ΔR_i^{AAM}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	<i>Returns p.a.</i>			<i>Outperformance p.a.</i>		
<i>Mean</i>	5.12%	5.26%	4.97%	-0.21%	0.12%	-0.33%
<i>Std</i>	2.13%	2.20%	2.28%	1.07%	0.30%	1.05%
<i>Max</i>	9.77%	9.63%	9.14%	1.73%	1.17%	1.86%
<i>Median</i>	4.59%	4.83%	4.61%	-0.17%	0.07%	-0.36%
<i>Min</i>	0.96%	1.18%	-0.48%	-3.65%	-0.65%	-3.65%
Panel B	<i>Volatility p.a.</i>			<i>Tracking Error p.a.</i>		
<i>Mean</i>	7.07%	6.98%	6.75%	2.42%	0.58%	2.30%
<i>Std</i>	4.29%	4.25%	4.16%	1.72%	0.44%	1.74%
<i>Max</i>	18.29%	18.15%	17.81%	6.63%	1.63%	6.63%
<i>Median</i>	5.99%	5.84%	5.84%	1.96%	0.54%	1.74%
<i>Min</i>	2.30%	2.28%	1.69%	0.30%	0.00%	0.19%

The sample consists of the "Main" institutional MMA sample from August 1988 through July 2008. In panel A columns 1 to 3 indicate returns for the SAA, the TAA and in total, while columns 4 to 6 show the performance attribution for the total active management (Total), investors' tactical allocations (Investors) and aggregated active management from the mandate level (AAM). TAA and AAM contribution are calculated as: $\Delta R_j^{TAA} = R_j^{TAA} - R_j^{SAA}$ and $\Delta R_j^{AAM} = R_j^{MMA} - R_j^{TAA}$. In panel B, columns 1 to 3 give volatilities for previous returns, while columns 4 to 6 give tracking errors for respective performance contributions per MMA.

calculate an average underperformance of -1.10% p.a. for U.S. pension funds from 1974 through 1983. In a successive study, covering 1977 through 1987, Brinson et al. (1991) find -0.08% p.a.

For mutual funds Gruber (1996) researched an underperformance of -0.65% p.a. from 1985 through 1994 after costs, while Wermers (2000) finds -1.0% p.a. from 1975 through 1994. Finally, in an extensive study, French (2008) calculated that all U.S.-American investors, private and institutional, had to sustain annual costs of -0.67% on average within the period from 1980 through 2006 to exploit alpha returns.

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In comparison to the former literature costs of active management in German institutional MMAs seem to be relatively low. We like to pinpoint that, in our analysis, transaction costs are fully ignored in benchmark values (thus in the SAA). A consideration of costs would decrease SAA and TAA returns relatively compared to observed MMA returns and improve MMA performance.

Next we analyze the sources of outperformance in more detail. Investors' investment choice, namely TAA, pays off slightly with 0.12% p.a. (0.07%) (see column 5), whereas aggregated active management (AAM) from the mandates contributes -0.33% p.a. (-0.36%) (see column 6). The distribution of outperformance shows a considerably wider distribution for aggregated active management than for investors' TAA. AAM's negative tail, with a maximum loss potential of -3.65% p.a., is considerably higher compared to investors' the one from timing activities.

However, we need to emphasize that this observation cannot lead to any conclusion on assigned managers' capabilities. The result is a combination of investors' capabilities to select managers, their employed weighting scheme, and selected managers' security selection and timing activities. Subsection 2.3.2 investigates this conjecture in more detail. But to come to the point, Table 2.11 on managers' outperformance suggests that active management yields close to zero annual returns, with 0.07% (-0.15%).

To check whether investors' tactical allocations and aggregated active management have any significant effect on performance, we conduct statistical tests on the time series. The null hypothesises are:

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H_{0_1} : Investor TAA does not lead to a change in MMA return.

H_{A_1} : Investor TAA leads to a positive/ negative change in
MMA return.

H_{0_2} : Manager AAM does not lead to a change in MMA return.

H_{A_2} : Manager AAM leads to a positive/ negative change in
MMA return.

In one-sided t-tests we reject H_{0_1} for positive outperformance in about 25% of all cases against the 10% significance level (see the first row in the upper part of Table 2.7).¹⁰ By the probability of error, we expect to reject H_{0_1} in 4 to 5 cases. However, 10 investors outperform their benchmark, while two do poorly (see the third column). For aggregated active management of managers we observe 12 MMAs to perform poorly, while only one beats its benchmark significantly (see the fourth column). If we conduct a large variety of statistical tests on the cross section of returns, we fail to reject H_{0_1} and H_{0_2} in any case, probably owing to the small sample size.¹¹

Institutional investors are particularly concerned with risk in their investment decisions (Funke et al., 2006). This probably motivates tactical decisions to reduce risk in bearish markets by shifting assets to less volatile markets, as in concepts of the Constant Proportion Portfolio Insurance (Black and Perold, 1992). Panel B of Table 2.6 depicts volatility and tracking error,

¹⁰Results for subsamples are structurally very similar and are available from the authors upon request.

¹¹These include two-sided t-tests, F-tests, Kolmogorov-Smirnow tests, Ansari-Bradley-tests or Wilcoxon ranksumstatistical tests.

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Table 2.7: Significantly Outperforming MMAs

$\#MMA = 44$	p-Val	Total	Investors	AAM
	(1)	ΔR_i^{MMA}	ΔR_j^{TAA}	ΔR_j^{AAM}
		(2)	(3)	(4)
Positive	10%	3	10	1
	5%	0	4	0
	1%	0	0	0
Negative	10%	9	3	12
	5%	5	0	7
	1%	2	0	1

The sample consists of the "Main" institutional MMA sample from August 1988 through July 2008. Column 1 indicates the level of significance (10%, 5%, 1%). Columns 2 to 4 indicate the number of MMAs for which the respective outperformance significantly deviates from zero. The total outperformance (Total) is calculated as: $\Delta R_i^{MMA} = R_i^{MMA} - R_i^{SAA}$. TAA and AAM outperformance are calculated as: $\Delta R_j^{TAA} = R_j^{TAA} - R_j^{SAA}$ and $\Delta R_j^{AAM} = R_j^{MMA} - R_j^{TAA}$.

two generally used risk measures. MMAs' volatilities are with 6.75% p.a. (5.84) on average lower as their SAA benchmarks with 7.07% p.a. (5.99). The TAA benchmark volatility lies in-between. The differences are minor, but match our suggestion. However, various statistical two-sided tests (as used for returns previously) for differences in cross sectional fail to reject $H0_3$ and $H0_4$ defined as:

$H0_3$: Investor TAA does not lead to a change in MMA volatility.

HA_3 : Investor TAA leads to a change MMA volatility.

$H0_4$: Manager AAM does not lead to a change in MMA volatility.

HA_4 : Manager AAM leads to a change in MMA volatility.

Tracking errors (TE), calculated as standard deviation of MMA returns and TAA over the SAA (see Equations (2.8) and (2.9)) are very low with 2.42% p.a. and 0.58% on average. If we calculate the standard deviation

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of MMA returns over TAA returns, Equation (2.10), 2.30% p.a. (see the last column), we conclude that the major part of the TE is contributed via aggregated active management rather than tactical activities of investors.

The observation of low TE's combined with hardly any divergence in volatility between benchmark and realized returns affirms the high risk aversion of German institutional investors. A second reason for our results of low tracking errors could be rooted in the underestimation of diversification effects of active risk, if aggregated on MMAs' level. Table 2.11 in section 2.3.2 supports our argument. For mandates the average TE is 2.87% p.a. (2.05% p.a.), which is roughly 15% higher as for MMAs, and shows far greater positive tails. Overall, tracking errors can be diversified to some extent.

$$TE_i^{Total} = std(R_{i,t}^{SAA} - R_{i,t}^{MMA}) \quad (2.8)$$

$$TE_i^{TAA} = std(R_{i,t}^{SAA} - R_{i,t}^{TAA}) \quad (2.9)$$

$$TE_i^{AAM} = std(R_{i,t}^{TAA} - R_{i,t}^{MMA}) \quad (2.10)$$

In summary, the SAA explains roughly 75% to 90% of MMA returns. Investors' timing activities as rotation between asset classes seems to pay off slightly with 0.12% p.a., however insignificantly. If we consider timing as shifting between a risk-free rate and the strategic portfolio, most investors fail to prove any timing capabilities. Moreover the investors' TAA does not promise success to reduce volatility significantly. These findings stress the need for investors to concentrate and allot most resources on the identification and review of their strategic allocation.

After costs MMAs show a small underperformance of -0.21% p.a. compared to their benchmark (which do not include transaction costs). Vis-à-vis mainly U.S. studies the outperformance is above average. Our results are similar to those reported in Johanning and Flöck (2009), however the tails of the distribution of total outperformance deviate. The authors observe a large positive tail, which stems from aggregated active management (AAM) on the mandate level. However, we find the opposite (negative) skew.

The findings coincide in so far as the tails for AAM and total outperformance are about similar in size. We attribute this to the by far larger sample period in this study. Their observations from 2003 to 2008 includes an up market, solely. Further, the crucial role of the SAA for the cross section of MMA returns in combination with low tracking errors, provides evidence for the relatively high risk aversion of German institutional investors compared to their U.S. American counterparts.

2.3.2 Managers' Investment Choice

Aggregated management skills in mandates account for the lion's share of underperformance. Albeit it is less costly compared to U.S. mutual funds, investors should gain knowledge on how much of overall mandate returns can be driven by active management decisions. Therefore we determine the role of a mandate's benchmark and thus the market risk factor for overall performance.

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Table 2.8: Regression Results for Mandates

	#M (1)	IK00		BHB86	
		Cross Sectional R^2		Time Series Mean R^2	
		Full	5 Years	Full	5 Years
	(1)	(2)	(3)	(4)	(5)
<i>Main</i>	193	0.659	0.872	0.856	0.871
<i>noSuspects</i>	180	0.640	0.861	0.855	0.866
<i>Old</i>	79	0.790	0.857	0.852	0.863

The samples consist of the "Main", "noSuspects", "Old" institutional mandate (sub)samples from August 1988 through July 2008. The first column indicates the number of available mandates (#M). Columns 2 to 3 show the goodness-of-fit of estimating Equations (2.3), proposed by Ibbotson and Kaplan (2000) (IK00), while columns 4 to 5 show results for Equation (2.4), proposed by Brinson et al. (1986) (BHB86). For each method results are depicted for the full period (Full) and the last five years (5 Years).

Secondly, if investors want their managers to engage in active management they need to identify those activities on the subordinate level which are the most promising. This may help to improve manager selection and the definition of investment objectives. Hence, the second target of this section is to analyze performance contributions of security selection (SES) and factor timing (TAA) in this sphere of activity in more detail. To do so, we decompose returns, calculate risk measures and test mandates' results.

As in the previous subsection we use cross sectional regressions where we explain mandate returns (R_j^M) by their benchmark returns (R_j^{BM}), similar to Equation (2.3). Column 2 to 3 in Table 2.8 present goodness-of-fit for mandate returns from July 1988 through June 2008 and for the last five years. Results, with 0.66 to 0.79, are somewhat lower than for MMAs but still extremely high compared to IK00 who find a R^2 of 0.4 in their U.S. sample.

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In a second step we employ a common market model on the time series for each mandate (j) (see Equation (2.11)).¹² Excess returns are regressed on excess benchmark returns, where we assume $r_f = 3\%$ p.a. as in the previous subsection. Δc represents transaction costs for buying the benchmark, but is set to zero for results in Table 2.8. This approach corresponds to the methodology of BHB86. On average R^2 is roughly 0.86 which is similar to other studies but slightly less compared to MMAs, independent from the sample or the observation period.

$$R_{j,i,t}^M - r_f = \alpha_j^t + \beta_j^t * (R_{j,i,t}^{BM} - r_f - \Delta c) + \epsilon_{j,i,t} \quad (2.11)$$

$$\xrightarrow{\Delta c=0} R_{j,i,t}^M = \underbrace{\alpha_j^t}_{\Delta R_{j,i,t}^{SES}} + \underbrace{(\beta_j^t - 1) * R_{j,i,t}^{BM} + (1 - \beta_j^t) * r_f + R_{j,i,t}^{BM}}_{\Delta R_{j,i,t}^{TAA}} + \epsilon_{j,i,t} \quad (2.12)$$

Note that Equation (2.11), maps active management decisions if it is transformed to Equation (2.12). We assume mandate returns ($R_{j,i,t}^M$) to consist of three sources which is standard in the literature: a SES contribution ($\Delta R_{j,i,t}^{SES}$), a TAA contribution ($\Delta R_{j,i,t}^{TAA}$) and the benchmark return ($R_{j,i,t}^{BM}$) (see, e.g. Coggin et al., 1993; Ferson and Schadt, 1996). Implicitly the former specification assumes that managers refrain from market timing, if they realize a unity beta. In this case all outperformance is rooted in security selection. On the contrary, if managers do not pursue any SES, the mandate return is a linear combination of the benchmark return and the risk-free rate.

¹²For a discussion on the link between the single factor model (Ross, 1976) and the Capital Asset Pricing Model, proposed by Sharpe (1964), Lintner (1965) and Mossin (1966) see Stapleton and Subrahmanyam (1983).

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Table 2.9: Market Model Results for Mandates

$\#M = 193$	α_j^t p.a.			β_j^t	R^2
	(1)	(2)	(3)		
Δc (BP)	0	25	50		
<i>Mean</i>	0.28%	0.51%	0.73%	0.905	0.856
<i>Std</i>	2.14%	2.14%	2.14%	0.183	0.176
<i>Max</i>	11.21%	11.43%	11.65%	1.251	1.000
<i>Median</i>	-0.09%	0.15%	0.40%	0.970	0.925
<i>Min</i>	-4.67%	-4.43%	-4.19%	0.193	0.115

The sample consists of the "Main" institutional mandate sample from August 1988 through July 2008. The table shows results of estimating a market model for each mandate (see Equation (2.11)). Columns 1 to 3 indicate descriptions for estimated and annualized α_j^t contingent on transaction costs of 0, 25 or 50 BP. Columns 4 to 5 give estimated β_j^t and the goodness-of-fit.

The systematic risk of our mandates is given by β_j^t and is 0.91 (0.97) on average (see column 4). Albeit a broad range from 0.19 up to 1.25 this means a slightly defensive alignment rather than market neutrality. Mandates do not participate fully in up and down markets. High R^2 's and betas below unity let us conclude that German institutional investors refrain from active management and pledge most of their managers to do so as well, probably rooting in a generally higher risk aversion.

The alpha coefficient (α_j^t) indicates the value proposition of security selection skills. Column one of Table 2.9 reveals an average risk adjusted outperformance of 0.28% p.a. (-0.09% p.a.). For comparability with Tables 2.6 and 2.11 coefficients are displayed on an annual basis. Noteworthy, alphas have a positive skew, which shows the large upside potential.

Gruber (1996) uses the same method to analyze active management skills of 270 U.S. mutual equity funds in the period from January 1985

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through December 1994. He finds relatively similar results for systematic risk and R^2 with averages of 0.963 and 80.1%. In contrast, he detects an average alpha of -1.55% annually. Managers available to institutional investors seem to outperform mutual funds considerably. For a discussion on the persistence of this outperformance see Carhart (1997) and Bollen and Busse (2004).

Note that our analysis ignores the relevance of trading and order fees for most investment strategies. To demonstrate the sensitivity of the SES contribution (alpha) to transaction costs, we estimated results for Δc ranging from 0 to 50 basis points (BP). Alphas increase necessarily by roughly the same size as the costs (columns 2 to 3). Naturally, beta coefficients as well as goodness-of-fit remain unchanged. Nevertheless, a large number of mandates yield an outperformance which does not deviate significantly from zero. Consequently, a crucial task for institutional investors is to identify skilled managers. The significance of realized alphas may be a first reference although ignoring transaction costs distorts the "big picture".

If no costs are considered, only 27 out of 193 managers provide significantly ($p = 0.9$) positive alphas, whereas 44 mandates (more than 20%) underperform significantly. But by increasing costs for buying the benchmark, we observe an increase of significant positive alphas, as expected. Equality of positive and negative ones can be observed between 9 and 13 BP depending on the level of confidence, see figure 2.2. As rough indication, Lesmond et al. (1999) report that trading stocks costs institutions roughly 1% to 2%.

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In a comprehensive analysis Wermers (2000) finds that U.S. mutual funds have an estimated total expense ratio of 0.79% p.a. while transaction costs amount to 0.8% annually from 1975 through 1994.¹³ Overall, net returns of his mutual fund sample yield an performance of -1% p.a.

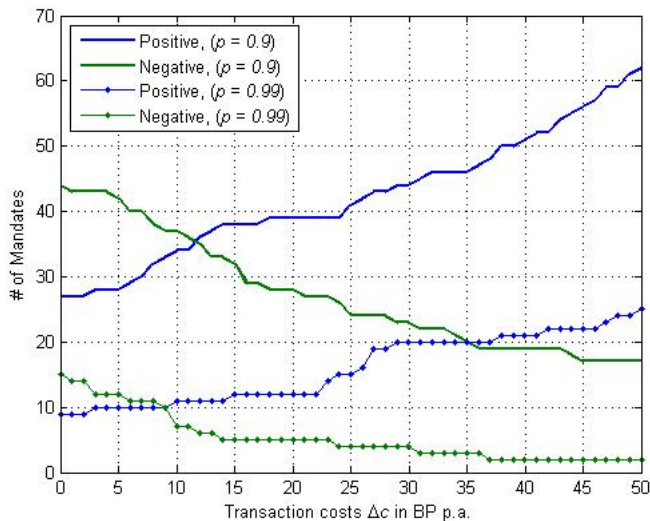
If we assume yearly transaction costs of 50 BP roughly 13% of our sample (25 out of 193) beat their benchmark significantly to the 1% significance level. In comparison to previous studies the managers' performance in our sample seems quite encouraging. Despite the importance of transaction costs for SES and mandate performance, we reduce complexity and do not consider them in our further empirical analysis. This guarantees comparability to the relevant literature on investment choice.

Our analysis hereto assumes beta to be constant. It thus offers no potential to analyze managers' TAA effort over time. But as defined in the introduction, we assume managers to have a leeway to change systematic risk exposure in the medium-term. As in the previous subsection we analyze timing capabilities applying two methods. First, we use the analyses proposed by HM66 and TM81. Estimation results similarly to Equations (2.5) and (2.6) are depicted in Table 2.10.

Compared to the TAA activities of investors (see Table 2.5) we observe an improvement of coefficients (γ_j) (see the first row of panel A). The average is zero for HM81 and negative for TM66, independent of the observation period. Interestingly the number of significant positive and negative observa-

¹³Note, that transaction costs have decreased steadily in Wermers's (2000) sample and are 0.48 in 1994.

Figure 2.2: Significance of Market Model α



The sample consists of the "Main" institutional mandate sample from August 1988 through July 2008. The data consists of the "Main" institutional mandates sample ($\#M = 193$) from August 1988 to July 2008. Alphas (α_j^{\pm}) are estimated contingent on the inclusion of transaction costs as denoted in Equation (2.12).

tions ($\#Sig$) for timing capabilities are roughly balanced. 15% show positive or negative timing skills to the 95% confidence level.

As second method to map managers' timing success we use the performance attribution technique from the previous subsection. While for MMAs, we were able to observe timing activities directly (by reallocations between asset classes), for mandates we estimate a time variant systematic risk exposure. For every mandate within our samples, we estimate market models as in Equation (2.11) on a rolling 12 basis (assuming $\Delta c = 0$). The time series of betas of every single mandate is then used to calculate the performance contribution by TAA activities. These are deviations from unity beta multiplied by benchmark returns plus the investment in the risk-free rate (see

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Table 2.10: Timing Capabilities in Mandates

Method Observation Model	TM66				HM81			
	Full		5 Years		Full		5 Years	
	(1)		(2)		(3)		(4)	
Panel A: Descriptions of γ_j								
Mean / Std	-0.12	3.84	-0.33	3.91	0.00	0.24	0.00	0.21
(Median)	(0.00)		(-0.01)		(0.00)		(0.00)	
#M	193		96		193		96	
Panel B: Significant Timing Capabilities (γ_j) with $p = 0.95$								
Positive (#Sig)	101	(28)	48	(12)	98	(25)	49	(10)
Negative(#Sig)	92	(23)	48	(11)	95	(23)	47	(8)

The sample consists of the "Main" institutional mandate sample from August 1988 through July 2008. Panel A shows cross sectional descriptions including means, medians in parentheses below, and standard deviations for timing capabilities (γ_j) derived by estimating Equations (2.5) in columns 1 to 2, proposed by Treynor and Mazuy (1966) (TM66), and Equation (2.6) in columns 3 to 4, proposed by Henriksson and Merton (1981) (HM81). Panel B gives the number of positive / negative timing coefficients (γ_j) and the number of significant coefficients (#Sig) at the 95% confidence level (in one-sided t-tests) in parentheses.

Equation (2.12)).¹⁴ Knowing benchmark, mandate and timing returns we estimate $\Delta R_{j,i,t}^{SES}$ as the residual.¹⁵

Table 2.11 shows performance and risk measures for a total of 193 mandates. On average, we observe lower returns in comparison to MMAs (see Table 2.6). Mandates yield 4.08% (3.29%) annually, panel A column 3, while MMAs gain 4.97% (4.61%). This indicates that investors underweight mandates that yield returns below average within their portfolio. Benchmarks (selected by investors) lead to lower returns of 3.93% (3.35%). If we attribute the total outperformance of active management of 0.07% (-0.15%) p.a. to its components, we find that on average security selection yields 0.10% (-0.15%)

¹⁴Results for 24 months estimated β_j^t 's are structurally very similar and are available from the authors upon request.

¹⁵We are aware that $\Delta R_{j,i,t}^{SES}$ includes $\epsilon_{j,i,t}$. But as $\epsilon_{j,i,t} = 0$ must hold, the mean of the contribution of the SES remains unaffected.

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while timing costs -0.01% (-0.03%) p.a. To test for significant differences in returns, we conduct one-sided t-tests under the nullhypothesises:

H₀₅: Manager TAA does not lead to a change in mandate return.

*H_A₅: Manager TAA leads to a positive/ negative change in
mandate return.*

H₀₆: Manager SES does not lead to a change in mandate return.

*H_A₆: Manager SES leads to a positive/ negative change in
mandate return.*

For the 99% confidence level we expect 1% of all managers to show significant deviations by error probability. However, the ratio of total positive outperformance of active management is larger than 3% (row 3 of panel A in Table 2.12). Six mandates (out of 193) outperform their benchmark, while 4.7% of all mandates perform poorly (nine out of 193).

When it comes to the components of active management, results are not as distinct as for MMAs (see Table 2.7). The number of mandates which exhibit a positive or negative and significant outperformance for SES and Timing balance mostly out for the 99% confidence level. Noteworthy, SES outperformers outweigh TAA outperformers considerably (11 vs. 7 and 13 vs. 6). Eleven manager have high selection skills while 13 show low skills.¹⁶

¹⁶Estimated alphas (see Equation (2.12)) depicted in figure 2.2, show a ratio of nine significantly positive to 15 negative outperformers. Note that the inclusion of transaction costs would lead to an improvement of performance in favor of the security selection activities.

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Table 2.11: Performance and Risk Data of Mandates

$\#M = 193$	Investor $R_{j,i,t}^{BM}$ (1)	Managers $R_{j,i,t}^{TAA}$ $R_{j,i,t}^M$ (2) (3)		Total $R_{j,i,t}^M - R_{j,i,t}^{BM}$ (4)	Timing $\Delta R_{j,i,t}^{TAA}$ (5)	SES $\Delta R_{j,i,t}^{SES}$ (6)
Panel A	<i>Returns p.a.</i>			<i>Outperformance p.a.</i>		
<i>Mean</i>	3.93%	3.99%	4.08%	0.07%	-0.01%	0.10%
<i>Std</i>	4.18%	4.36%	4.19%	2.42%	1.53%	2.40%
<i>Max</i>	24.35%	22.35%	19.54%	13.97%	9.26%	12.39%
<i>Median</i>	3.35%	3.39%	3.29%	-0.15%	-0.03%	-0.15%
<i>Min</i>	-12.06%	-10.63%	-6.85%	-7.53%	-12.48%	-8.05%
Panel B	<i>Volatility p.a.</i>			<i>Tracking Error p.a.</i>		
<i>Mean</i>	9.36%	8.84%	9.10%	2.87%	1.51%	2.28%
<i>Std</i>	6.00%	5.92%	6.00%	2.64%	1.87%	1.91%
<i>Max</i>	25.35%	23.95%	24.88%	15.36%	12.72%	8.45%
<i>Median</i>	10.52%	7.75%	8.18%	2.05%	0.90%	1.70%
<i>Min</i>	1.58%	1.27%	1.28%	0.08%	0.03%	0.08%

The sample consists of the "Main" institutional mandate sample from August 1988 through July 2008. In panel A columns 1 to 3 indicate returns for the benchmark, the TAA and the mandate. Tactical returns are calculated as: $R_{j,i,t}^{TAA} = \beta_j^t * R_{j,t}^{BM}$. The time variant market model betas (β_j^t) are calculated on a rolling 24 month window (see Equation (2.12)).¹⁷ Columns 4 to 6 show the performance attribution for the total active management (Total), managers' tactical allocations (TAA) and security selection (SES). TAA and SES outperformance are calculated as: $\Delta R_{j,t}^{TAA} = (\beta_j^t - 1) * R_{j,t}^{BM} + (1 - \beta_j^t) * r_f$ and $\Delta R_{j,t}^{SES} = R_{j,t}^M - R_{j,t}^{TAA}$. In panel B, columns 1 to 3 give volatilities for previous returns, while columns 4 to 6 give tracking errors for respective performance contributions per mandate.

The outperformance of active management of 0.07% is slightly higher compared to MMAs' level with -0.21% p.a. While institutional investors overweight mandates with high returns, they seem to underweight outperforming managers within their MMAs on average. Especially newly established mandates play a minor role within MMAs, but account for the majority of outliers in our sample.

It seems difficult for managers to prove superior performance in the long-run. This is backed by the "Old" mandates in panel B of Table 2.12.

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The ratio of positive to negative performers is less in favor of managers in the long-run. Both findings constitute the need for sound manager selection. Again statistical tests for differences (as in section 2.3.1) on the cross section of outperformance fail to reject $H0_5$ and $H0_6$.

We like to stress a second aspect of Table 2.11 – the tails of the performance contributions. Not only does the TAA cost money on average, but it is also negatively skewed, while the SES contributions are positively skewed. Security selection offers 3% to 4% p.a. of return at the upside, compared to the TAA activities, and compared to its own loss potential. This coincides with estimated alphas in Table 2.9. More than half of all mandates lose 15 BP and more every year. Nevertheless investors might be willing to bear these costs for the upside potential.

A second reason to conduct active management, related to the previous, is probably based on the idea to manage (reduce) risk. Panel B of Table 2.11 shows that the volatility of mandates is on average 9.10% (8.18%). Risk slightly decreases from benchmarks to SES and TAA returns. Testing the cross section for differences applying two-sided t-, F-, Kolmogorov-Smirnow, Ansari-Bradley or Wilcoxon Ranksum fails again to reject $H0_7$ and $H0_8$.

$H0_7$: Manager TAA does not lead to a change in mandate volatility.

HA_7 : Manager TAA leads to a change in mandate volatility.

$H0_8$: Manager SES does not lead to a change in mandate volatility.

$H0_8$: Manager SES leads to a change in mandate volatility.

Thus, we can not detect a valuable decrease of systematic risk.¹⁸ Total tracking errors (TE) are on average 2.87% (see Table 2.11), and higher as for MMAs with 2.42% (compare Table 2.6). Medians are more or less equal (2.05% vs. 1.96%). MMAs allow investors to diversify especially large tracking errors from their mandates. TE's induced by manager timing, defined as standard deviation of timing outperformance (see Equation (2.14)) are roughly 65% in size compared to active risk from security selection (see Equation (2.15)).

$$TE_j^{Total} = std(R_{j,i,t}^{BM} - R_{j,i,t}^M) \quad (2.13)$$

$$TE_j^{TAA} = std(R_{j,i,t}^{BM} - R_{j,i,t}^{TAA}) \quad (2.14)$$

$$TE_j^{SES} = std(R_{j,i,t}^{TAA} - R_{j,i,t}^M) \quad (2.15)$$

Completing this section, we summarize our findings so far. Benchmark returns are the main driver of mandate returns, in the time series as well as in the cross section. They determine between 75% to 90% of mandate returns. The high levels of explanatory power in the cross section, compared to previous U.S. studies, probably stem from the high risk aversion. German institutional investors tend to invest more passively. Active management in German multi-manager accounts is less costly (close to zero) compared to the U.S. fund industry, probably due to investors' access to above average skilled managers.

¹⁸Risk reducing strategies may target on the downside rather than systematic risk. A future investigation could use shortfall risk measures as the value-at-risk (VaR) or lower partial moments (see, e.g., Brandolini et al., 2004; Jorion, 1985; Herold et al., 2007).

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Table 2.12: Significantly Outperforming Mandates

	p-Val	Panel A: 'Main', #M = 193			Panel B: 'Old', #M = 79		
		Total	Timing	SES	Total	Timing	SES
	(1)	$\Delta R_{j,i,t}^M$	$\Delta R_{j,i,t}^{TAA}$	$\Delta R_{j,i,t}^{SES}$	$\Delta R_{j,i,t}^M$	$\Delta R_{j,i,t}^{TAA}$	$\Delta R_{j,i,t}^{SES}$
		(2)	(3)	(4)	(5)	(6)	(7)
<i>Positive</i>	10%	21	28	32	6	10	10
	5%	15	15	21	5	8	8
	1%	6	7	11	3	3	3
<i>Negative</i>	10%	48	34	54	26	16	30
	5%	25	21	39	15	10	20
	1%	9	6	13	5	5	8

The samples consists of the "Main" institutional mandate sample from August 1988 through July 2008 in panel A, while panel B consists of the the 'Old' subsample. Column 1 indicates the level of significance (10%, 5%, 1%). Columns 2 to 7 indicate the number of mandates for which the respective outperformance significantly deviates from zero. The total outperformance (Total) is calculated as: $\Delta R_{j,i,t}^M = R_{j,i,t}^M - R_{j,i,t}^{BM}$. TAA and SES contribution are calculated as: $\Delta R_{j,t}^{TAA} = (\beta_j^t - 1) * R_{j,t}^{BM} + (1 - \beta_j^t) * r_f$ and $\Delta R_{j,t}^{SES} = R_{j,t}^M - R_{j,t}^{TAA}$. Time series of betas for the TAA outperformance are calculated on a 24 month rolling window (see Equation (2.12)).

If we decompose active management, we find that timing activities have no significant effect on risk and return but exhibit a negative skew of outperformance. On average, security selection yields a positive return and holds a considerable upside potential. In the worst cases it even features less losses, while increases in active risk seem moderate. We conclude that employing security selection rather than tactical asset allocation yields far better chances to create positive value proposition on the mandate level. These findings support the "Fundamental Law of Active Management" (Grinold and Kahn, 2000).

2.4 Conclusion

The analysis of investment choices in German multi-manager for the 1989-2008 period reveals that benchmarks for single mandates and the strategic asset allocation (SAA) for investors are, with 75% to 90%, the main driver of portfolio returns. The effect is by far larger compared to the U.S. in the cross section. Investors therefore should put comparable levels of effort (75% to 90%) into determining the SAA and defining benchmarks for their appointed managers in the investment process.

On the investor level the negative outperformance of -0.21% p.a. on average is less costly compared to mainly U.S. studies. We find a slightly positive return contribution of a rotation between asset classes (TAA). On average this is equal to 1% in relation to SAA returns and at most ranges from -0.65% to +1.17% p.a. – no more than one fifth of the overall MMA return. Further the majority of investors fail to prove significant timing capabilities. We therefore suggest that investors should rather forebear from timing.

Aggregated active management of mandates is the main source for overall underperformance, although considerably less compared to mutual funds. The selection and weighting of mandates within MMAs can further improve results. Future studies should analyze the selection process similar to Goyal and Wahal (2008), but explicitly in multi-manager accounts.

Remarkably, managers available to institutional investors offer active management which seems less costly or even costless. Regarding managers' investment choices, we observe that their timing capabilities are on average

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zero. The outperformance by employing market timing (TAA) is null, and we observe a negative skew. On the contrary, SES activities yield on average zero to slightly positive returns with a right skew. Coinciding with Cremers and Petajisto (2009), stock picking seems more promising than factor bets.

Nevertheless, why is timing still conducted? Risk considerations may include not only symmetric risks measures. Further research should pay attention to the avoidance of downside risks. Especially in multi-manager accounts this seems adequate as e.g. insurance corporations and pension funds have to meet their liabilities at all costs.

We stated that mandates' active management is costless. An obvious reason are their superior skills. An alternative explanation might be improved incentives for control compared to retail mutual funds (for a discussion of shareholder activism see, e.g., Smith, 1996; Gillan and Starks, 2000). One (or very few) investors holding all shares have larger incentives for efficient control which should mitigate agency conflicts, such as the "tournament behavior" (Brown et al., 1996; Kempf et al., 2009). The following chapter will analyze whether MMAs can offer an improvement for investors in this context.

Appendix: Time Series Descriptions

Table 2.13: Time Series Data of Mandates

<i>Panel A: Asset Classes</i>							
Year	<i>#M</i>	<i>Money</i>	<i>Bonds</i>	<i>Equity</i>	<i>AI</i>	<i>AR</i>	<i>Other</i>
Jan-90	5	0%	79%	21%	0%	0%	0%
Jan-92	6	0%	79%	21%	0%	0%	0%
Jan-94	6	0%	79%	21%	0%	0%	0%
Jan-96	6	0%	79%	21%	0%	0%	0%
Jan-98	12	0%	40%	60%	0%	0%	0%
Jan-00	23	0%	29%	71%	0%	0%	0%
Jan-02	43	0%	42%	52%	0%	1%	5%
Jan-04	126	2%	44%	49%	1%	1%	4%
Jan-06	193	0%	42%	51%	2%	1%	3%
Jan-08	193	1%	42%	51%	2%	2%	3%

<i>Panel B: Regional Allocation</i>							
Year	<i>#M</i>	<i>Global</i>	<i>Europe</i>	<i>N. America</i>	<i>Japan</i>	<i>EM</i>	<i>Other</i>
Jan-90	5	0%	100%	0%	0%	0%	0%
Jan-92	6	0%	100%	0%	0%	0%	0%
Jan-94	6	8%	92%	0%	0%	0%	0%
Jan-96	6	8%	92%	0%	0%	0%	0%
Jan-98	12	11%	64%	8%	8%	8%	0%
Jan-00	23	12%	54%	13%	4%	17%	0%
Jan-02	43	18%	59%	7%	2%	9%	5%
Jan-04	126	18%	62%	8%	1%	6%	5%
Jan-06	193	13%	61%	12%	2%	8%	4%
Jan-08	193	14%	58%	11%	3%	8%	5%

The sample consists of the "Main" institutional mandate sample from August 1988 through July 2008. Panel A shows the frequency of asset classes, which are money market, bonds, equity, alternative investments (AI), absolute return (AR) and others in columns and years in rows. Panel B shows the regional allocation, including Global, Europe, North America, Japan, Emerging Markets (EM), and others in columns and years in rows.

CHAPTER 2. INVESTMENT CHOICE IN MULTI-MANAGER
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Table 2.14: Time Series Data of MMAs

<i>Panel A: General Information</i>					
Year	#MMA	#M	M_{cons}	#OL	#AR
Jan-90	3	5	100%	0	1
Jan-92	3	6	100%	0	1
Jan-94	3	6	100%	0	1
Jan-96	3	6	100%	0	1
Jan-98	8	13	90%	6	10
Jan-00	11	29	85%	6	14
Jan-02	18	57	82%	6	24
Jan-04	39	163	80%	8	71
Jan-06	44	275	81%	11	74
Jan-08	44	381	77%	11	74

<i>Panel B: Avg. Asset Class Weights</i>						
Year	Money	Bonds	Equity	AI	AR	Other
Jan-90	0%	84%	16%	0%	0%	0%
Jan-92	0%	84%	16%	0%	0%	0%
Jan-94	0%	84%	16%	0%	0%	0%
Jan-96	0%	84%	16%	0%	0%	0%
Jan-98	0%	28%	72%	0%	0%	0%
Jan-00	0%	42%	58%	0%	0%	0%
Jan-02	0%	52%	37%	0%	0%	11%
Jan-04	1%	59%	36%	0%	0%	3%
Jan-06	0%	52%	43%	1%	0%	3%
Jan-08	1%	54%	35%	1%	4%	5%

The sample consists of the "Main" institutional MMA sample from August 1988 through July 2008. Panel A shows the number of MMAs (#MMA) and mandates (#M), the ratio considered mandates (M_{cons}), the number of overlay mandates (#OL) and absolute return mandates (#AR) within the MMA in columns and years in rows. Panel B shows the allocation by asset class, including money market, bonds, equity, alternative investments (AI), absolute return (AR) and other mandates within MMAs by columns in each year by rows.

Chapter 3

Risk-Taking in Institutional Investments

3.1 Introduction

Most of the extant empirical literature on asset management has concentrated on mutual funds. However, OECD annual statistics reveal that institutional investments accounted for U.S. \$14.2 trillion of financial assets in 2008, while U.S. mutual funds accounted for only U.S. \$9.7 trillion. In addition to the economic relevance, there are regulatory implications for institutional investments, as they have become subject to decreased legislative restrictions. This article explores whether internal control mechanisms and considerable differences in investment behavior can fill this research gap in the behavior of institutional investors and/or facilitate improved corporate

governance. However, research on institutional investments is quite lacking, which we believe stems from limited data access.

Retail investors are the most common investors in mutual funds, which can be subject to tournament behavior, a principal-agent problem. Brown et al. (1996) and Chevalier and Ellison (1997) were among the first to analyze this phenomenon, which occurs when fund managers with relatively poor performance during the first half of the year, denoted as "losers," increase portfolio risk during the second half of the year in order to improve performance. "Winner" funds, on the contrary, lock in their intermediate returns to reduce risk in the second half of the year. Tournament behavior is generally attributable to two specific incentives. First, rather than using detailed and highly frequent data, private investors tend to pay more attention to annual performance rankings published by, e.g., newspapers and magazines.¹

Second, empirical evidence has shown a convex relationship between fund flows and past performance for mutual funds (Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). In fact, "losers" tend to be less affected by fund outflows than "winners" are affected by fund inflows.

Less frequent monitoring and disproportionate fund flows, however, can impede effective governance. In combination with management fees, which increase along with AuM, a tournament for inflows can arise. Instead of

¹For the U.S., see e.g., "Money 70: The Best Mutual Funds You Can Buy," Money Magazine, February 2009. <http://money.cnn.com/magazines/moneymag/bestfunds/2009/index.html>. For Germany, see e.g., "Fondskompass", Capital, <http://www.capital.de/tools/fondskompass/index.html>.

maximizing risk-adjusted returns (favored by retail investors), mutual fund managers often start "gambling" in the hopes of improving returns. In the process, they produce excessive turnover and higher transaction costs. Methods to alter a fund's risk makeup include the use of derivatives, the selection of more risky assets, changes in cash holdings, and the omission of rebalancing activities.

In summary, a misalignment of incentives as well as less frequent and less effective monitoring can lead to a considerable and undesirable change in risk structure. Basak et al. (2008), Chen and Pennacchi (2009), and Kempf et al. (2009) are among the authors who have recently studied this phenomenon.

Institutional investors are a valuable subject for an investigation of tournament behavior, and not only because of their sheer market size. Such an exploration also holds great academic and practical relevance. Goyal and Wahal (2008), for example, posit that tournament behavior will not be as prevalent for institutional investors as for retail investors because of diverging customer relationships.

However, more important from our viewpoint is that institutional investors typically have more investment experience, a broader knowledge base, more systematic data collection and more frequent performance evaluation (Bank for International Settlements, 2003; Paller, 2006). Goyal and Wahal (2008) show that investors use excess returns as a means for professional manager selection. They also exhibit better and more frequent monitoring, professional risk management strategies, and risk budgeting techniques

(e.g., managers face strict tracking error limits) (Sharpe, 2002b; Blome et al., 2007). Finally, in contrast to mutual funds, Del Guercio and Tkac (2002) show a linear relationship between performance and fund flows.

The frequent use of modern performance attribution techniques enables investors to gauge manager performance more effectively, and to penalize poor performance by withdrawing assets. This paper thus analyzes investors' performance-based reallocations that are conducted to prevent undesirable risk-taking by multi-manager account (MMA) managers. MMAs are pooled investment vehicles accessible only to groups such as insurance companies, corporate pension funds, unions, foundations, endowments, etc. After choosing an overall strategic asset allocation, institutional investors can appoint several managers to control different parts of their total portfolios, e.g., one for a bond mandate and another for an equity mandate.

Active reallocation can be conducted by either launching a new mandate or by shifting assets between existing mandates. Refraining from rebalancing, e.g., to avoid transaction costs, is considered a passive reallocation. However, it is also a deliberate investor decision. From our perspective, it would reflect an exploitation of positive momentum in single mandates, or an appreciation of past performance.

Using this governance tool not only demonstrates improved investment skills (because of the use of advanced performance measures), but it should also help reduce any associated agency conflicts. Thus, we hypothesize that the prospect of losing AuM (because of poor performance) mitigates (or at least reduces) the incentives for managerial risk-taking. If institutional

investments reduce principal-agent conflicts, they may add value and justify their existence, contrary to Lakonishok et al. (1992).

In our analysis, we use an audited but publicly non-available German dataset for the 1998-2007 period. Our sample consists of forty-seven MMAs that include more than 400 single mandates, which represents approximately 17% of the German market. Note that European and U.S. MMAs are very similar structurally, which allows us to generalize our findings.

With this analysis, we contribute to the literature in three ways. First, we investigate tournament behavior in delegated portfolio management solely on an institutional investment level. Despite their relevance to the capital markets and to structural differences in effective governance, to the best of our knowledge, previous analyses have only considered mutual funds.

Second, we explore institutional investors' reallocations among mandates based on past performance measures, which include raw returns, abnormal returns, alpha, and timing returns. Besides contributing to the positive feedback trading literature, we demonstrate how institutional investors implement more frequent monitoring and improved control. Previous work has used either case-based evidence or analyzed net cash inflows (again for mutual funds only). Our analysis relies on a portfolio view, where MMA managers do not compete for inflows from other investors.² Rather, they strive to increase the relative size of their mandates by reallocating within the same account.

²In practice, managers do compete for new mandates. However, we have no information on that in our dataset.

Third, in addition to equities, we explicitly analyze bond investments, which comprise the largest share of total institutional assets. To the best of our knowledge, previous empirical work on delegated money management and tournament behavior has only focused on equity or balanced funds. Deli (2002) finds different compensation structures for equity and bond fund managers in mutual funds. If this is also the case for institutional investments, there will be a strong argument for different competition intensities between equity and bond managers within MMAs. We develop a new method to measure this intensity among managers of the same asset class within MMAs. We measure whether an investor's decision to increase the sum of all, e.g., equity mandates (except for one) within the MMA has a negative effect on the size of a single equity mandate.

Our main findings are as follows. First, reallocation as a governance tool is more pronounced among bond managers. This should reduce incentives to participate in tournaments.

Second, the swift actions of institutional investors to reallocate portfolio shares among mandates are based on past performance. This behavior underlines financial sophistication, mitigates hidden actions, and highlights our argument of "effective governance". We attribute past mandate returns to components such as security selection, market timing, and benchmark returns, and we find that institutional investors statistically significantly rely on manager alpha. Note that bond and equity mandates are governed similarly.

In line with Busse (2001), we find an ostensibly hidden action phenomenon in univariate tests. However, the individual contract specifications allow for a large heterogeneity of mandates. Thus, the effect disappears completely when using advanced panel methods. The failure to find evidence of harmful risk-taking, for both equity and bond managers, supports our hypothesis of "effective governance in" MMAs.

The remainder of this article is structured as follows. Section 3.2 explores the commercial practices of German MMAs that are available to institutional investors. Section 3.3 describes the data and compares our dataset to previous U.S. analyses. Subsection 3.4.1 discusses whether investors behave differently in regard to bond and equity mandates, while subsection 3.4.2 investigates reallocations conducted by investors due to performance measures. The tournament behavior of fund managers is explored further in subsection 3.4.3. Section 3.5 summarizes our results and gives our conclusions.

3.2 Institutional Investor Practices

3.2.1 Institutional versus Retail Investments

This section discusses the relevant studies on the structural differences between institutional and retail mutual fund investments. In this subsection, we review the empirical evidence on retail and institutional investments, which is mainly from the U.S. In subsection 3.2.2, we present the structure of German pooled investment vehicles, which are similar to the U.S. and European

MMAAs analyzed here. This is followed by a description of some key regulatory aspects and the relevant consequences for monitoring and governance.

The literature on mutual funds can be divided into two strands: 1) studies on performance that include the question of persistence and fund managers' abilities to engage in market timing or security selection, and 2) studies on agency problems in delegated portfolio management which focus on incentives of typical fund manager compensation schemes, e.g., relative performance evaluation. It is important to understand the causes of tournament behavior in mutual funds to make the case for institutional investments. Overall, most studies find neither outperformance nor persistence of performance for mutual funds in the long run see, e.g., Bollen and Busse, 2001; Chen et al., 2000.

Carhart's (1997) seminal paper attributes any persistence to systematic risk factors. However, there is some evidence of persistent outperformance for short time frames (see Gruber, 1996 or Bollen and Busse, 2004). Cremers and Petajisto (2009) find outperformance only for funds with a high "active share", a measure of security selection skills.

Several papers have contributed important insights into the drivers of risk-taking by mutual fund managers. Although the basic idea of evaluating relative performance is appealing, Admati and Pfleiderer (1997) show that benchmarking can have detrimental effects on portfolio managers' efforts and portfolio composition. Elton et al. (2003) find that positive stock selection ability is favored by incentive fees, but they can also give rise to undesirable risk-taking after poor performance.

For a somewhat opposing perspective, see Gehrig et al. (2009), who find that bonus payments induce more effort, but do not increase risk-taking. Chevalier and Ellison (1999) find that career concerns and fear of job loss lead younger managers to herd into conventional investments in an effort to avoid unsystematic risk.

Studies on the performance and persistence of institutional investments also reveal ambiguous results. Bogle and Twardowski (1980) were the first to study a large set of institutional equity portfolios, but they only compared returns. Lakonishok et al. (1992), Coggin et al. (1993) and Goyal and Wahal (2008) find largely poor performance, although persistence exists to some extent. Others find similar evidence of persistence, for example, Christopherson et al. (1998), Ferson (2002), and Tonks (2005). However, their results suffer from survivorship bias or small sample size. Busse et al. (2010) conclude that it is 'difficult to make the case for persistence'.

A study on U.S. pension funds by Brinson et al. (1986) finds that strategic asset allocation is the predominant determinant of performance, while security selection and timing diminish returns on average. These findings are supported by Blake et al. (2002), who analyze a sample of U.K. pension funds and find a cluster of performance around the median fund manager. However, they ascribe this to reputation effects, e.g., when a fund manager's priority is not to stand out negatively against peers. And compensation schemes are a strong disincentive for active management because they depend largely on year-end AuM rather than on performance.

Our conclusion from this review is twofold. First, insights from previous literature suggest it is difficult for investors to motivate desired investment decisions, and that implementing incentive structures to lead to effective governance in delegated portfolio management is essential. Second, over the long term, it is difficult to find any evidence of persistence. However, it seems possible to identify successful active managers in short time frames.

Both our conclusions indicate that a performance-based (re)allocation of assets to managers might be reasonable. In order to understand how this would be implemented in institutional investments, we first discuss their structures in more detail.

3.2.2 MMA Structure

Nowadays, professional German investment institutions have access to vehicles referred to as special funds ("Spezialfonds"), which were established in 1968. These are typically structured as MMAs,³ but they diverge from standard retail mutual fund investments as depicted in Figure 3.1. Investment decisions in the latter are delegated to one manager, while in MMAs, as their name suggests, they are delegated to multiple managers. Assets are held by the asset management firm (AMF, which in Germany is called the KAG, the "Kapitalanlagegesellschaft") on behalf of the sponsor (referred to as "investors", although sponsors and beneficiaries need not be the same).

³Other terms used for MMAs are multiple-style portfolios, multi-disciplinary portfolios, multiple-style accounts, multi-disciplinary accounts, and multi-manager funds. See, e.g., Stein and McIntire (2003) and Tobler-Oswald (2008).

The asset management firm, by order of the investor, appoints specialized internal and/or external investment managers in the form of single mandates. Investors normally use consultants to assist in selecting the AMF or the managers.

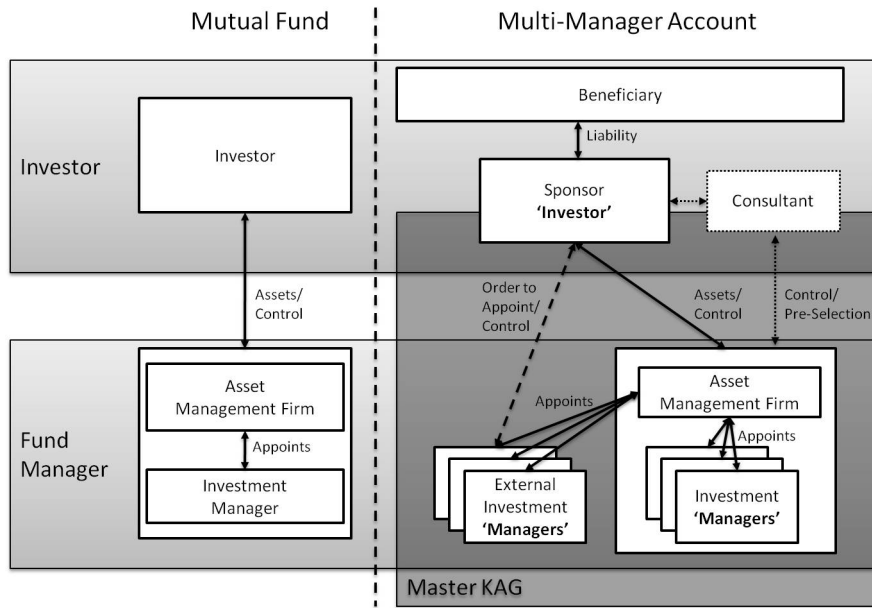


Figure 3.1: Public Mutual Fund versus Institutional Investment Fund

German law assumes institutional investors have greater investment skills and better information than retail investors. Thus, lower protection and regulation would be required. This immediately highlights the need for internal control mechanisms to ensure effective delegation. The major features we describe subsequently were originally intended to provide tailor-made solutions to investors. But we believe they also impact managers' risk-taking abilities.

For example, contracts between investors and AMFs are designed individually, and normally include investment goals, fees, and agreements on reporting. Legal permissions are not required. Investment constraints such as minimum cash holdings, maximum asset class weights, and short-selling constraints are seldom used and are far less restrictive. Thus, managers are allowed to reduce cash holdings to zero. Compared to mutual funds, the number of legally permitted asset types is larger. However, the arguments for the former can lead to heterogeneity. Thus, we need to control for mandate-specific characteristics in further analysis.

Furthermore, AMFs are only required by law to provide information annually to investors. This usually takes the form of brief private reports at the end of each financial year. Mutual funds, in contrast, must publish reports every six months. At first glance, it may seem that a benefit accrues from the decrease in reporting responsibilities and publishing expenses, but there is also less monitoring of managers compared to retail mutual funds.

In recent years, a specialization has emerged within the German market for institutional asset management, Master-KAGs. Master-KAGs are AMFs that exploit economies of scale in formal portfolio management. They typically offer administrative services such as accounting, tax reporting, monitoring and reporting to regulatory authorities, and risk management. They also offer monitoring services by providing IT information gateways and risk and return reports on a weekly or monthly basis. The systematic collection and aggregation of investors' portfolio data, the enhancement of reporting

schemes, and the ongoing review of manager performance likely facilitates effective governance compared to retail mutual funds.

In addition to AMFs, as we noted, investors are supported by consultants who can improve transparency in performance and risk-taking behavior. They guarantee access to small investment management boutiques and an extensive list of highly skilled managers, and they even offer manager preselection.

Another factor that drives monitoring and control is the much lower number of institutional investors due to restricted access. In fact, private investors have been excluded since March 1990.⁴ In contrast to the thousands of retail investors who can hold minor stakes in a single mutual fund, having only one owner (or at most a few) can improve control by reducing the free-rider problem (see Shleifer and Vishny, 1986).

Finally, institutional investors frequently pursue a top-down investment approach. Determining the long-term strategic asset allocation for the entire portfolio is the responsibility of the investor. Managers are then in charge of security selection, and determining systematic exposures to market risk and other risk factors such as value, size, and momentum (Fama and French, 1993; Carhart, 1997). If a manager's efforts are not in line with investor

⁴The details were outlined in the Investment Trust Act ("Gesetz über Kapitalanlagegesellschaften", KAGG), which was replaced by the German Investment Act ("Investmentgesetz", InvG) on January 1, 2004. The latter was implemented to meet EU UCITS (Undertakings for Collective Investment in Transferable Securities) Directives 2001/107/EC and 2001/108/EC from January 21, 2002. The previous maximum number of shareholders (thirty) was abolished by the Amendment to the German Investment Act ("Investmentmodernisierungsgesetz"). But the number of investors per MMA has not increased significantly.

goals or expectations, there are two alternatives. In the short term, investors can reallocate assets quickly (we analyze this behavior in more depth in subsection 3.4.2). In the long term, investors may appoint a new investment manager. As Kempf et al. (2009) note, the possibility of losing one's job may also help mitigate tournament behavior.

In summary, institutional investors have access to tailor-made investment products that are not readily available to retail investors. Institutional investors usually have larger investment stakes, greater skills, and higher information frequency and quality, which is guaranteed by consultants and the AMF. Furthermore, job incentives seem stronger, as low-performing managers are liable to lose their mandates. Ex ante, the overall effect of monitoring and control should ameliorate "effective governance" and at least reduce harmful risk-taking by managers. We believe the large systematic differences between standard mutual funds and institutional MMAs warrant a more detailed study of this conjecture.

3.3 Data

In this section, we describe our data and statistically analyze its reliability. The dataset was provided by one of the three largest AMFs (or Master-KAGs) in Germany. The institutional investors considered here include the whole range of legal bodies mentioned earlier.

As of December 2009, total AuM for institutional investments was roughly €111 billion in 52 MMAs, with 431 subordinate mandates. Thus, the average investor portfolio had about €2.1 billion in AuM, while each mandate was on average €250 million. The German asset management association, BVI (2010c), estimates there were 3,900 local institutional funds in 2008, with a total of €641 billion AuM. Although the dataset seems relatively small in absolute numbers, it accounts for 17% of AuM, and thus represents a significant share of the German institutional investment industry.

Our analysis covers ten years, from January 1998 through December 2007. The data consist of weekly mandate and benchmark portfolio values,⁵ as well as monthly weight information within MMAs. Additionally, we have explicit benchmark names for mandates, which allow us to distinguish among the following asset classes:⁶ money market, bonds, equities, alternative investments (AI), absolute return (AR), and others (unspecified).⁷ We study returns net of any costs such as trading, management fees, and overhead expenses.

Next, we describe our five-step construction process for the entire sample, which consists of 91,215 weekly observations for 431 mandates. In the first step, we exclude overlay mandates, which reduces our sample to 89,011 observations. The former are commonly governed by AMFs (but not single

⁵To avoid inferences about specific investors based on asset size, we obtained standardized values. These assume a value of 1 at the launch of the mandate.

⁶Some mandates have balanced benchmarks consisting of an equity and a bond share. We categorize by asset class if the respective share is larger than 50%. Although not reported, more than half of all managers invest in Europe. Only 10% of all fund managers compete with a North American benchmark, mostly from the U.S.

⁷Some funds lack benchmark information, for example, in the case of no investor agreements.

managers) to manage risk over all mandates for net positions (see subsection 3.2.2).⁸

For some mandates, portfolio values are reported on only a monthly basis, mostly prior to 2000. The diverging granularity of the data thus hampers the comparability of performance and risk measures that we need in section 3.4. So if there were two or more consecutive missing weekly returns in a mandate time series, we deleted all the observations prior to the missing values.

In our second step, we revised the mandated time series in four ways: 1) we linearly interpolate 678 single missing weekly portfolio values (0.8% of the dataset),⁹ which probably stem from data errors, 2) we set the nine negative mandate portfolio values to zero, which prevents short-selling, 3) we calculate weekly geometric returns for each mandate, and 4) we winsorize extreme returns at the 0.25% and 99.75% levels to ensure that outliers do not drive performance or risk measures.¹⁰ Our dataset consist of 84,640 mandate-weeks.

In the third step, we calculate monthly MMA returns as the value-weighted sum of all mandate returns (see Figure 3.2). A discussion of descriptions for MMAs follows in subsequent paragraphs.

⁸For more details on overlay management, see Jorion (1985), Heidorn and Siragusano (2006) and Stein and McIntire (2003). Note that we use the information about whether an MMA has an overlay mandate in subsequent analyses.

⁹We are aware that this procedure smooths volatility slightly. Note, however, that later results remain unchanged if we bootstrap missing returns.

¹⁰The quantiles for mandates are -8.47% and 9.88%; for benchmarks, they are -7.56% and 9.60%.

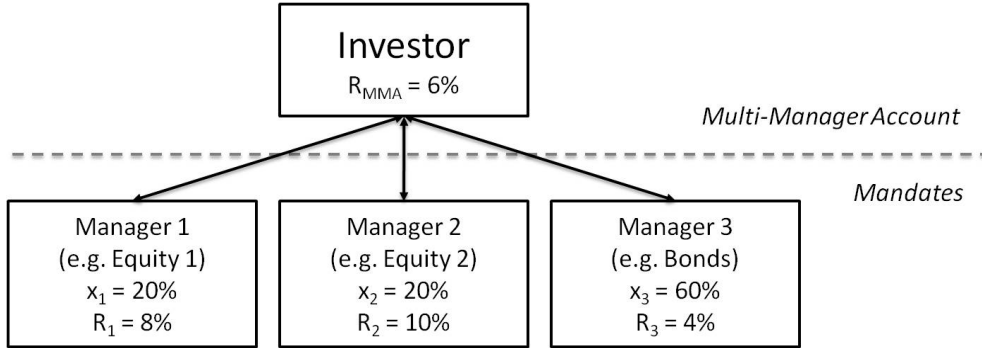


Figure 3.2: Sketch of Multi-Manager Account in the Dataset

As a fourth step, we consider traditional asset classes, equities and bonds, in our mandate sample only. Both account for more than 80% of our yearly observations. From our perspective, money market investments are not great opportunities for risk-taking, but alternative and absolute return investments are extremely heterogeneous and of minor relevance within MMAs.¹¹ Our methodology requires a full calendar year (fifty-two weeks) of data per mandate. Table 3.1 gives yearly time series descriptions for this mandate sample, denoted as "Main".

For robustness checks, we define various mandate subsamples in our fifth step. We already excluded absolute return mandates, which were identified by their benchmark names. However, some of our equity and bond mandates feature many zero benchmark returns that can impede otherwise sound performance attribution techniques used in the latter section.¹²

¹¹Note that the number of mandates within money market, absolute return, and alternative investments is fairly small and clustered in the last few years.

¹²We set benchmark-related performance and risk measures to zero in this case.

CHAPTER 3. RISK-TAKING IN INSTITUTIONAL INVESTMENTS

Table 3.1: Time Series Descriptions for Mandates

Year	#M	R_i Mean (Median)	Std	σ_i Mean (Median)	Std	$TE_{i,t}$ Mean (Median)	Std	x_i Mean (Median)	Std	Δx_i Mean (Median)	Std
Panel A: Main Mandates											
Total	993	6.35 (4.71)	11.88	8.85 (8.91)	6.25	3.41 (1.73)	5.97	24.85 (16.16)	25.20	-3.69 (-0.45)	13.71
Panel B: Bond Mandates											
1998	4	10.12 (10.29)	0.57	6.32 (5.56)	2.14	3.60 (3.26)	0.81	50.00 (36.30)	33.69	0.00 (-0.27)	0.89
1999	4	7.09 (6.58)	1.70	6.90 (6.74)	1.16	2.44 (2.36)	0.52	50.00 (36.57)	33.69	0.00 (-0.07)	0.58
2000	7	7.37 (7.11)	1.60	4.93 (5.99)	2.36	2.70 (2.34)	1.12	67.94 (75.59)	33.71	-3.12 (0.00)	9.33
2001	11	2.85 (2.23)	3.83	4.27 (3.51)	2.33	1.71 (1.63)	0.70	62.63 (75.82)	35.64	1.24 (0.00)	2.08
2002	19	4.98 (7.35)	5.19	3.76 (3.17)	1.50	1.99 (1.77)	1.15	47.79 (31.72)	33.53	-2.79 (0.40)	15.88
2003	38	5.00 (4.63)	2.41	3.81 (3.56)	1.10	1.32 (1.29)	1.08	45.01 (40.86)	23.66	-5.25 (-2.83)	9.75
2004	60	6.29 (6.38)	1.54	3.13 (2.61)	1.86	1.77 (0.80)	3.40	36.73 (30.01)	26.25	-3.58 (-0.21)	13.15
2005	80	4.45 (3.90)	3.18	3.09 (2.78)	1.37	1.38 (0.74)	1.78	36.20 (27.31)	29.62	-10.60 (-2.26)	24.05
2006	103	1.57 (0.39)	3.03	2.74 (2.47)	1.34	1.23 (0.82)	1.27	22.03 (15.61)	20.65	-2.21 (-1.23)	4.99
2007	137	1.93 (1.73)	2.56	3.71 (2.75)	2.38	1.95 (1.37)	1.97	17.84 (12.10)	19.11	-1.32 (-0.08)	5.62
Total	463	3.45 (3.21)	3.41	3.40 (2.78)	1.91	1.64 (1.13)	1.96	30.23 (20.44)	27.23	-3.74 (-0.62)	12.88
Panel C: Equity Mandates											
1998	7	11.23 (13.83)	11.17	15.52 (14.68)	5.94	11.81 (9.46)	6.57	73.52 (100.00)	36.46	-19.20 (-0.83)	33.60
1999	12	38.92 (36.25)	18.81	11.79 (10.76)	4.20	4.91 (3.46)	4.64	58.47 (53.74)	39.97	-21.63 (-2.20)	36.51
2000	15	-0.68 (0.74)	12.42	12.81 (11.05)	6.41	10.61 (6.77)	9.51	38.36 (28.65)	35.31	-7.46 (-1.55)	20.85
2001	18	-12.63 (-15.53)	9.64	14.03 (11.83)	4.80	5.78 (4.66)	5.61	29.36 (20.92)	28.78	-5.26 (-0.29)	11.58
2002	23	-32.66 (-37.69)	10.34	19.71 (18.88)	7.57	11.57 (4.81)	17.37	23.02 (17.74)	25.40	-3.25 (-1.30)	10.91
2003	41	11.56 (10.97)	6.01	19.10 (19.97)	3.49	7.43 (3.13)	12.31	22.53 (19.56)	17.83	-0.05 (-0.36)	6.93
2004	69	8.83 (8.20)	6.51	11.87 (11.40)	2.75	5.04 (2.11)	9.56	20.33 (14.56)	16.00	-2.72 (-0.56)	9.73
2005	96	23.81 (22.79)	7.26	10.70 (9.91)	2.60	3.23 (2.00)	4.51	22.36 (11.31)	26.81	-7.05 (-0.03)	23.75
2006	112	12.12 (13.33)	8.44	12.40 (12.28)	3.46	3.67 (2.32)	4.37	14.91 (10.08)	13.17	-2.03 (-1.06)	5.45
2007	137	3.07 (2.68)	9.22	14.97 (14.71)	3.96	4.26 (2.97)	4.71	12.30 (8.13)	11.12	-1.17 (-0.37)	5.00
Total	530	8.88 (9.09)	15.51	13.62 (12.99)	4.63	4.96 (2.69)	7.64	20.15 (11.78)	22.26	-3.64 (-0.41)	14.40

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. The table gives time series descriptions including means, medians in parentheses below, and standard deviations for variables by columns and years by rows. The number of mandates is indicated by #M.

Panel A shows cross-sectional data for the cleaned sample, while panels B and C give time series descriptions for bond and equity mandates. Annualized variables are return (R_i), volatility (σ_i), and tracking error (TE_i). We also provide mandate weights at the beginning of the year (x_i) and changes in these weights within the MMA for the same year (Δx_i).

Thus, if benchmark returns are zero for more than 5% of all weekly observations, we consider these as virtually identical to absolute return mandates, and we exclude them from our "noAR" subsample.¹³ In a second subsample, "noSuspects", we also exclude all mandates where the data has been cleaned. In our most restrictive subsample, "Survivors", we require mandates to have more than five years of observations.

Panel A in Table 3.1 gives cross-sectional descriptions for the main sample; panels B and C show time-series and cross-sectional descriptions for the equity and bond mandates.¹⁴ We have 993 mandate-years, of which 463 are bond and 530 are equity mandates. The average mandate return (R_i) is 6.35% p.a., while the median was lower, at 4.71% (medians are in parentheses). For risk, annualized volatility (σ_i) is 8.85% (8.91%), while tracking errors are 3.41% (1.73%) on average.¹⁵

The average mandate share (x_i) within an investor's portfolio is slightly below 25% (16.16%), but it ranges from 100%, for investors with only one mandate, to 0% for those who have withdrawn all funds. Changes in portfolio weights (Δx_i) are negative, with -3.7% (-0.45%) and investors have increased the average number of mandates within the observation period. The rationale for this could be simply to diversify manager skills (see Sharpe, 1981, for a discussion of "diversification of judgment").

¹³The number of mandate-years that we classify as absolute return mandates is roughly 9%. More than half of all MMA-years saw investments in such a mandate.

¹⁴We do not show results for the subsample analyses here (noAR, noSuspect, Survivors), as they are structurally very similar. However, the tables are available from the authors upon request.

¹⁵Tracking errors (TE_i) are calculated as: $TE_i = std(R_i - R_{BM})$ and range from roughly 60% to 0%.

Indeed, if we split our sample into bond (panel B) and equity (panel C) mandates, we observe that the number of mandates increases strongly over time. In 1998, we begin with eleven (four bond and seven equity), and by 2007 the number has increased to 274 (see Table 3.1). Bond mandates yield lower returns, 3.45% p.a., compared to equity, 8.88%. The latter fluctuate between -33% in 2002 and +39% in 2000, which both represent the boom and bust of the new economy.

Table 3.2: Time Series Descriptions for Multi-Manager Accounts (MMAs)

Year	#MMA	R_{MMA_j}		σ_{MMA_j}		# M_j		$\Delta\#M_j$	
		Mean (Median)	Std	Mean (Median)	Std	Mean (Median)	Std	Mean (Median)	Std
1998	8	15,56 (13,80)	8,11	16,58 (17,69)	6,56	1,63 (1)	0,92	0,88 (0)	2,10
1999	8	33,62 (35,65)	18,20	12,75 (14,00)	3,77	2,50 (2)	2,00	0,50 (0)	0,93
2000	11	1,70 (2,58)	3,95	9,74 (9,76)	3,98	2,64 (2)	2,34	0,09 (0)	0,30
2001	14	-3,71 (-2,12)	7,20	10,56 (9,22)	6,86	2,64 (2)	2,47	0,43 (0)	1,09
2002	17	-8,59 (-6,70)	11,47	8,34 (5,83)	6,70	3,12 (3)	2,42	0,35 (0)	0,61
2003	28	8,79 (8,73)	3,57	6,50 (5,19)	3,82	3,39 (3)	1,95	0,61 (0)	0,92
2004	39	6,92 (6,70)	2,58	3,53 (3,24)	1,54	4,10 (4)	2,45	1,03 (0)	2,40
2005	43	12,64 (12,41)	5,51	4,92 (4,87)	2,11	5,00 (4)	3,50	1,19 (0)	1,89
2006	44	6,46 (6,34)	3,83	4,12 (3,96)	1,69	6,16 (5)	4,41	1,50 (1)	2,14
2007	47	2,92 (2,67)	1,81	3,94 (3,72)	1,95	7,49 (6)	5,86	0,94 (0)	1,37
Total	259	6,55 (5,76)	9,41	5,90 (4,36)	4,53	4,81 (4)	4,09	0,93 (0)	1,73

The sample consists of all institutional MMAs from 1998 through 2007. The table gives time series descriptions including means, medians in parentheses, and standard deviations for variables in columns and years in rows. Variables are return p.a. (R_{MMA_j}), annualized volatility (σ_{MMA_j}), number of total mandates in January ($\#M$), and changes in the number of mandates ($\Delta\#M_j$) in the same year. The last two rows show cross-sectional descriptions. The number of total MMAs per year is indicated by #MMA.

Such a variation is also observable in annualized volatilities, with bond mandates being generally less risky. As expected, tracking errors are on average three times as high for equity as for bond mandates. However, both decrease over time, indicating a possibly increasing sensitivity of investors

toward active risk. Finally, bond mandates, with roughly 30% (20%), represent larger fractions of MMAs than equity mandates, with about 20% (12%). Changes in relative mandate size are similar in terms of percentage points.

Table 3.2 gives descriptions for MMAs instead of mandates. These consist of all volume-weighted mandates (money market, bond, equity, absolute return, alternative investments, unknown). Overall, we have 259 MMA-years, ranging from eight in 1998 to forty-seven at the end of 2007. The average return of 6.55% (5.76%) is slightly higher than the mandate average.¹⁶ Investors earned positive raw returns every year except for 2001 and 2002. The volatility (σ_{MMA_j}) of 5.90% is less than the mandate average because of diversification, and decreases significantly as new mandates are added ($\Delta\#M_j$). On average, one mandate was added nearly every year, but no investor reduced the number of mandates. Overall, each MMA consisted of roughly five (four) mandates (ranging from one to thirty-three).¹⁷

We are confident that our MMA dataset is representative of U.S. and European institutional investments, not only in investment structure, but also in investment policy and success. Table 3.3 summarizes key figures from our dataset and compares them to previous relevant studies (e.g., Brinson et al., 1986 and Ibbotson and Kaplan, 2000). The important conclusions are:

1. The medians of time series R^2 are 86.95% for mandates and 83.15% for MMAs. These are close to the results for U.S. pension funds.

¹⁶The divergence from mandate returns stems from the inclusion of money market, absolute return, alternative investment, and unknown benchmark mandates.

¹⁷In about one third of all MMA-years, risk was managed on a global level within a risk overlay fund.

2. Particularly for the last years of our sample, we find institutional investors had become aware of risk management techniques and were demanding a reduction in active management (Bank for International Settlements, 2003). Ibbotson and Kaplan (2000) predict the cross-sectional R^2 will double if active management decreased by half. Our dataset reflects this.
3. German institutional investors realize similar outperformance as U.S. pension funds, but higher outperformance than Drobetz and Köhler's (2002) mutual fund sample.
4. International standards for performance evaluation, reporting, monitoring, preselection and termination of mandates, as well as worldwide access to managers, should guarantee a structurally similar environment (Bank for International Settlements, 2003). Overall, we conclude our sample is representative to use as a basis for further analysis.

Table 3.3: Overview of Studies on Investment Policy and Success

Authors	Fund Type	#	Region	Period	Investment Policy		Success	
					Time Series R^2 Mean Median	Cross Sectional R^2	Outperf. p.a. Mean Median	
Brinson et al. (1986)	Pension Funds	91	USA	1974 - 1983	93.60%	NA	NA	NA
Brinson et al. (1991)	Pension Funds	82	USA	1977 - 1987	91.50%	NA	NA	-1.10%
Ibbotson and Kaplan (2000)	Pension Funds	58	USA	1988 - 1998	81.40%	87.60%	40.00%	-0.08%
Ibbotson and Kaplan (2000)	Mutual Funds	94	USA	1988 - 1998	88.00%	90.70%	35.00%	-0.44%
Hoernemann et al. (2005)	Synthetic Portfolios	-	USA	1970 - 2004	77.48%	NA	NA	-0.27%
Drobetz and Köhler (2002)	Mutual Funds	51	GER&CH	1995 - 2001	82.90%	85.70%	65.00%	0.14% ^a
This Study	Mandates	274	GER	1998 - 2007	78.96%	86.95%	79.10%	-2.37%
This Study	Multi-Manager Accounts	47	GER	1998 - 2007	74.49%	83.15%	57.27%	-0.17%
								0.21%
								-0.03%

The first column shows authors and publication years of various relevant studies. Columns 2 through 5 provide basic information about the data samples used in these studies, including fund type, number of funds (#), region, and observation period. Columns 6-7 indicate mean (median) explanatory power (R^2) of benchmark returns for fund returns in time series regressions proposed by Brinson et al. (1986). This results in a standard market model of the form $R_{i,t} = \alpha_i + \beta_i * R_{B,M,t} + \epsilon_{i,t}$. In column 8, we show Ibbotson and Kaplan (2000) cross-sectional R^2 from regressions of full-period annualized returns of all funds on their respective benchmark returns ($R_i = \alpha_i + \beta_i * R_{B,M} + \epsilon_i$). Columns 9 and 10 depict outperformance, calculated as $R_i - R_{B,M}$. "Inst. Mandates"^a denotes the "main" institutional equity and bond mandate sample from 1998 through 2007. "Multi-Manager Accounts"^a denotes the entire MMA sample. For MMAs, we consider the initial weights of each asset class in an investor's portfolio as the strategic asset allocation and benchmark, respectively. A change in the benchmark is executed if 1) new mandates are added to the MMA, and 2) any mandate changes its benchmark name. All mandates in all asset classes are used to calculate MMA and its benchmark returns.

^aNo transaction costs considered.

3.4 Empirical Results

3.4.1 Are Bond and Equity Mandates Considered Differently by Investors?

Before we can examine our two main questions about performance-based reallocations and risk-taking behavior, we need to address the differences between bond and equity mandates from an investor perspective. This is an important point, as we consider both standard asset classes in subsequent analyses. Lakonishok et al. (1992) argue that bond portfolios offer less room to stand out from competitors, because they use more generic products. This is confirmed by Blake et al. (1993) for bond mutual funds.¹⁸ Furthermore, Elton et al. (1995) and Detzler (1999) find that historical alphas are not useful in predicting subsequent alphas for bond funds, which implies non-persistence. This implies that a reputation for stable results is far more important than investment performance.

Therefore, we use two different approaches. First, we explore how large and frequent reallocations between mandates are made. The magnitude gives us insight into how extensively this tool of governance is used. We also test for differences in bond and equity mandates. Second, we investigate whether assets are reallocated within the same or different asset classes. We posit that a shift from a bond to an equity mandate is probably motivated by

¹⁸Blake et al. (1993) find that returns are largely attributable to three factors: government and corporate investment-grade bonds, mortgage-backed securities, and high-yield bonds. One-index models already yield a high goodness-of-fit of more than 70%. Elton et al. (1995) and Detzler (1999) find very similar results.

tactical considerations.¹⁹ Furthermore, reallocations from one bond mandate to another may indicate the competitiveness of the environment managers face within their own asset class.

Panel A of Table 3.4 shows the magnitude of yearly reallocations in mandates in percentage points of an MMA (Δx_i). We observe a trend toward hiring more managers over time, which leads to an average reduction in mandate size in percentage points. In approximately 25% of the observations, mandate size is reduced by more than 3% of the overall MMA. However, above the 75% quantile, in terms of reallocation magnitude, we note mandates exhibit a positive reallocation (see the third row of panel A).²⁰

In panel B, reallocations are sorted by magnitude in relation to each mandate's size ($\frac{|\Delta x_i|}{x_i}$), independent of sign. Here, we note that in more than 25% of all mandate-years, mandates are increased/decreased by more than 25% of their own size. With an average AuM per mandate of €250 million, the boundary value of the 75% quantile corresponds to a reallocation of \pm €64.6 million.

After discussing the size of in- and outflows, we next use standard χ^2 -tests to examine whether investors use reallocations similarly for bond and equity mandates. In both panels, we can reject the hypothesis that bonds and

¹⁹Rule-based strategies include portfolio insurance, "best of n assets" concepts, and shortfall risk approaches. Forecast-based strategies target expectations about future developments of asset classes relative to each other (MacBeth and Emanuel, 1993; Bollen and Busse, 2001). For a detailed discussion on timing strategies, see Herold et al. (2007). For tests on market timing ability, see Treynor and Mazuy (1966), Henriksson and Merton (1981) and Bollen and Busse (2001).

²⁰Results for subsamples are structurally very similar and are available from the authors upon request.

Table 3.4: Magnitude of Reallocations in Equity and Bond Mandates

Quantile	Magnitude of Reallocation	# Observations			χ^2	p-Val
		Total	Bonds	Equity		
Panel A: Changes of Mandates' Weights in Percentage Points (Δx_i)						
25%-Quant.	< -2.94%	248	127	121	8.15**	0.02
25% - 75%-Quant.	-2.94% to 0.37%	497	239	258		
75% Quant.	> 0.37%	248	97	151		
Panel B: Relative Changes of Mandates' Weights in Percent ($\frac{ \Delta x_i }{x_i}$)						
25%-Quant.	< 4.17%	248	148	100	23.46***	0
25% - 75%-Quant.	4.17% to 25.84%	497	216	281		
75% Quant.	> 25.84%	248	99	149		

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. Panel A shows the analysis of reallocations within equity and bond mandates in MMAs by magnitude in percentage points (Δx_i). Panel B shows reallocations in mandates in relation to each mandate's size ($\frac{|\Delta x_i|}{x_i}$). The first two columns indicate the quantiles and the respective magnitudes over all observations in which we sort reallocations (below 25%, 25% to 75%, above 75%). Columns 3 to 5 show the absolute number of observations and are separated by bond and equity mandates. χ^2 indicates the test statistic, and p-Val is the corresponding p-value, where we test for independence of the frequencies of observing changes in equity and bond mandates. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

equities are independently distributed among quantiles. In panel A, we see that equity mandates exhibit comparatively more reallocations in the upper quartile (which is similar to the increases in portfolio weights). In relative terms (see panel B), equity managers face larger reallocations compared to the amount of their AuM. This suggests investors use larger reallocations for equity mandates.

We argued previously for effective governance and penalization of inferior performance. However, combined with Table 3.4, this raises the question of whether competition among bond managers within an MMA is more or less intense than for their equity peers. The answer will shed light on bond manager governance.

For every year, we calculate the change in mandate size (Δx_i) for all equity and bond mandates (i) in our sample. Next, we identify all mandates (M_j) in the same MMA (j) and their asset class. We can then calculate the aggregate weight changes for these mandates by asset class (ΔAC_i^j). We use four categories: bonds (B), equities (E), others (O) (money market, alternative investments, and unknown benchmark mandates), and new mandates (N), denoted as $\Delta B_i^j, \Delta E_i^j, \Delta O_i^j, \Delta N_i^j$. We can thus estimate a binary response model. The dependent variable (y_i) is equal to 1 if a positive reallocation (weight increase) has occurred in a mandate ($\Delta x_i > 0$); it takes a value of 0 otherwise. We add multi-manager (MMA_j) and year (Y_t) fixed effects, both as least squares dummy variables (LSDV) (see Equation (3.1)). This accounts for fixed effects such as institutional investor type and seasonal effects (e.g., up and down markets).

The explanatory variables are an intercept (γ_0), a dummy for bond mandates (B_i) and the sum of reallocations of the remaining mandates ($m = 1, \dots, M_j$ with $m \neq i$) of an MMA (j) by asset class ($\Delta AC_i^j = \sum_{m=1; i \neq m}^{M_j} \Delta x_m^{j, AC}$ with $AC \in [B, E, O, N]$). Asset class reallocations interacted with a dummy for bond mandates will allow for slope differences.

$$\begin{aligned}
 P(y_i = 1 | \Delta x_i) &= \gamma_0 + \gamma_B * B_i + \gamma_{MMA} * MMA_j + \gamma_y * Y_t \\
 &+ \sum (\lambda_{\Delta AC} * \Delta AC_i^j) + \sum (\lambda_{B, \Delta AC} * B * \Delta AC_i^j) + \epsilon_i
 \end{aligned}
 \tag{3.1}$$

Table 3.5 gives estimation results for linear probability (LPM, LPM II) and logit models (Logit, Logit II). We use the latter to account for heteroscedastic and non-normally distributed errors (ϵ_i) and to avoid predicted probabilities exceeding the unit interval. In models (1) and (2), we use dummy variables if the sum of weight changes in the remaining mandates within an asset class is larger than 0. This is also shown in the first row by $\Delta x_i = 1 | \Delta AC_i^j > 0$, when an investor has decided to increase the sum, for example, of all equity mandates.

For the LPM II and Logit II in models (3) and (4), the explanatory variables are observed changes. This is indicated in the first row by "*Observed* ΔAC_i^j ". Thus, we estimate the probability that a mandate will increase contingent on an increase of, say, 10% in the sum of all remaining equity mandates. For both logit models, we provide average partial effects (APE), which are easier to interpret.²¹

As discussed earlier, we need to determine whether there are differences in penalization and competition within asset classes, e.g., whether there are reallocations from one equity mandate to another (ΔE). The results from the logit estimation in model (2) reveal that the probability of any equity mandate being increased (decreased) is not affected by an investor's decision to increase all remaining equity mandates in the MMA.

²¹For model (2), we estimate the partial effect for each explanatory variable jumping from 0 to 1, holding all other variables constant. For model (4), we calculate the partial effect averaged across the population distribution. Both are denoted as APEs.

CHAPTER 3. RISK-TAKING IN INSTITUTIONAL INVESTMENTS

Table 3.5: Intensity of Competition in Multi-Manager Accounts by Asset Classes

Explanatory Model	$\Delta x = 1 \Delta AC_i^j$			Observed ΔAC_i^j		
	LPM (1)	Logit (2)	APE	LPM 2 (3)	Logit II (4)	APE
γ_0	0.64*** (4.05)	0.81 (1.00)		0.38*** (2.64)	-1.27 (-1.23)	
B_i	0.04 (0.54)	0.32 (0.79)	0.06	0.01 (0.20)	-0.19 (-0.84)	-0.03
ΔB_i^j	-0.28*** (-5.12)	-1.39*** (-4.95)	-0.23***	-1.86*** (-4.47)	-22.05*** (-6.14)	-0.32***
ΔE_i^j	0.07 (1.24)	0.26 (1.04)	0.05	-1.31*** (-4.23)	-21.39*** (-6.82)	-0.31***
ΔO_i^j	-0.07 (-1.12)	-0.29 (-0.96)	-0.05	-1.57*** (-4.57)		
ΔN_i^j	-0.14*** (-2.68)	-0.63** (-2.54)	-0.12**	-1.49*** (-5.29)	-21.41*** (-7.23)	-0.52***
$B_i * \Delta B_i^j$	0.17** (2.28)	0.70* (1.84)	0.14*	0.48 (0.80)	-29.17*** (-3.57)	-0.34***
$B_i * \Delta E_i^j$	-0.40*** (-5.53)	-2.31*** (-5.41)	-0.31***	-0.57 (-1.10)	-37.40*** (-4.99)	-0.33***
$B_i * \Delta O_i^j$	0.07 (0.91)	0.45 (1.12)	0.09	-0.01 (-0.02)		
$B_i * \Delta N_i^j$	-0.04 (-0.67)	-0.38 (-1.03)	-0.07	-0.39 (-0.85)	-36.84*** (-5.06)	-0.46***
SER	0.20	0.35		0.19	0.35	
$\tilde{R}^2 / McFadden R^2$	0.12	0.16		0.17	0.31	
DW	1.92			1.91		
$F-p / LR-p$	0.00	0.00		0.00	0.00	
LL		-543.4			-441.7	
Obs	993	993		993	993	
FE_Y	Yes	Yes		Yes	Yes	
FE_{MMA}	Yes	Yes		Yes	Yes	

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. We estimate a binary response model (see Equation (3.1)), where y equals 1 if the change in a single mandate weight is larger than 0 ($y = 1|\Delta x_i > 0$). Models (1) and (3) show linear probability model results (LPM, LPM II); models (2) and (4) show maximum likelihood logit results (Logit, Logit II).

For explanatory variables, we use an intercept (γ_0), a dummy for bond mandates (B_i), and the sums of changes in weights of the remaining mandates ($n = 1, \dots, N$), summed by asset class in an MMA (j) in the same observation period. These changes in asset classes (ΔAC_i^j) for equities, bonds, other asset classes, and newly entrusted mandates are $\Delta B_i^j, \Delta E_i^j, \Delta O_i^j, \Delta N_i^j$.

In models (1) and (2), the explanatory variables are binary variables that equal 1 if $\Delta AC_i^j > 0$. In models (3) and (4), we use observed reallocations in asset classes ('Observed ΔAC_i^j '). For the logit models, we provide estimated changes in probabilities and partial effects (APE), respectively. In model (2), APE is calculated for each explanatory variable jumping from 0 to 1, holding all other variables constant. For model (4), we calculate the partial effect averaged across the population distribution (see, e.g., Wooldridge, 2009).

The standard summary statistics are below the estimated coefficients. These are standard errors of the regression (SER), adjusted goodness-of-fit (\tilde{R}^2) and McFadden pseudo- R^2 for logit, and Durbin-Watson Statistics (DW) for LPM. Joint hypothesis testing is conducted via Wald statistics (F-p) for the LPM, and the likelihood ratio statistic (LR-p) for the logit, which is χ^2 distributed. We also provide the value of the log-likelihood function (LL). Indicators for the inclusion of fixed effects for years and investors (FE_Y, FE_{MMA}) as least squares dummy variables (LSDV) are in the last rows. Standard errors and t-statistics of coefficients are White heteroscedasticity-corrected and shown in parentheses below the coefficients. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

However, for bond mandates, the situation is different. We reject the null hypothesis of no effect. If we inspect average partial effects (APE), the decision to increase all other bond mandates leads to an economically

significant reduction of 9% in the probability of observing an increase in the bond mandate as well ($\lambda_{B*\Delta B} + \lambda_{\Delta B} = 0.14 - 0.23$). The same holds for the LPM (see model (1)).²²

We note a similar situation from the results from models (3) and (4). Assume an investor decides to increase the share of all equity mandates by, e.g., 10%. In this case, the probability of an increase in the considered equity mandate decreases by 3.1% ($\Delta E_i^j * \lambda_{\Delta E} = 0.1 * (-0.31)$). For bond mandates, reallocations within the same asset class appear to have a greater effect. The same 10% increase in bond mandates leads to an effect that is twice as high as for equity mandates. The probability of an increase is reduced by 6.6% ($\Delta B_i^j * (\lambda_{B*\Delta B} + \lambda_{\Delta B}) = 0.1 * (-0.34 - 0.32)$).

Interviews with practitioners suggest that the willingness to reallocate may be higher because of lower transaction costs. The LR statistic for logit estimations and the Wald F-tests for the linear probability models reveal significance at the 99% confidence level for testing on joint hypotheses. Furthermore, respective restricted models include an intercept, as well as investor and year fixed effects. Overall, our results suggest that reallocations for bond mandates are smaller than those for equity mandates, but they are driven more by asset class competition. Therefore, any existing tournament behavior among equity managers should be more pronounced than for bond managers.

²²Probit results are structurally very similar and are available from the authors upon request.

3.4.2 Performance-Based Reallocations by Institutional Investors

Tables 3.4 and 3.5 provide an interesting picture of the size of portfolio reallocations and of asset class competition. However, they do not reveal any information about the relevant factors that drive investor decisions. We assume effective governance mitigates harmful risk-taking, primarily because of greater skill levels, more frequent monitoring, and more immediate action to "penalize" inferior performance. Thus, we expect reallocations will be somewhat linked to past performance.

We follow Blake et al.'s (1999) approach to decompose changes in portfolio weights of single mandates (Δx_i) in an MMA (MMA_j) with a total of $m = 1, \dots, M_j$ mandates. Here, reallocations depend on passive buy-and-hold returns for mandates and MMAs ($R_{i,t}, R_{MMA_j,t}$), as well as relative, active cash flows ($cf_{i,t}, cf_{MMA_j,t}$). Note that the latter are not measured in €, but in relation to the MMA's total assets (see Equation (3.2)).

$$\begin{aligned}
 x_{i,t} &= x_{i,t-1} * \frac{1 + R_{i,t} + cf_{i,t}}{1 + \sum_{m=1}^{M_j} x_{m,t-1}(R_{m,t} + cf_{m,t})} \\
 \Leftrightarrow \ln \frac{x_{i,t}}{x_{i,t-1}} &= \ln(1 + R_{i,t} + cf_{i,t}) - \ln\left(1 + \sum_{m=1}^{M_j} x_{m,t-1}(R_{m,t} + cf_{m,t})\right) \\
 \Leftrightarrow \ln \frac{x_{i,t}}{x_{i,t-1}} &\approx \underbrace{R_{i,t} - R_{MMA_j,t}}_{\text{passive}} + \underbrace{cf_{i,t} - cf_{MMA_j,t}}_{\text{active}} \tag{3.2}
 \end{aligned}$$

Next, we investigate performance-based investor actions by estimating the impact of mandate returns on their weight changes (see Equation (3.3)).

For simplicity, we do not depict any time indexes (t). Note that the relationship only holds if we omit rebalancing to retain strategic weights (Faff et al., 2005). We would thus expect cash flows across mandates to exactly offset buy-and-hold returns, which results in $\beta_i = 0$. If the coefficient for mandate returns is positive, then at least a passive reallocation must be allowed. In this case, investors exploit positive momentum in single mandates, and appreciate past performance. A negative coefficient implies the opposite.

$$\Delta x_i = \gamma_0 + \gamma_B * B_i + \beta_i * R_i + \beta_{i,B} * B * R_i + \sum \beta_C * C \quad (3.3)$$

The literature and our previous results suggest that reallocations for bond mandates differ from equity in terms of size and competition intensity. This motivates us to explicitly allow for slope differences and the intercept for bond mandates. A positive (negative) coefficient means institutional investors will pay more (less) attention to bond performance measures when reallocating assets within portfolios. Insignificant (zero) coefficients mean both are treated equally. We also add mostly contemporaneous control variables to reflect the impact of mandate, investor, and risk management considerations. For simplicity, these are referred to as $\sum \beta_C * C_i$ in Equation (3.3).²³

- Investors increase the number of mandates over time, so the size of the mandate at the beginning of the year (x_i) should have a negative co-

²³In Table 3.10, we indicate variable correlations to address questions of multicollinearity. However, we find no critical values.

efficient. We use a dummy variable for absolute return funds ($isAR_i$) so that we can identify structural differences in this type of mandate. A tracking error (TE_i) over the entire time series captures the mandate's active risk. We expect a negative coefficient, which would be justified by the rise of passive investments over the last decade (Bank for International Settlements, 2003 and section 3.3).²⁴

- We find that an increase in the number of mandates, along with investor awareness for risk management (Sharpe, 2002a) enables to invest in more volatile mandates. This is due to superordinate diversification effects. Annual mandate volatility (σ_i) should exhibit a positive coefficient. Investors impose TE budgets on managers to limit active risk and optimize risk-adjusted relative performance (see Ammann and Zimmermann, 2001 and Brandolini et al., 2004). We note that violations approximated by excess tracking errors ($ExTE_i$) could result in withdrawals.²⁵ Investors with overlay mandates ($\#OL_j$) probably have improved risk management systems, however, allowing for larger reallocations. We expect a positive relationship.
- The need to account for MMA returns on an annual basis (R_{MMA_j}) stems from Equation (3.2). For the number of total mandates in a portfolio ($\#M_j$), we expect a negative coefficient, because changes in mandate size become smaller on average. From section 3.3 and Table 3.1, we know that investors aim to improve MMA structures by assign-

²⁴The stake of U.S. pension funds invested passively has risen to 35%; in continental Europe it is 10%-20%.

²⁵Mandate excess tracking errors are calculated as yearly deviations of tracking errors from full period tracking errors: $ExTE_i = TE_i - TE_{i,t}$.

ing new managers ($\Delta\#M_j$). By mathematical consequence, this leads to a negative coefficient.

We posit that the impact of mandate returns on portfolio shares could lead to endogeneity problems. A cash redemption would force managers to liquidate portfolio holdings quickly, a practice referred to as a "fire sale" (Coval and Stafford, 2007). And risk management strategies within specialized mandates, such as constant proportion portfolio insurance (Black and Perold, 1992), could cause a shift in assets leading to a negative market impact, transaction costs, or the abandonment of investment strategy and a realization of losses.

To account for endogeneity, we use two-stage least squares estimation, where a market model is used to estimate returns (\hat{R}_i).²⁶ By rearranging, we obtain Equation (3.4), which allows for performance attribution, namely alpha, timing returns, and benchmark returns.²⁷

$$\hat{R}_i = \hat{\alpha}_i + (\hat{\beta}_i - 1) * R_{BM} + R_{BM} \quad (3.4)$$

Consistent with Treynor and Black (1973) and Admati and Pfleiderer (1997), we assume managers are able to contribute active returns compared

²⁶Note that we assume managers keep the weights of all the securities in their mandate constant while they sell assets to meet cash redemptions. If this is not the case, our method will not solve endogeneity problems, because α_i and systematic risk (β_i) of the mandate are likely to change.

²⁷Note that the first two components are similar to estimated abnormal returns, which is another performance measure we analyze. We calculate abnormal returns as the difference between mandate and benchmark returns: $ANR_i = R_i - R_{BM}$, while estimated abnormal returns are $AN\hat{R}_i = \hat{\alpha}_i + (\hat{\beta}_i - 1) * R_{BM}$. As subsequent analyzes are insignificant we foreclose to show results. Tables available by the authors upon request.

to a passive benchmark, but we make no further assumptions about how they do so (Van Binsbergen et al., 2008). This enables us to risk-adjust mandate returns, and to account for institutional investors' more advanced processes in manager monitoring and evaluation.²⁸

Table 3.6 presents our results for standard pooled ordinary least squares (POLS) estimation (see Equation (3.3)). However, we find that the bursting of the new technology bubble, divergent backgrounds and investor target objectives, and individually specified mandate characteristics can all lead to a problem of omitted variables and biased coefficients. Therefore, we allow for year and investor fixed effects ($FE_{Y,MMA}$) as least squared dummy variables (LSDV), and for mandate fixed effects by using within-transformation ($FE_{M,Y,MMA}$) (see Equation (3.5)).²⁹ Note that, by adding fixed effects for years, MMAs, and mandates, we lose control variables. So if we control for FE_{MMA} we lose the number of overlays, total mandates, and absolute return mandates ($\#M_j, \#OL_j, \#AR_j$), which can remain constant within an MMA. The within-transformation excludes any intercepts ($\gamma_i, B_i, isAR_i$) and time-invariant mandate variables, such as the full time-series tracking error (TE_i).

$$\begin{aligned} \Delta\ddot{x}_i = & \gamma_{MMA} * MMA_j + \gamma_y * Y_t \\ & + \beta_i * \ddot{R}_i + \beta_{B,i} * B * \ddot{R}_i + \sum \beta_C * \ddot{C} + \ddot{\epsilon}_i \end{aligned} \quad (3.5)$$

²⁸Del Guercio and Tkac (2002) point out that institutional investors use advanced monitoring techniques to justify behavior such as manager selection.

²⁹Symbols with double dots denote time-demeaned (within-transformed) variables, where we deduct time series means from every observation, e.g., $\ddot{z} = z_t - \bar{z}$.

We find that mandate weights are driven by returns. The coefficients are significant at least at the 95% confidence level, independent of the applied estimation method (see Table 3.6). The results are very similar for instrument returns (see columns 2, 4, and 6). With coefficients ranging from 7.3 to 8.6, we find that the partial effect of a 6.35% mandate return (the average in our sample) leads to an 0.46%-0.55% increase in investor portfolios (see rows 1 and 3). In absolute terms, this is equivalent to gains of €1.15 million to €1.38 million for our average mandate size of €250 million. We consider this evidence that investors appreciate past performance (at least by omitting rebalancing/passive reallocations). Separate effects for bonds are not significantly different from 0.

When we apply performance attribution (see column 7), we observe that the main driver is manager alpha. The coefficient of 23.46 is significantly different from zero at the 5% level. An average alpha of 0.54% p.a. (see Table 3.1) would result in a roughly 0.13% increase in mandate size, or €0.3 million (mandate size: €250 million).³⁰ Again, there is no difference between bond and equity mandates. Although not reported, abnormal returns, where managers must beat a benchmark, have no significant effect on weights.³¹

³⁰We assume $\alpha_i = 0$ for all absolute return mandates. Note that this may lead to a slight underestimation of the true coefficients.

³¹The respective tables are available from the authors upon request.

CHAPTER 3. RISK-TAKING IN INSTITUTIONAL INVESTMENTS

Table 3.6: Reallocations as a Result of Mandate Performance

Method Model	Panel A: POLS		Panel B: FE _{Y, MMA}		Panel C: FE _{M, Y, MMA}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R_i	8.04*** (2.67)		7.78** (2.57)		8.59*** (2.69)		
$B_i * R_i$	-1.56 (-0.07)		-6.21 (-0.27)		4.29 (0.19)		
\hat{R}_i		7.31** (2.44)		7.49** (2.50)		7.53** (2.45)	
$B_i * \hat{R}_i$		-2.37 (-0.11)		-5.40 (-0.24)		6.03 (0.26)	
α_i							23.46** (2.51)
$(\beta_i - 1) * R_{BM}$							13.01 (1.38)
R_{BM}							5.03 (1.39)
$B_i * \alpha_i$							-28.09 (-0.88)
$B_i * (\beta_i - 1) * R_{BM}$							-11.71 (-0.29)
$B_i * R_{BM}$							10.62 (0.40)
γ_0	6.10*** (2.89)	6.22*** (2.95)	14.60** (2.21)	14.61** (2.21)			
B_i	1.74 (1.35)	1.65 (1.33)	1.47 (1.08)	1.32 (1.03)			
x_i	-24.17*** (-6.08)	-24.24*** (-6.11)	-36.68*** (-7.30)	-36.76*** (-7.34)	-56.61*** (-9.95)	-56.71*** (-9.96)	-56.37*** (-10.14)
σ_i	2.11 (0.28)	1.64 (0.21)	-0.93 (-0.12)	-1.51 (-0.19)	20.20* (1.84)	19.08* (1.74)	19.99* (1.80)
TE_i	-9.55 (-1.41)	-9.53 (-1.41)	-23.58*** (-3.36)	-23.48*** (-3.33)			
$isAR_i$	0.04 (0.04)	0.48 (0.45)					
$ExTE_i$	16.95 (1.34)	17.32 (1.38)	33.98*** (2.80)	34.30*** (2.84)	9.36 (1.50)	9.84 (1.59)	8.34 (1.38)
R_{MMA_j}	-13.04** (-2.14)	-11.63** (-2.02)	-2.82** (-2.39)	-2.41* (-1.93)	-4.85 (-0.72)	-2.94 (-0.46)	-2.72 (-0.43)
$\#OL_j$	-1.37*** (-3.02)	-1.41*** (-3.09)					
$\#AR_j$	0.43** (2.48)	0.43** (2.51)	-9.21 (-1.22)	-7.77 (-1.06)			
$\#M_j$	-0.23*** (-2.80)	-0.24*** (-2.90)	-0.07 (-0.41)	-0.08 (-0.42)			
$\Delta\#M_j$	-1.29*** (-7.18)	-1.29*** (-7.22)	-1.03*** (-4.53)	-1.03*** (-4.55)	-0.99*** (-6.07)	-0.99*** (-6.10)	-0.99*** (-6.08)
SER	74.25	74.32	65.15	65.18	47.51	47.56	47.45
\hat{R}^2	0.28	0.28	0.37	0.37	0.44	0.44	0.45
DW	1.86	1.86					
LM-p	0.02	0.05	0.03	0.04	0.02	0.03	0.04
Obs	993	993	993	993	932	932	932
FE_M	No	No	No	No	Yes	Yes	Yes
FE_Y	No	No	Yes	Yes	Yes	Yes	Yes
FE_{MMA}	No	No	Yes	Yes	Yes	Yes	Yes

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. The table represents estimation results for Equations (3.3) and (3.5). The dependent variable is Δx_i , the change in a mandate's weight in an MMA. The estimation methods used are regular pooled OLS (POLS) regressions in panel A, and year and investor fixed effects (FE_Y, FE_{MMA}), as least squares dummy variables (LSDV) in panel B. In panel C, we further control for mandate fixed effects (FE_M) by the within-transformation method.

Explanatory performance measures are mandate raw, estimated, alpha, timing, and benchmark returns ($R_i, \hat{R}_i, \alpha_i, (\beta_i - 1) * R_{BM}, R_{BM}$). For absolute return mandates, except for raw returns, we assume performance is 0. We also add an intercept (γ_0), a bond intercept (B), and interaction terms of performance measures for bond mandates (e.g. $B * R_i$) to allow for differences. Mandate control variables are portfolio weight at the beginning of the year (x_i), volatility p.a. (σ_i), tracking error (TE_i), excess tracking error ($ExTE_i$), and dummy variables for absolute return ($isAR_i$) and bond mandates (B_i). Investor control variables are return p.a. (R_{MMA_j}), number of overlays ($\#OL_j$), absolute return ($\#AR_j$), total ($\#M_j$), and newly added mandates ($\Delta\#M_j$).

The standard summary statistics are below the control variables. These are standard errors of the regression (SER), adjusted goodness-of-fit (\hat{R}^2), Durbin-Watson statistics (DW) for POLS only, heteroscedasticity-robust Lagrange-multiplier statistic probabilities (LM-p), and the number of observations (Obs). Standard errors and t-statistics of coefficients are White heteroscedasticity-corrected and shown in parentheses below the coefficients. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Overall, our results confirm those of Del Guercio and Tkac (2002), who find a linear relationship for pension fund inflows. We find comparable results for reallocations.³² They allow investors to temporarily deviate from their strategic asset allocations (and shift between asset classes), as noted by Blake et al. (1999).

We also summarize our findings in the extensive $FE_{M,Y,MMA}$ model (7) for control variables. We find that size and the number of newly added mandates are negatively related to reallocations, which indicates that investors tend to increase the number of mandates. A mandate that is 30% the size of the MMA, for example, will be reduced by approximately 16.9%, while a new mandate will lead to a 1% average reduction. Mandate volatility exhibits a positive coefficient. Investors can afford more mandate risk because of the diversification over an increased number of mandates. In model (8), we find investors have enforced passive investments, which is indicated by the negative coefficient for TE_j .

To summarize our results thus far, investors react to performance-based measures, especially to manager alpha. They omit full rebalancing of returns in single mandates, but appreciate past performance. Although investors consider bond mandates differently, we do not find differences in performance-based reallocations compared to equity mandates. We thus hypothesize that the perspective gained by both losing and gaining AuM similarly should

³²If we use exponential performance measures to account for non-linear relationships, however estimated coefficients are mostly statistically insignificant and always economically insignificant.

weaken the attractiveness of harmful risk-taking for both bond and equity mandates.

3.4.3 Managers' Risk-Taking Behavior

Institutional investment fees are usually linked to AuM, but not directly to performance. We know from the previous subsection that AuM is driven by past performance. This linkage may lead managers to engage in yearly tournaments. Nevertheless, as we argued in subsections 3.2.2 and 3.4.2, institutional investors perform effective governance. They tend to have more sophisticated investment knowledge, and they monitor their managers more frequently by analyzing historic performance.

If our assumptions on "effective governance" hold, we should not observe harmful risk-taking. Managers will not be able to revise portfolio compositions during the year based on their relative performance and alter risk makeup, as stated by the tournament hypothesis. In any case, we expect less risk-taking for bond managers if our conclusion of more competition from the previous subsection holds. To test these predictions, we use two alternative methods: 1) contingency tables, as in Brown et al. (1996), Chevalier and Ellison (1997), and Busse (2001), and 2) regression approaches as in Kempf and Ruenzi (2007).

We analyze manager risk-taking in mandate (i) within calendar years by using return data to calculate volatility changes ($\Delta\sigma_i$) from the first period ($t1$) of the year to the second ($t2$), as defined in Equation (3.6). The

assessment periods we use for $(t1/t2)$ are $(4/8)$, $(5/7)$, $(6/6)$, $(7/5)$, and $(8/4)$ months.

$$\Delta\sigma_i = \frac{\sigma_{t2}}{\sigma_{t1}} - 1 \quad (3.6)$$

Contingency tables, where funds are ranked by performance after a prespecified period ($t1$) every year, are a non-parametric and univariate test method that can be used to analyze manager behavior. Ranks are equally distributed between 0 and 1. "Winners" in the first period exhibit above-median performance; "losers" exhibit performance below 0.5 (the median rank). We also identify mandates in the upper and lower quartiles of return ranks (quartile rank).

In a second step, we rank mandates similarly by categorizing changes in previously presented risk measures into 'High $\Delta\sigma_i$ ' and 'Low $\Delta\sigma_i$ '. Finally, we classify each mandate-year observation within a 2x2 contingency table, and we calculate frequencies for all five assessment periods (see the rows in Table 3.7). Note that bond (panel A) and equity mandates (panel B) are investigated separately. This accounts for the diverging characteristics of these asset classes, such as size and volatility of returns, and the differences in magnitude of reallocations and competition intensity (see subsection 3.4.1).

As a null hypothesis, we expect to find independence between risk and return sample frequencies. If tournament behavior exists, frequencies should cluster in the center of the table, but be less pronounced for bond managers. For bonds, we observe that median "loser" mandates exhibit frequencies

above 25% for low risk adjustment for four out of five median ranks (see the upper part of panel A). "Winners" increase risk in the first four assessment periods. However, our results are not statistically significant, as indicated by the χ^2 -test statistic. Thus, we doubt that risk adjustment depends on performance rank for bond mandates.

When we analyze quartile performance ranks in the lower part of panel A, we observe that "losers" cluster on the left side, while "winners" cluster primarily in the center. We reject the null hypothesis for the (4/8) and (5/7) assessment periods, but the clustering contradicts the tournament hypothesis. Overall, the divergence in risk adjustment patterns for bonds precludes a clear interpretation. We reject any harmful risk-taking behavior, but we believe it signals a need for more analysis of tournament behavior.

For equity mandates, our results at first seem to support the tournament hypothesis (see panel B). Based on a χ^2 -test, we reject identical sample frequencies at least at the 1% significance level for four out of the five assessment periods for both median and quartile return ranks. Comparing both types of mandates, we find that bonds, due to more intense competition, are governed more effectively.

Table 3.7: Contingency Tables for Risk-Taking ($\Delta\sigma_i$) in Institutional Mandates

Sorting	Assessment	Sample Frequency (% of Observations)				χ^2	p-Val	Obs
		Low $\Delta\sigma_i$	High $\Delta\sigma_i$	Low $\Delta\sigma_i$	High $\Delta\sigma_i$			
<i>Panel A: Bond Mandates</i>								
Median Rank	(4/8)	Low R_i (Losers)		High R_i (Winners)		1.14	0.29	463
	(5/7)	25.7%	23.8%	23.5%	26.8%	1.57	0.21	
Quartile Rank	(6/6)	25.9%	23.5%	23.5%	27.0%	0.78	0.38	230
	(7/5)	25.5%	24.0%	23.5%	27.0%	1.57	0.21	
	(8/4)	23.3%	26.1%	26.1%	24.4%	0.96	0.33	
	(4/8)	32.6%	16.1%	24.8%	26.5%	8.18***	0.00	
Quartile Rank	(5/7)	31.3%	17.4%	26.1%	25.2%	4.24***	0.04	230
	(6/6)	27.8%	20.9%	29.6%	21.7%	0.01	0.94	
	(7/5)	29.1%	19.6%	28.7%	22.6%	0.36	0.55	
	(8/4)	26.5%	22.2%	32.6%	18.7%	1.97	0.16	
<i>Panel A: Equity Mandates</i>								
Median Rank	(4/8)	Low R_i (Losers)		High R_i (Winners)		2.19	0.14	396
	(5/7)	22.8%	26.6%	26.6%	24.0%	8.24***	0.00	
Quartile Rank	(6/6)	21.3%	28.1%	28.1%	22.5%	8.24***	0.00	199
	(7/5)	21.1%	28.3%	28.3%	22.3%	9.27***	0.00	
	(8/4)	19.2%	30.2%	30.2%	20.4%	22.86***	0.00	
	(4/8)	23.4%	25.3%	24.5%	26.8%	0.00	0.97	
Quartile Rank	(5/7)	18.5%	30.2%	27.5%	23.8%	6.56**	0.01	199
	(6/6)	18.1%	30.6%	28.7%	22.6%	9.27***	0.00	
	(7/5)	17.0%	31.7%	27.5%	23.8%	9.47***	0.00	
	(8/4)	20.0%	28.7%	31.3%	20.0%	10.54***	0.00	

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. Contingency tables are as in Brown et al. (1996). We sort mandates by their risk adjustment ratio ($\Delta\sigma_i$) (see Equation (3.6)), and their return rank as either above or below the median (rank) or in the upper/lower return quartile (quartile rank) for each assessment period (assessment) by rows. For example, assessment period (4/8) indicates that the first period is January to April, and the second period includes the remaining months (May to December).

In addition to frequency ratios, we indicate χ^2 -statistics, testing for equally distributed frequencies, corresponding p-values, and the number of observations (Obs). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Table 3.8: Contingency Tables for Active Risk-Taking (ΔTE_i) in Institutional Mandates

Asset Class	Assessment	Sample Frequency (% of Observations)				χ^2	p-Val	Obs
		Low ΔTE_i	High ΔTE_i	Low ΔTE_i	High ΔTE_i			
Panel A: Ranks(R_i)								
		Low R_i (Losers)	High R_i (Winners)					
Bonds	(4/8)	22.4%	26.9%	26.9%	23.9%	2.28	0.13	398
Median	(5/7)	23.1%	26.1%	26.1%	24.6%	0.82	0.36	
	(6/6)	22.1%	27.1%	27.1%	23.6%	2.92*	0.09	
	(7/5)	21.9%	27.4%	27.4%	23.4%	3.65*	0.06	
	(8/4)	22.9%	26.4%	26.4%	24.4%	1.23	0.27	
Equity	(4/8)	23.0%	26.3%	26.3%	24.5%	1.02	0.31	396
Median	(5/7)	22.0%	27.3%	27.3%	23.5%	3.29*	0.07	
	(6/6)	23.0%	26.3%	26.3%	24.5%	1.02	0.31	
	(7/5)	23.0%	26.3%	26.3%	24.5%	1.02	0.31	
	(8/4)	22.0%	27.3%	27.3%	23.5%	3.29*	0.07	
Panel B: Ranks(α_i)								
		Low α_i (Losers)	High α_i (Winners)					
Bonds	(4/8)	23.9%	25.4%	25.4%	25.4%	0.09	0.76	398
Median	(5/7)	22.6%	26.6%	26.6%	24.1%	1.71	0.19	
	(6/6)	23.6%	25.6%	25.6%	25.1%	0.26	0.61	
	(7/5)	23.4%	25.9%	25.9%	24.9%	0.50	0.48	
	(8/4)	24.6%	24.6%	24.6%	26.1%	0.09	0.77	
Equity	(4/8)	24.5%	24.7%	24.7%	26.0%	0.04	0.84	396
Median	(5/7)	24.2%	25.0%	25.0%	25.8%	0.00	1.00	
	(6/6)	23.2%	26.0%	26.0%	24.7%	0.65	0.42	
	(7/5)	24.0%	25.3%	25.3%	25.5%	0.04	0.84	
	(8/4)	24.2%	25.0%	25.0%	25.8%	0.00	1.00	

The subsample consists of the "noAR" institutional bond and equity mandate sample from 1998 through 2007. We excluded absolute return mandates. Contingency tables are as in Brown et al. (1996). We sort mandates by their active risk adjustment ratio (ΔTE_i) (see Equation (3.7)), and their performance ranks for raw returns (R_i) in panel A and alpha returns (α_i) in panel B as either above/below the median (median rank) for each assessment period (assessment) by rows. For example, assessment period (4/8) indicates that the first period is January to April, and the second period includes the remaining months (May to December). The performance measures we used are raw returns (panel A) and manager alpha (panel B). In addition to frequency ratios, we indicate χ^2 -statistics, testing for equally distributed frequencies, corresponding p-values, and the number of observations (Obs). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

We further find that a test for changes in overall volatility ignores how much single managers can impact their mandate's risk structure. One can argue that managers actually influence benchmark deviations. Thus, we calculate an active risk adjustment ratio (ΔTE_i), based on tracking errors (see Equation (3.7)). Table 3.8 depicts median rank results for changes in active risk by using the same methodology for return and alpha ranks. However, this limits our observations to the "noAR" subsample.

$$\Delta TE_i = \frac{std(R_{i,t2} - R_{BM,t2})}{std(R_{i,t1} - R_{BM,t1})} - 1 \quad (3.7)$$

Note that the frequencies of bond and equity mandates for sorting by raw return ranks (panel A) cluster in the center of the table and are always above 26%. However, statistical significance is rather weak. If we analyze contingency tables based on manager alphas (see panel B), we find no evidence at all.³³

To get a clearer picture of managers' risk behavior, we instead perform multi-variate regressions of return ranks, distributed equally between 0 and 1, on changes in risk and active risk, respectively (see Equation (3.8)). We use a performance rank interaction term to map higher competition among bond managers. If there is any undesirable risk-taking, the coefficients of performance ranks will be negative, but less so for bonds. This specification

³³Tests for ranks based on abnormal returns and for various subsamples reveal structurally similar and predominantly insignificant results. However, for the sake of brevity, we do not show the details here. All respective tables are available from the authors upon request.

allows us to control for various factors, similarly to how Kempf et al. (2009) argue for seasonal effects.

During times of crisis, job incentives might supersede incentives for tournament behavior. Corporate pension funds may also take fewer investment risks, as required by regulations, and impose a higher degree of control, contrary to private foundations. Hence, we use investor and year LSDV. Following Busse (2001), we control for mandate heterogeneity by using within-fixed effects transformation.

$$\begin{aligned} \Delta\ddot{\sigma}_{i,t} = & \gamma_{MMA} * MMA_j + \gamma_y * Y_t \\ & + \delta_R * R\ddot{a}n\ddot{k}_{i,t} + \delta_{B,R} * B * R\ddot{a}n\ddot{k}_{i,t} + \sum \delta_C * \ddot{C} + \ddot{\epsilon}_i \end{aligned} \quad (3.8)$$

With our literature review and our findings thus far, we identify several control factors ($(\sum \delta_C * \ddot{C})$). We categorize these by mandate, multi-manager account, and risk management perspectives. This method seems to be beneficial compared to univariate or non-parametric analyses of contingency tables, because we can already account for a large number of factors, as follows.³⁴

- Assume mandate age affects willingness to alter risk, because poor short-term performance is worse for funds with shorter track records.

Younger funds tend to be more aggressive in order to survive, and an

³⁴We also estimate Equation (3.8) without any control variables ($\sum \delta_C * \ddot{C}$) leading to a potential omitted variables bias. However, our results for various methods (POLS, FE_{MMA} , $FE_{Y,MMA}$, $FE_{M,Y,MMA}$) cast doubt on any tournament behavior. Tables are available upon request. The same held for changes in active risk.

investor clientele effect may exist for older funds (Brown et al., 1996). Thus, we expect managers with younger mandates (measured as the number of days a mandate exists within our dataset) to increase risk more aggressively. Size (x_i), as a share of the portfolio, can reveal information about the relevance of a mandate to the investor. However, larger funds are likely to have more cash available to engage in risk-taking activities.

Busse (2001) states that volatility increases may not be based on managerial discretion, but on a bias in standard deviation estimates caused by autocorrelation in daily returns. Less autocorrelation stems from lower exposure to small-cap stocks and lower average returns. Another source arises from momentum strategies (Jegadeesh and Titman, 1993), and a third occurs when more illiquid securities exhibit higher autocorrelation due to smoothed returns (Roll, 1984.) To control for common risk factors, we use the first-order correlation coefficient of an AR(1) process for weekly mandate returns (φ_i) (see Equation (3.9)). We expect a positive coefficient.

$$R_{i,t} = \mu_i + \varphi_i * R_{i,t-1} + \epsilon_{i,t} \quad (3.9)$$

- Institutional investors engage in risk budgeting (Ammann and Zimmermann, 2001; Sharpe, 2002b; Brandolini et al., 2004; Bank for International Settlements, 2003). For example, if investors observe high tracking errors during the first half of the year, they may reduce their

exposures for the second half of the year. We use the actual tracking error in period ($t1$) as a proxy, and we expect a negative coefficient.

Furthermore, a higher number of overlay mandates ($\#OL_j$) may influence mandate risk. Because risk is managed on the MMA level, derivatives investments may be forbidden, which reduces the tools available to alter the risk structure. However, the release from risk management tasks and risk limits can increase risk-taking flexibility. Both arguments are important to our analysis.

With a simple market model as a return-generating process, it follows that risk as the standard deviation of returns is a combination of systematic and unsystematic risk and covariance. Thus, we expect a positive relationship between changes in benchmark risk ($\Delta\sigma_{BM}$) and changes in mandate risk. We add benchmark volatility of the first assessment period (σ_{BM}) to reflect any potential mean reversion, and we expect a negative coefficient (Kempf et al., 2009). In other words, if benchmark risk is high in $t1$, we assume market risk, and thus portfolio risk, will decline.

- We control for investors' experience with MMA investing, and for monitoring mandates (Age_{MMA_j}). We use the age of the investor's MMA as a proxy within our dataset. We also plug in their return and risk levels ($R_{MMA_j}, \sigma_{MMA_j}$). Investors may desire managers to decrease risk and lock in actual returns once overall targets are met. Indeed, investors with high overall risk will likely strive to reduce their MMA's volatility. Both should lead to a negative coefficient.

Note that changes in mandate size due to, e.g., superior past performance indicate that investors believe in a manager's potential to contribute persistent superior performance. Managers may thus be encouraged to further increase risk in order to reach performance goals. On the other hand, if managers experience "fire sale" losses due to excessive withdrawals, they may tend to increase risk (Coval and Stafford, 2007). In the first case, we expect a positive relationship; in the latter case, we expect a negative relationship.

Table 3.9 shows fixed effects estimation results for multi-variate models for the (6/6) assessment period for three performance ranks ($R_i, \alpha_i, (1 - \beta_i) * R_{BM}$) and two risk measures ($\Delta\sigma_i, \Delta TE_i$) (see Equation (3.8)). As we noted earlier, we account for bond-specific characteristics.³⁵ From the first two rows, it is obvious that we can reject any effect of performance ranks on risk-taking and tournament behavior, respectively, in MMAs. This holds for raw, abnormal returns (not depicted), alpha, and timing returns, and is independent of asset class.³⁶

Next, we briefly summarize the key findings for estimating changes in mandate volatility, (see models (1), (3), and (5)). Overall, given the high explanatory power of our model of approximately 50%, we believe it is reliable.

³⁵The respective tables exclude bond-rank interaction terms and Wald F-statistics, and are available from the authors upon request.

³⁶Tables for ranks based on abnormal returns are available from the authors upon request.

CHAPTER 3. RISK-TAKING IN INSTITUTIONAL INVESTMENTS

Table 3.9: Multivariate Regression for Risk-Taking in Institutional Mandates

Method Perf. Rank Dep. Variable Model	Assessment (6/6) - $FE_{M,Y,MMA}$					
	R_i		α_i		$(1 - \beta_i) * R_{BM}$	
	$\Delta\sigma_i$ (1)	ΔTE_i (2)	$\Delta\sigma_i$ (3)	ΔTE_i (4)	$\Delta\sigma_i$ (5)	ΔTE_i (6)
Mandate Level						
$Rank_i$	-0.05 (-0.87)	-1.30 (-1.51)	0.01 (0.13)	0.08 (0.17)	-0.04 (-0.91)	0.32 (0.57)
$B * Rank_i$	0.09 (1.07)	0.90 (1.08)	0.00 (0.05)	-0.14 (-0.27)	-0.08 (-0.96)	-0.99 (-1.48)
Age_i	0.04 (0.81)	-0.42 (-0.82)	0.04 (0.80)	-0.43 (-0.85)	0.03 (0.67)	-0.44 (-0.88)
x_i	0.30*** (2.69)	1.52* (1.81)	0.29*** (2.68)	1.43* (1.76)	0.29*** (2.66)	1.45* (1.77)
φ_i	0.15*** (2.93)	-0.02 (-0.05)	0.15*** (2.96)	0.00 (0.00)	0.15*** (2.87)	-0.05 (-0.14)
Market Risk and Risk Mngt.						
TE_i	0.15 (0.39)	-5.89 (-1.51)	0.14 (0.35)	-6.23 (-1.58)	0.11 (0.29)	-5.85 (-1.44)
$B_i * TE_i$	-7.24*** (-4.05)	-16.91*** (-3.18)	-7.10*** (-4.10)	-15.59*** (-2.65)	-7.32*** (-4.15)	-17.33*** (-3.05)
$\#OL_j$	-0.03 (-1.09)	-0.21 (-0.94)	-0.04 (-1.12)	-0.21 (-0.93)	-0.03 (-1.08)	-0.18 (-0.83)
σ_{BM}	0.15 (0.33)	12.56* (1.86)	0.12 (0.27)	12.05* (1.80)	0.16 (0.36)	11.47* (1.66)
$\Delta\sigma_{BM}$	0.58*** (8.67)	4.68*** (2.81)	0.58*** (8.67)	4.66*** (2.80)	0.58*** (8.78)	4.63*** (2.79)
$B_i * \Delta\sigma_{BM}$	-0.23** (-2.51)	-3.97** (-2.48)	-0.23** (-2.52)	-3.95** (-2.47)	-0.23** (-2.58)	-3.95** (-2.47)
Investor Level						
Age_{MMA_j}	-0.04 (-0.71)	1.63* (1.81)	-0.04 (-0.71)	1.58* (1.78)	-0.03 (-0.50)	1.66* (1.85)
R_{MMA_j}	-0.38 (-0.86)	5.11 (1.29)	-0.41 (-0.97)	3.24 (0.89)	-0.32 (-0.78)	3.78 (1.05)
σ_{MMA_j}	-1.71*** (-3.06)	4.79 (1.28)	-1.69*** (-3.04)	4.34 (1.17)	-1.66*** (-3.00)	4.80 (1.29)
Δx_i	0.30** (2.48)	0.30 (0.37)	0.30** (2.50)	0.25 (0.31)	0.30** (2.52)	0.28 (0.34)
SER	0.08	14.30	0.08	14.35	0.08	14.34
\tilde{R}^2	0.52	0.06	0.51	0.05	0.52	0.05
Obs	932	932	932	932	932	932

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. We estimate the impact of mandate ranks by using $(R_i, \alpha_i, (1 - \beta_i) * R_{BM})$ performance measures for the (6/6) assessment period on changes in mandate risk ($\Delta\sigma_i$) and mandate active risk (ΔTE_i) (see Equation (3.8)). For mandates, we use within-fixed effects transformation (FE_M), and for years and investors (FE_Y, FE_{MMA}), we use least squares dummy variables (LSDV).

Control variables are age, weight, and change in weight of the mandate, the first-order serial correlation of mandate returns (see Equation (3.9)), $(Age_i, x_i, \Delta x_i, \varphi_i)$, tracking error, number of overlay funds within the investor's portfolio, mandate benchmark volatility, and the change in benchmark risk similar to Equation (6) for the entire year ($TE_i, \#OL_j, \sigma_{BM}, \Delta\sigma_{BM}$), investor experience, portfolio return, and portfolio volatility ($Age_{MMA_j}, R_{MMA_j}, \sigma_{MMA_j}$), all measured in the first observation in July. For bond mandates, (B_i) we include $Rank_i, TE_i$ and $\Delta\sigma_{BM}$ with an interaction term to allow for varying slopes.

The standard summary statistics are below the control variables. These are standard errors of the regression (SER), adjusted goodness-of-fit (\tilde{R}^2). Standard errors and t-statistics of coefficients are White heteroscedasticity-corrected and shown in parentheses below the coefficients. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

We find that changes in underlying benchmark risk, investor portfolio volatility during the first assessment period, mandate size within investor MMAs, and active risk (TE_i) for bond mandates only are all statistically and

economically significant drivers. As we expected, an increase in a mandate's benchmark volatility transmits to the overall risk of equity mandates by a considerable amount (0.58), and to a lesser extent to bond mandates (0.58-0.23). If an investor realizes, say, 5.90% p.a. portfolio volatility in the first six months (the mean of MMAs from Table 3.2), mandate risk will be reduced by about 10.01% ($-1.71 * 5.90\%$). Investors control MMA risk and probably require that managers try to reduce mandate volatility if overall volatility is not in line with the target risk level.

We also find that mandate size has a significantly positive impact on risk changes. Larger funds are more likely to increase risk during the second half of the year. This supports the idea that larger funds have more cash available to engage in risk-taking activities. For example, mandates with a 25% share may ultimately increase risk by up to 8.75% toward the end of the year. Although larger mandates are more important to investors, they also seem to have more risk-taking flexibility. Bond tracking errors have a large coefficient in terms of absolute size. A tracking error of 1.95% (the average in 2007) was followed by a reduction in risk of roughly 15% ($-7.24 * 1.95\%$).

For equity mandates, however, we find no similar partial effect. We interpret this as an implication of investors' abilities to control investment strategies. Enforcing risk limits seems easier for relatively stable products such as bond investments, which is in line with Lakonishok et al. (1992).

Changes in mandate size and autocorrelation of the return series ($\Delta x_i, \varphi_i$) are statistically significant, although their economic relevance is rather limited. Mandates that see an increase in size of approximately 3% will see a

concomitant increase in return volatility of approximately 1%. Increases in AuM are deliberately allowed by investors to appreciate past performance. We assume investors grant managers who have positive alphas more flexibility to increase risk and pursue their investment strategies. And, as Busse (2001) notes, the average autocorrelation ($\varphi = 0.1$) leads to an increase in risk of nearly 2%.

To analyze changes in active risk, we estimated Equation (3.9) after replacing the dependent variable $\Delta\ddot{\sigma}_{i,t}$ with $\Delta\dot{T}E_{i,t}$ (see models (2), (4), and (6)). The estimation exhibits a goodness-of-fit of about 5% to 6%. None of the linear model assumptions requires a high R^2 . However, our model's ability to explain variation in ΔTE_i is rather small, and leaves room for further research.

Changes in benchmark risk lead to large changes in tracking errors. Thus, a 20% increase in volatility would cause an almost 100% increase in equity tracking errors ($0.2 * 4.68 = 93.6\%$). The transmission factor for bond mandates is considerably lower, at 0.71. And, on the contrary, large tracking errors in the first period lead to a significant subsequent reduction, but only for bond mandates. Mandates with tracking errors of about 2% can see active risk reduced by approximately 33% over the subsequent six months. We assume investors consider bonds as passive investments, and are thus less likely to tolerate high levels of active risk. Systematic risk factors especially do not affect changes in active risk.

Overall, we reject any tournament behavior for several measures of risk and performance that conform to the existence of effective governance in

MMAAs. Instead, investor volatility and tracking errors of bond mandates in our first observation period lead to an economically significant reduction in mandate risk. We believe this indicates investors closely monitor overall risk, and take effective measures to determine mandate risk structure.

3.5 Conclusion

In summary, institutional investments, especially multi-manager accounts (MMAAs) diverge structurally from standard mutual funds in several key aspects. Investors exhibit higher financial sophistication and experience, more frequent monitoring, and they react immediately to performance measures of appointed managers. The combination of these factors improves "effective governance" and reduces risk-taking behavior of appointed managers.

We analyze equity and bond mandates within MMAAs and find that investors reallocate assets based on past performance. In this context, the market-model alpha is the most important performance measure. The prospect of investors' willingness to penalize poor risk-adjusted performance tempers potentially harmful risk-taking by managers. This governance tool is even more pronounced among investors' bond mandates, which leads to fewer incentives for tournament behavior. Indeed, in contingency tables for bond mandates, we find no evidence of risk-taking. For equity mandates, the non-parametric tests show at least some type of risk-taking.

When accounting for a large set of control variables, we ultimately concur with Goyal and Wahal (2008) and find it difficult to make a case for tournament behavior in institutional investments. Ranks based on four performance measures, raw returns, abnormal returns, timing, and alpha returns, have no impact on managers' risk-taking. This holds for bond and equity mandates as well.

We find that the underlying benchmark is the key driver of changes in mandate volatility, while investor risk strategy is the second main source. Led by their MMA's risk and the active risk of bond mandates, investors may require additional adjustments in mandate risk. We believe this is likely due to improved monitoring, control, and risk management capabilities. Reallocations and mandate size have a positive effect on risk-taking, but they are of only minor relevance in economic terms. This suggests the need for further research.

In line with Busse (2001), our empirical evidence casts further doubt on previous research on mutual funds. Simple methods, such as contingency tables and pooled ordinary least squares, suffer from omitted variables. Future work needs to demonstrate the persistence of tournament behavior after accounting for mandate-specific characteristics.

Until now this thesis has concentrated on investment performance and risk. Besides "effective governance" institutional investors diverge in a second main aspect from retail investors – the need to consider asset liquidity. With AuM of €2.1 billion per portfolio, they are exaggerated to considerable market impact and transaction costs. Besides, the last financial crisis in

2007/08 has shown dramatically that dried up markets can jeopardize institutional investors' economic sustainability. Therefore actual risk management regulation and accounting standards (see section 1.2), require to take asset liquidity into account.

But there exists a second motivation. Investors with long-term investment horizons, may be willing to bear the limitation of their leeway by market frictions for a premium as argued by Amihud and Mendelson (1986), Amihud and Mendelson (1989), and Acharya and Pedersen (2005). In both cases a liquidity forecasting model is necessary. The following chapter deals with the second step of the investment process on systematic data collection and research (see subsection 1.1). It shows how fundamental firm characteristics are used by market participants (of which institutional investors are a major share of) to anticipate firms' financing policy, ultimately driving equity liquidity.

Appendix

Table 3.10: Correlations of Variables – Pearson's ρ

	R_i	α_i	σ_i	TE_i	$ExTE_i$	$isAR_i$	x_i	Δx_i	R_{MMA_j}	σ_{MMA_j}	$\#M_j$	$\#OL_j$	$\#AR_j$
R_i	1												
α_i	0.38	1											
σ_i	0.09	0.01	1										
TE_i	0.01	0.20	0.40	1									
$ExTE_i$	-0.09	0.03	0.02	0.49	1								
$isAR_i$	0.01	-0.03	0.05	-0.18	0.07	1							
x_i	-0.01	0.00	-0.21	-0.08	0.07	0.01	1						
Δx_i	-0.02	0.03	0.05	0.03	0.06	0.04	-0.44	1					
R_{MMA_j}	0.71	0.24	-0.02	-0.05	-0.15	0.05	0.03	-0.11	1				
σ_{MMA_j}	-0.06	0.05	0.48	0.31	-0.09	0.03	0.03	-0.09	0.00	1			
$\#M_j$	0.01	0.00	0.15	0.04	-0.04	-0.03	-0.54	0.13	0.02	0.06	1		
$\#OL_j$	0.00	0.14	0.21	0.28	-0.10	0.02	-0.08	-0.04	0.07	0.40	0.06	1	
$\#AR_j$	0.11	0.10	0.27	0.21	-0.11	0.24	-0.24	-0.01	0.20	0.42	0.56	0.46	1

The sample consists of the "main" institutional bond and equity mandate sample from 1998 through 2007. Spearman rank correlations are structurally very similar, and are available from the authors upon request.

Chapter 4

Anticipated Capital Structure and Equity Liquidity

4.1 Introduction

What are the determinants of corporate financial structure? This has been one of the most enduring and challenging questions in corporate finance literature since the pioneering works of Modigliani and Miller (1958) and Myers (1984). Most studies on this topic have investigated certain firm characteristics (e.g., profitability, tangibility, size) or country and industry effects as determinants of leverage or the speed of adjustment toward a target capital structure. Our analysis focuses on the subsequent information revealed by the process firms take toward these targets.

In this sense, we posit that firm managers (or "insiders") have a target capital structure in their mind's eye. Capital structure is normally stable over time (see Lemmon et al., 2008), until some type of change in, e.g., the financial environment makes an adjustment necessary (see Korajczyk and Levy, 2003). By comparing current capital structure with target leverage, we can predict future financial securities issuances (e.g., seasoned equity offerings or bonds). If the issuance realized deviates from expectations, this information can be a valuable sign for market participants ("outsiders") because it would reduce asymmetric information. The information content will be either positive or negative depending on whether, e.g., profitability is higher or lower than expected. However, the inherent information content of issuances can also be estimated today using current financial stocks' liquidity, which we assume can proxy for asymmetric information.

The cash flow information hypothesis of Ross (1977) states that more profitable firms can afford higher debt. Previous work has tested this hypothesis, but only for observed changes in capital structure. Masulis (1980) and Erwin and Miller (1998) use event studies to measure the effect of leverage signalling on short-term returns. Dann et al. (1991) and Shah (1994) analyze firm performance after capital structure transactions by measuring, e.g., operating cash flow. Other authors, such as Ofer and Siegel (1987) or Israel et al. (1989), have examined adjustments of financial analysts' forecasts in response to leverage signalling.¹

¹For a detailed survey of the early literature, see Masulis (1988); for a more recent overview, see Klein et al. (2002).

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In contrast, we use expected changes in leverage here, denoted as "target leverage changes," proxied for by estimated changes in capital structure from leverage regressions. We believe this is a sound method, because investors use available information to form expectations about firms' future performance and risk. From the pioneering works of Merton (1973) and Modigliani and Miller (1958), we know that firm leverage is related to both. Therefore, market participants should also develop expectations about future capital structure as well.

Our work deviates from the previous literature in a second key aspect, because we measure information revelations by using liquidity. We thus avoid using analyst coverage, which can be affected by conflicts of interest etc. (see, e.g., Lin and McNichols, 1998; Michaely, 1999). Furthermore, we do not need to rely on static balance sheet items such as size or growth opportunities, which are potentially driven by accounting policy and cannot react as immediately as equity liquidity.

We thus propose equity liquidity, although imperfect, as a viable proxy for measuring information asymmetries between managers (insiders) and the remaining market participants (outsiders). In the market microstructure literature, asymmetric information between traders as an illiquidity source has been modeled and discussed extensively (see, e.g., Kyle, 1985; Easley and O'Hara, 1987; Glosten, 1989; Foster and Viswanathan, 1993; Brennan and Subrahmanyam, 1996).²

²Liquidity is also considered a result of order processing, transaction costs (Amihud et al., 2006) and inventory costs (Stoll, 1978; Ho and Stoll, 1981; O'Hara and Oldfield, 1986). For a detailed overview of the theoretical concepts of liquidity, see O'Hara (1995).

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In our case managers are well-informed. They have improved capabilities in the assessment of good (bad) news on their own firm and are more likely to buy (sell) larger volumes of stocks to use their information advantage. Therefore, market makers who step in if orders fail to arrive will lose money (Bagehot, 1971). In awareness of these expected losses, trading volume will either be reduced, or higher discounts in the form of spreads or price impacts will be expected (Amihud et al., 2006). The classic adverse selection problem described by Akerlof (1970) is a direct consequence. So we propose that liquidity should proxy for managers' information advantages about a firm's future prospects.

As per Bharath et al. (2009), our argument is based on the assumption that managers constitute a subgroup of informed traders for three reasons: 1) They naturally have access to insider information, 2) they own considerable shares of the company, and 3) they trade in their own firms' stocks. The first argument is common sense. Regarding (2), studies have shown that management compensation usually includes granted common stock and stock option awards (Jensen and Meckling, 1976; Agrawal and Mandelker, 1987; Yermack, 1995). As Morck et al. (1988) show, these instruments can amount to a considerable share of the firm. (3) comes from the results of several studies on company executives' and directors' trades that find they use their information for trading and tend to earn abnormal returns (Jaffe, 1974; Finnerty, 1976; Lakonishok, 2001; Jeng et al., 2003).

We therefore propose using liquidity, despite its imperfections, as a proxy for the market's view on information asymmetries between insiders

and outsiders. Higher informational asymmetries involve less liquidity, and liquidity measures are sensitive to information-revealing firm characteristics such as ownership structure (Gompers and Metrick, 2001), asset liquidity and ratings (Odders-White, 2006), and events such as takeover announcements (Jennings, 1994). Moreover, firms with less liquid equity (equivalent to higher information asymmetries) exhibit higher levels of debt (Baker and Stein, 2004; Butler et al., 2005).

In summary, linking liquidity to corporate capital structure can yield valuable insights into three related strands of literature. First, we analyze the signalling effect of anticipated (targeted) leverage changes. We therefore contribute to the discussion on whether changes in leverage convey information to the public from an innovative perspective. Second, we expand the work of Bharath et al. (2009) by analyzing the entire chain from information asymmetries to (target) leverage, as well as its feedback effects to information asymmetries. Third, we improve the understanding of the drivers of liquidity. For owners and managers, this is extremely relevant, because liquidity has a direct effect on equity returns (see, e.g., Pastor and Stambaugh, 2003; Amihud, 2002; Acharya and Pedersen, 2005), the cost of capital, and thus shareholder value. Amihud and Mendelson (1986, 1988, 2008), for example, have regularly called for an analysis of the link between capital structure and liquidity. For academia, it is also valuable to better understand the variations in liquidity that have been observed in the cross-section of firms and over time by Chordia et al. (2000, 2001), Hasbrouck (2001) and Huberman and Halka (2001).

To test the link between capital structure and information asymmetry, we use daily stock and annual balance sheet data for U.S. firms from 1989 through 2008. Our procedure encompasses four steps:

1. Using a principal component analysis, as per Bharath et al. (2009), we derive the common informational component of six different liquidity measures.
2. We then use the resulting year-by-year information asymmetry index to estimate (book and market) leverage targets, as is commonly done in the literature (see Titman and Wessels, 1988; Rajan and Zingales, 1995). Here, we find that leverage is a linear function of our information asymmetry index, and that an increase (of information asymmetry) by one standard deviation results in a roughly 2% increase in leverage.
3. Next, we calculate the distance between a firm's actual leverage and its target capital structure (mainly used in leverage adjustment regressions) as a proxy for expected development. We also demonstrate its reliability for predicting true changes.
4. Finally, we determine the effect of these target leverage changes on our information asymmetry index (measures of liquidity), in order to model feedback effects.

Note that steps (2)-(4) yield a two-stage system estimation. Target leverage changes transmit to our information asymmetry index by a significantly negative amount, a factor ranging from -0.25 to -0.29. If we use observed changes, we find diverging signs for the coefficients for book and

market leverage in similar estimations. This is a consequence of endogeneity between market prices (and thus market leverage) and liquidity (used for our index). We take both results to mean that market participants anticipate capital structure decisions of managers, which is reflected in our index. Targeted increases in leverage tend to also increase liquidity, which supports Ross's (1977) signalling hypothesis.

For robustness, we estimate results for several indexes constructed on liquidity risk measures and for single measures of liquidity. Further we find that our results are even stronger if we ignore small changes in leverage. We control for the latter, because small changes in capital structure due to, e.g., maturing bonds that require refinancing, should not reveal any significant information to market participants.

The remainder of the article proceeds as follows. Section 4.2 describes our data sources, sample construction, and definitions. In section 4.3, we present our information asymmetry index. Subsection 4.4.1 describes the determination of leverage targets, while subsection 4.4.2 discusses their effect on information asymmetries. In section 4.5, we conduct robustness checks. Section 4.6 gives our conclusions.

4.2 Data, Definitions, and Descriptions

4.2.1 Database and Sample Construction

All of the daily stock data we use come from the Center for Research in Security Prices (CRSP) North America database.³ Included are U.S. stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ). We limit our analysis to all non-ADR and regular shares.

Balance sheet items come from Standard & Poor's (S&P) Compustat database,⁴ where we account for varying fiscal year-ends. For a detailed description of all the data items used here, see Table 4.11 in the Appendix. Our observation period is from 1989 through 2008. 4.6 describes our liquidity measures. We also use the three factors provided on Kenneth French's webpage.⁵ All absolute U.S. \$ values are deflated by GDP growth, also from S&P's Compustat database.

Table 4.1 gives an overview of our general selection rules. After the matching procedure, we exclude all financial firms (SIC: 6000-6999),⁶ all

³Source: CRSP[®], Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. <http://crsp.uchicago.edu>.

⁴Source: Standard&Poor's Compustat[®]. Used with permission. All rights reserved. http://www.compustat.com/Research_Insight/.

⁵See <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>.

⁶We exclude banks because the high level of deposits can generate extremely high levels of leverage. Publicly administrated firms have access to higher levels of debt due to government guarantees. Results remain structurally unchanged if the finance, insurance,

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firms that are publicly administrated (SIC: 9200-9999), and all firms with a zero standard industrial classification (SIC) code. We also eliminate duplicate entries for unique firms (PERMCO) in the CRSP database by restricting our data to the largest market cap issues.

Furthermore, by trimming the 1% per item outliers on both sides of the variable distribution, as per Lemmon et al. (2008), we can mitigate the effects of outliers or misrecorded data.⁷ We then restrict leverage to the unit interval, so as to exclude any technically bankrupt firm.

We also exclude stocks with less than 200 return observations per year, in order to limit problems from unreliable liquidity measure calculations. We subsequently restrict our analysis to stocks with prices between U.S. \$1.00 and \$1,000.00 per share, as in Acharya and Pedersen (2005). This guarantees that we capture only regularly traded stocks.⁸ Next, we limit our sample to firms that have all balance sheet and P/L items available. We also exclude firm observations with no measures of liquidity or liquidity risk except for spreads. Day-end bid and ask prices are only available from 1992 in the CRSP database. We decided to use both, but we denote the latter as the "Full" sample.

and real estate divisions are included, however, as the subsequent trimming alleviates the high leverage problem. Tables are available from the authors upon request.

⁷Chang and Dasgupta (2009) exclude 0.5% of the outliers. Winsorizing leads to qualitatively similar results. Tables are available from the authors upon request.

⁸By doing this, we also reduce price discreteness problems that can impact liquidity. At the NYSE, the minimum price variation for all stocks above U.S. \$1 is now U.S. \$0.01, but it was U.S. \$0.125 prior to May 1997 (see NYSE Rule 62, <http://nyserules.nyse.com/NYSE/Rules/>). This has an automatic effect on spreads.

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Table 4.1: Data Construction

Steps	Obs	Share	Selection Rules
<i>General</i>			
1	137,080	100.0%	<i>Matched Data</i>
2	109,970	80.2%	<i>SIC</i>
3	108,656	79.3%	<i>Eliminate Duplicate Entries</i>
4	88,347	64.4%	<i>Trimming Outliers per Item</i>
5	88,143	64.3%	<i>Leverage Unit Intervall</i>
6	76,758	56.0%	<i>Minimum Daily Obs</i>
7	73,369	53.5%	<i>Stock Price</i>
8	30,474	22.2%	<i>No Missing Data</i>
<i>Full Samples</i>			
9	29,687	21.7%	<i>Measures of Liquidity and Liquidity Risk ex. Spreads ("FullexS")</i>
10	26,396	19.3%	<i>Measures of Liquidity and Liquidity Risk ("Full")</i>
<i>Subsamples</i>			
11	10,821	7.9%	<i>"exNASDAQ"</i>
12	5,557	4.1%	<i>"Survivors" (15years)</i>

The data consists of all U.S. listed firms in the CRSP[®], Center for Research in Security Prices North America database, and the Standard & Poor's Compustat[®] database from 1989 through 2008. The general selection rules are described in detail in subsection 4.2.1.

Lastly, we construct two subsamples for robustness checks. In the first subsample, we exclude all NASDAQ firms ("exNASDAQ"). This accounts for the NASDAQ effect found by Brennan et al. (1998) or Lesmond et al. (2008), where some liquidity measures such as trading volume and the Amihud (2002) liquidity measure are exaggerated, as follows. On NASDAQ interdealer trades, as well as on after-hours trades, volumes are included in the current day. Trades on all exchanges connected to NASDAQ's composite pricing network are also included in the volume. In the CRSP, bid, ask, and missing price quotes are paired with non-zero volumes in some cases. Finally, prior to June 15, 1992, volumes were reported differently for the NASDAQ National Market and the NASDAQ Small-Cap Market. In the former, traded

volumes were reported for one party, while for the latter they were reported for both parties.

In the second subsample, we included firms in our panel only if they had existed for at least fifteen years ("survivors"), to avoid any potential survivorship bias, as in Lemmon et al. (2008). We refrain from presenting results here because they are structurally similar.

4.2.2 Measures of Capital Structure

We define our capital structure measures in a traditional manner (see, e.g., Titman and Wessels, 1988; Fama and French, 2002; Baker and Wurgler, 2002; Kayhan and Titman, 2007), where book leverage ($Lev_{i,t}^B$) is the ratio of total book debt-to-total assets of firm (i) in period (t). Note, however, that market leverage ($Lev_{i,t}^M$) is the ratio of total book debt-to-market value of assets.⁹ We use both measures in order to account for this discrepancy.

Table 4.2 shows that both measures fall within the "typical" leverage range. Rajan and Zingales (1995) report an average (median) of 0.31 (0.27) for book leverage, and 0.24 (0.20) for market leverage (see also Lemmon et al., 2008; Shyam-Sunder and Myers, 1999). In our sample, the average book and market leverage ratio is 0.21 (see columns 1 and 2); excluding NASDAQ firms in columns 3 and 4 leads to slightly higher debt ratios. Note that market leverage shows a higher variation.

⁹Titman and Wessels (1988) state that firms refer mostly to book leverage when adjusting their leverage ratios. Most of our control variables are scaled to book value of total assets, but equity liquidity is linked to market capitalization and market equity.

Table 4.2: Cross Sectional Data on Leverage

	Full		exNASDAQ		Survivors	
	(1)	(2)	(3)	(4)	(5)	(6)
	$Lev_{i,t}^B$	$Lev_{i,t}^M$	$Lev_{i,t}^B$	$Lev_{i,t}^M$	$Lev_{i,t}^B$	$Lev_{i,t}^M$
<i>Mean</i>	0.21	0.21	0.25	0.26	0.22	0.23
<i>Std</i>	0.18	0.22	0.17	0.22	0.15	0.20
<i>Skew</i>	0.97	1.25	0.75	0.99	0.92	1.16
<i>Kurt</i>	3.76	3.90	3.60	3.36	4.21	3.89
<i>95% Quant</i>	0.56	0.68	0.57	0.72	0.51	0.64
<i>Median</i>	0.18	0.13	0.24	0.21	0.20	0.17
<i>5% Quant</i>	0.00	0.00	0.02	0.01	0.01	0.01
<i>Firm Years</i>	29,687	29,687	10,821	10,821	5,557	5,557

The sample consists of the "Full" sample from 1992 through 2008. The table shows cross-sectional data on book and market leverage $Lev_{i,t}^B, Lev_{i,t}^M$ by samples, as indicated in the columns. For the former, it is total debt to value of total assets; for the latter, it is total debt to total debt plus market equity (shares outstanding times year-end market price). See Table 4.12 for calculation methods.

4.2.3 Control Variables for Leverage

The number of leverage determinants analyzed in the literature is large (see, e.g., Titman and Wessels, 1988; Shyam-Sunder and Myers, 1999; Fama and French, 2002; Frank and Goyal, 2003; Flannery and Rangan, 2006; Chang and Dasgupta, 2009). We limit our research to a concise set of control variables that have been shown to be correlated with capital structure: size ($Size_{i,t-1}$), profitability ($Profit_{i,t-1}$), market-to-book ($M2B_{i,t-1}$), collaterals ($Coll_{i,t-1}$), uniqueness ($Uni_{i,t-1}$), tax rate ($Tax_{i,t-1}$) and industry effects ($Ind_{i,t}$).¹⁰ Each variable is discussed in more detail below.

- Size is a commonly used explanatory variable that reflects higher diversification and less risk of financial distress. Less bankruptcy prob-

¹⁰Table 4.12 depicts methods of calculation for each variable.

ability should lead to a higher debt capacity for larger firms (Rajan and Zingales, 1995). We use sales ($Size_{i,t-1}$), scaled using a natural logarithm, as an indicator of firm size instead of total assets. Leverage ratios directly incorporate total asset value and may lead to endogeneity problems.

- The key prediction of Myers (1984) and Myers and Majluf (1984) is that profitability is negatively related to leverage, while growth opportunities are positively related. If investments are fixed, higher profitability allows management to avoid external financing due to higher information costs. If profitability is fixed, higher growth opportunities should lead to an increase in debt, which leads to a positive relationship.

In contrast, trade off-theory would argue that increasing cash flows lead to higher agency costs. Firms thus commit a larger percentage of pre-interest earnings to debt and interest payments in order to gain improved control over investment opportunities (Fama and French, 2002). We use the market-to-book asset ratio (M2B), as defined in Fama and French (1993), and profitability ($Profit_{i,t-1}$) as operating income before depreciation to total assets.

- Firms with more tangible assets should exhibit higher leverage for two reasons: Collaterals retain more of their value to debtors in case of liquidation, and agency costs of debt, such as risk-shifting, can be reduced (see Rajan and Zingales, 1995). We use inventory plus property, plant, and equipment net to total assets as our collateral measure ($Coll_{i,t-1}$), which proxies for a lender's willingness to lend to a firm.

- Titman and Wessels (1988) argue that more specialized firms impose higher costs on their customers, suppliers, and employees in case of bankruptcy, which leads to a lower debt capacity. The ratio of research and development expenses to sales ($Uni_{i,t-1}$) should reflect specialization.
- The value of the leveraged firm is the sum of the unlevered firm and the tax shield effect. Low tax ratios ($Tax_{i,t-1}$) reflect a low tax shield, which drives managers to increase debt (higher leverage), ultimately increasing firm value.
- All explanatory variables are lagged variables from the previous period to explain the dependent actual leverage. Actual forces, such as market or industry conditions, may drive financial decision making as well. Low levels of goodness-of-fit in standard leverage regressions support this argument. To mitigate the omitted variables problem, we include an actual industry control variable ($Ind_{i,t}$), following Lemmon et al. (2008). We calculate industry effects as the actual time series median for one-digit SIC industry classifications (see Table 4.13).

Panel A in Table 4.3 gives brief descriptions of all the control variables in our three samples except the industry factor. A quick inspection reveals that the means, medians, and standard deviations are comparable to those in Lemmon et al. (2008), who analyze a similar period. Size, as expected, is larger for survivors and exNASDAQ firms, but exhibits a little less variation.

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Table 4.3: Cross Sectional Data

Variable	Full		exNASDAQ		Survivors	
	Mean	Std	Mean	Std	Mean	Std
<i>Panel A: Control Variables for Leverage</i>						
$Size_{i,t}$	18.59 (18.60)	2.09	19.98 (20.20)	1.85	19.50 (19.65)	1.67
$Profit_{i,t}$	0.05 (0.11)	0.21	0.12 (0.13)	0.13	0.13 (0.13)	0.10
$M2B_{i,t}$	1.80 (1.22)	1.95	1.43 (1.07)	1.31	1.42 (1.10)	1.11
$Coll_{i,t}$	0.42 (0.41)	0.23	0.47 (0.47)	0.20	0.48 (0.48)	0.18
$Tax_{i,t}$	0.23 (0.31)	0.20	0.29 (0.34)	0.18	0.29 (0.35)	0.17
$Uni_{i,t}$	1.46 (0.03)	44.28	0.22 (0.02)	12.80	0.24 (0.02)	5.51
<i>Panel B: Control Variables for Liquidity</i>						
$V_{i,t}$	0.65 (0.58)	0.35	0.45 (0.39)	0.23	0.49 (0.44)	0.25
$R_{i,t}$	0.10 (0.00)	0.64	0.11 (0.05)	0.51	0.16 (0.08)	0.55
$AV_{i,t}$	0.51 (0.45)	0.31	0.32 (0.27)	0.18	0.37 (0.33)	0.21
$Z''_{i,t}$	162.34 (8.98)	2,465.90	42.49 (8.05)	729.41	34.50 (9.44)	316.14
<i>Panel C: Further Information</i>						
<i>Obs</i>	251.9 (252)	3.0	251.9 (252)	3.2	252.0 (252)	2.3
<i>Firms</i>	5,362		1,637		330	
<i>Firm Years</i>	29,687		10,821		5,557	

The table shows cross-sectional data of the control variables for the "Full", "exNASDAQ", and "Survivors" samples, indicated by columns for leverage (panel A) and liquidity (panel B) from 1989 through 2008. See Table 4.12 for calculations. Panel C gives further information, where "Obs" indicates daily observations per year and firm, "Firms" is the total number of firms in the sample, and "Firm years" is the total number of observations in the sample period. Medians are given in parentheses.

By economic intuition, we hypothesize that profits will be negatively correlated with the probability of bankruptcy. The internal sources of funding variable, with a profitability of 0.13, is the largest in our survivor subsample. Collaterals, reflecting the assets of a firm that are available to back debt and financial distress, also slightly increase from 0.42 to 0.48. In addition, the market-to-book ratio decreases from our largest sample to our smallest subsample. Many firms on the NASDAQ are small, innovative tech companies, and are characterized by higher growth opportunities, less collateral, less actual profitability, and larger R&D investments.

4.2.4 Control Variables for Liquidity

To extract the impact of leverage on liquidity, we control for firm-specific variables that also impact liquidity (described below). We use equity volatility ($V_{i,t}$), annual returns ($R_{i,t}$), asset volatility ($AV_{i,t}$), Z"score ($Z''_{i,t}$) and profits ($Profit_{i,t}$).¹¹

- Increased leverage leads to increased equity volatility (Merton, 1974). This is equivalent to a higher sensitivity of equity prices to private information and can attract insider trading (Harris and Raviv, 1993) and uninformed investors, who may gamble on investment decisions (Kumar, 2009). But the increased probability of information-based trading increases the inventory risk of market makers and subsequently decreases liquidity (Amihud and Mendelson, 2008; Lesmond et al., 2008).

¹¹Table 4.12 depicts methods of calculation for each variable.

Stoll (2000) also proposes that stock volatility measures the risk of adverse price changes, which reflects inventory arguments in Stoll (1978), Ho and Stoll (1981) and O'Hara and Oldfield (1986).

- We assume that changes in fair prices must exceed transaction costs and minimum price variations to obtain any observable price variation. Thus, prices could have an effect. Authors such as Brennan and Subrahmanyam (1996), Stoll (2000) and Chordia et al. (2000) find a significant negative relationship between prices and relative spreads. We may also establish prices to proxy for other variables. Annual returns (price differences) could reflect a firm's economic prosperity, because we assume that firms with positive future earnings have positive returns. However, as per Subrahmanyam (1991), insiders with firm-specific information might be able to anticipate returns and use strategic trading to exploit the information.
- Higher firm risk increases the attractiveness of equity, a contingent claim (Black and Scholes, 1973; Merton, 1973). We use annual asset volatility to proxy for general business risk and the volatility of a firm's total value (Merton, 1974).
- Any theory on capital structure considers information asymmetries as a driving force, where managers use profits to their own advantage. In the case of higher profits, information asymmetries could become more severe. On the other hand, increased profits could ease the predictability of future returns, and reduce information asymmetries on firm value. Consequently we add profits to our liquidity regressions.

- According to Odders-White (2006) we control for proximity to bankruptcy as a final firm characteristic, using a newer version of Altman's (1968) original Z-score model ($Z''_{i,t}$).¹²

While the Z'' -scores are high on average (see Altman and Saunders, 1998), the medians are about 8.98 (see Table 4.3). Firms thus have a AAA-rating in more than 50% of all firm-year observations.¹³ Asset and equity volatility are higher for our largest sample, and equity returns are highest for our survivor subsample. Both findings follow economic intuition. Our restricted subsamples include older, larger, and more profitable firms. The last rows give daily observations per year and by firm, numbering at least 200 by selection rules but on average closer to 252 per year. The total number of firms in our subsample is 5,362, but it decreases to 330 if we require firms be in our subsample for at least fifteen years.

4.3 Liquidity and Information Asymmetry

Index

Our analysis concentrates solely on equity liquidity for several reasons. First, bond payments are fixed, thus uncertainty about the future predictability of returns is limited to defaults, which are marginal compared to equity. Second,

¹²The insolvency ratio (Z'') is a linear combination of the ratio of working capital to total assets (Z_1), retained earnings to total assets (Z_2), EBIT to total assets (Z_3), and book value of equity to total liabilities (Z_4). This results in: $Z'' = 3.25 + 6.56 * Z_1 + 3.26 * Z_2 + 6.72 * Z_3 + 1.05 * Z_4$.

¹³Altman and Saunders (1998) provide an U.S. bond rating equivalent.

our aim is to investigate information asymmetries between management and the remaining owners. Third, we assume that the capital structure is defined in favor of the equityholders, due to management compensation.

The research on market microstructure, mainly asset pricing, is vast. Assets that can be traded in very large volume, and within a marginal time frame without any price impact, are considered perfectly liquid (Bernstein, 1987). However, although the quality of the concept is widely accepted, neither a generally recognized definition of liquidity, nor a unique measure capturing all its aspects, exists (Chordia et al., 2009). We can categorize the large variety of liquidity measures into three groups: trading activity, trading costs, and the price impact of order flow.¹⁴

Chordia et al. (2000, 2001), Hasbrouck (2001) and Huberman and Halka (2001) show that absolute liquidity varies over time, which implies the existence of liquidity risk. The asset pricing literature claims this type of risk must also be paid off (Pastor and Stambaugh, 2003; Amihud, 2002; Acharya and Pedersen, 2005). Considerations about liquidity risk were introduced by Ellul and Pagano (2006) in corporate finance by modeling impacts on IPO underpricing. They study newly listed firms on the London Stock Exchange using observed liquidity in the subsequent four weeks of the IPO. Post-IPO proxies showed significant explanatory power for underpricing.

In our context, we could interpret this to mean that high volatility in liquidity measures is evidence of strong variation in informational asym-

¹⁴In fact, most measures represent illiquidity. We use both terms – illiquidity and liquidity – equivalently, but we must be careful about the contrary properties.

metries over time. Holding everything else equal, higher volatility should increase adverse selection problems. Thus, for the sake of robustness, we must also consider liquidity risk in our analysis. Various concepts and measures of liquidity and liquidity risk have contributed to the understanding of the underlying problem (Hasbrouck, 2007). However, the amount of diversity means no single measure can fully capture all aspects of this elusive concept, although they all will contain information asymmetries.

We thus follow Bharath et al. (2009) and construct a composite, time-varying (but still imperfect) index by using principal component analysis (PCA) on six measures: 1) trading volume ($TV_{i,t}$), 2) the proportion of zero returns, ($LOT_{i,t}$), as proposed by Lesmond et al. (1999), 3) the relative bid-ask-spread ($S_{i,t}$), 4) the effective spread, ($ROLL_{i,t}$), as proposed by Roll (1984), 5) round-trip transaction costs ($RTC_{i,t}$) from Lesmond et al. (1999), and 6) the Amihud (2002) price impact measure ($ALM_{i,t}$). We also calculate an index based on the variations in these measures to capture liquidity risk. We do not limit our analysis to a single measure, because we wish to retain the largest possible amount of available information on market perceptions.¹⁵ However, as a robustness check, we provide relevant results for liquidity measures separately in subsection 4.5.2.

We assume that our set of empirical liquidity measures $(x_{i,t}, x_{j,t})$, with (n) realizations in period (t) , can be fully described by a linear combination

¹⁵For a more detailed description of the measures of liquidity and methods of calculation, see 4.6.

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$(\theta_{k,t})$ of (k) hypothetical and orthogonal factors $(f_{i,t,k})$ including noise. The first factor is our information asymmetry component (see Equation (4.1)).¹⁶

$$x_{i,t} = \bar{x}_i + \sum_{k=1}^K (\theta_{k,t} * f_{i,t,k}) + \epsilon_{i,t} \quad (4.1)$$

We use all the liquidity and liquidity risk measures mentioned earlier to calculate two year-by-year indexes for any firm (i) . Due to the availability of CRSP spreads, our index covers only 1992 to 2008.¹⁷ We denote the isolated first common factor in liquidity measures as $ASY_{i,t}$, and as $\sigma_{ASY_{i,t}}$ for liquidity risk measures.

As panel A in Table 4.4 shows, the different factor loadings exhibit the expected signs and do not change over time for absolute liquidity measures. Furthermore, our index does not exclude any single measure by close to zero factor loadings. In 1992, the weights of the spread, the trading volume, and the round-trip transaction costs were the highest in relative terms.

¹⁶Panel A in Table 4.15 shows firm means of Spearman rank correlations in our fifteen-year survivor subsample. All measures show positive correlations except trading volume, which is between 0.39 and 0.88. We note that liquidity risk measure values are all positive, while the Roll (1984) measure exhibits correlations of close to zero with the remaining liquidity risk measures. The linear relationship between risk and absolute measures is also very high, except for the Roll (1984) risk measure, which is around zero. We do not report Pearson correlation coefficients here, but they are very similar and statistically significantly different from zero. We consider this as strong evidence of the appropriateness of PCA.

¹⁷We also calculate two information asymmetry indexes that exclude spreads and spread risk. But an inclusion seems adequate as spreads are largely used in market microstructure literature. The results are not shown here, but factor loadings $(\theta_{i,k})$ are slightly higher. Our latter results remain qualitatively unchanged. Tables are available from the authors upon request.

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Table 4.4: Constructing a Liquidity Index

Year	Factor Loadings of Liquidity Measures						VarEx (%)	Obs
	$S_{i,t}$	$TV_{i,t}$	$ALM_{i,t}$	$ROLL_{i,t}$	$LOT_{i,t}$	$RTC_{i,t}$		
Panel A: Index $ASY_{i,t}$ Based on Absolute Measures of Liquidity								
1992	0.53	-0.42	0.37	0.32	0.35	0.42	76.39	1191
1993	0.50	-0.41	0.40	0.38	0.29	0.44	79.75	1572
1994	0.50	-0.40	0.41	0.38	0.28	0.45	78.31	1729
1995	0.50	-0.41	0.41	0.37	0.28	0.44	77.93	1792
1996	0.49	-0.42	0.43	0.39	0.29	0.41	77.06	1939
1997	0.47	-0.43	0.45	0.36	0.32	0.40	77.02	2115
1998	0.40	-0.45	0.48	0.37	0.34	0.39	75.30	2020
1999	0.38	-0.48	0.50	0.35	0.35	0.35	72.54	1784
2000	0.39	-0.51	0.52	0.33	0.35	0.29	68.50	1717
2001	0.34	-0.53	0.55	0.32	0.34	0.27	72.17	1650
2002	0.32	-0.56	0.58	0.28	0.33	0.25	70.21	1515
2003	0.25	-0.59	0.62	0.28	0.29	0.20	70.15	1292
2004	0.22	-0.59	0.62	0.34	0.26	0.19	68.53	1303
2005	0.19	-0.57	0.64	0.35	0.24	0.21	68.03	1264
2006	0.17	-0.57	0.67	0.33	0.24	0.17	69.33	1176
2007	0.19	-0.57	0.67	0.29	0.21	0.22	64.42	1253
2008	0.32	-0.52	0.66	0.25	0.18	0.32	67.90	1084
Mean	0.36	-0.50	0.53	0.34	0.29	0.32	72.56	1552.71
Panel B: Index $\sigma_{ASY_{i,t}}$ Based on Measures of Liquidity Risk								
1992	0.22	0.53	0.52	0.11	0.35	0.52	53.45	1191
1993	0.48	0.50	0.52	-0.15	0.24	0.42	55.52	1572
1994	0.48	0.48	0.51	-0.18	0.24	0.43	53.65	1729
1995	0.48	0.48	0.52	-0.10	0.26	0.45	55.07	1792
1996	0.48	0.50	0.54	-0.04	0.29	0.39	53.75	1939
1997	0.55	0.45	0.50	-0.02	0.30	0.38	55.23	2115
1998	0.56	0.41	0.47	0.03	0.35	0.42	57.65	2020
1999	0.56	0.42	0.47	0.01	0.35	0.41	54.50	1784
2000	0.49	0.41	0.49	0.07	0.43	0.39	56.36	1717
2001	0.60	0.40	0.47	0.12	0.41	0.29	55.99	1650
2002	0.40	0.48	0.55	0.04	0.48	0.28	61.52	1515
2003	0.27	0.52	0.55	0.10	0.54	0.23	62.69	1292
2004	0.25	0.53	0.56	0.15	0.54	0.20	58.52	1303
2005	0.23	0.50	0.60	0.14	0.51	0.25	55.58	1264
2006	0.19	0.49	0.62	0.28	0.48	0.17	56.19	1176
2007	0.28	0.43	0.61	0.24	0.49	0.26	55.13	1253
2008	0.69	0.29	0.49	0.07	0.32	0.30	60.73	1084
Mean	0.42	0.46	0.53	0.05	0.39	0.34	56.56	1552.71

The table gives results for the "Full" sample from 1992 through 2008. Panel A shows time series of factor loadings for the first component derived using year-by-year principal component analysis (PCA) on absolute liquidity measures. These include spread ($S_{i,t}$), trading volume ($\ln TV_{i,t}$), the adjusted Amihud (2002) liquidity measure ($\ln ALM_{i,t} * 10^6$), the Roll (1984) liquidity measure ($ROLL_{i,t}$), the ratio of zero trades ($LOT_{i,t}$), round trip transaction costs based on market returns ($RTC_{i,t}$). Panel B shows results for measures of liquidity risk. The last two columns indicate the explained variance (VarEx) of the first principal component in percentage, and firm observations per year (Obs).

The decrease of factor loadings over time, especially for $S_{i,t}$, $LOT_{i,t}$, $ROLL_{i,t}$ may be a hint of their reduced relevance. In other words, spreads tightened considerably over time because of improvements in exchange technology. On the other hand, however, $ALM_{i,t}$ and $TV_{i,t}$ gained strongly, and the former is the single most important measure in 2008. For measures of liquidity risk, we expect all factor loadings to take effect in the same direction, so that a

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high variation in trading volume would characterize increased uncertainty, which also holds for a higher variation in spreads. Note in panel B that for measures of liquidity risk, all factor loadings exhibit positive signs except for the Roll (1984) factor loading, which alters around zero, indicating low relevance.

The full cross-sectional distribution of our firm-level illiquidity index exhibits a mean of zero, which comes from the z -transformation of original liquidity measures and a standard deviation of 1.89 ($std(\sigma_{ASY_{i,t}}) = 1.79$).¹⁸ The distribution is slightly positively skewed, similarly to standard measures of illiquidity. The explained variance for the absolute values of liquidity is roughly 72.6%, and fluctuates between 60% and 80%. In contrast, for liquidity risk, it is lower with a mean of 56.6% (see the penultimate column in Table 4.4).

Bharath et al. (2009) find that their index captures about 50% in any year, and is an adequate proxy for information asymmetries. But the authors refine their measures of liquidity twice to derive the index, which we believe could lead to a loss of information. First, they filter spreads and the Roll (1984) measure for their informational component, and, second, they construct the index by using the PCA. We see no reason not to use the standard measures of liquidity directly for the component analysis. We conclude that our index, $ASY_{i,t}$, however, captures a higher share of variation and thus would have an advantage because it better reflects available market information. Our subsequent results in subsection 4.4.1 support our arguments.

¹⁸Cross-sectional information is available from the authors upon request.

4.4 Empirical Results

4.4.1 Target Leverage and Leverage Adjustment

To investigate the effect of expected changes in capital structure (target leverage changes) on information asymmetries, we implement a two-stage equation model that can simultaneously include the determination of leverage and liquidity.

Our first step is to use standard leverage regressions, as proposed by Titman and Wessels (1988), Rajan and Zingales (1995) and Shyam-Sunder and Myers (1999) (see also Equation (4.2)). The fitted value of this regression is then used as the leverage target. In order to show that the distance from this target leverage has predictive power for observed changes in leverage, we conduct adjustment regressions. Third, we use these target leverage changes in subsection 4.4.2 to estimate their effect on our information asymmetry index. We estimate target leverage as:

$$Lev_{i,t} = \beta_0 + \beta_{ASY} * ASY_{i,t-1} + \sum \beta_C * C_{i,t-1} + \epsilon_{i,t} \quad (4.2)$$

where $Lev_{i,t}$ is the actual leverage in year t of firm i and $\sum \beta_C * C_{i,t-1}$ describes the effect of control variables and the actual industry leverage factor, presented in subsection 4.2.3. We explicitly account for the fact that the

impact of lagged information asymmetries on leverage is driving manager decision making.¹⁹

This specification of the model makes the following question testable: Do information costs drive capital structure decisions? To cope with the notation problem that arises from having used various indexes of information asymmetry, as well as measures of liquidity and liquidity risk for robustness, we use $ASY_{i,t}$ as a replacement character in our analysis.

The error term ($\epsilon_{i,t}$) is a well behaved, classically uncorrelated disturbance term with constant variance. Although it can be considered the "work horse" when analyzing capital structure, pooled ordinary least squares (POLS) methods lead to an estimation bias. We find that omitted variables, such as the disregard of time-invariant components (Lemmon et al., 2008), explain the higher importance of cross-sectional variation versus time series variation in capital structure, as noted by Flannery and Rangan (2006).

The sources for individual effects, such as strategic focus and market, technology, and resource leads, constantly shape a business model. But the independent sampling assumption is thus violated (Petersen, 2008). Panel methods such as fixed effects are the most appropriate method to use to account for firm-specific effects in capital structure. If changing slowly (see

¹⁹This specification of the empirical model seems valuable, in contrast to Frieder and Martell (2006), who assume capital structure is driven by fitted values of lagged liquidity. From an economic point of view, using fitted liquidity measures implies that managers know what drives liquidity, and have a rich data source from which to derive a subsequent estimate of lagged spread that they can consider in their decision making process. In a model that uses simple lagged liquidity values to proxy for informational asymmetries, this assumption is redundant.

Lemmon et al., 2008), they can even absorb unidentified transitory components.

However, we are not interested in the size of the firm fixed effect, which allows for the use of within-transformation. By subtracting the firm-specific time series mean ($\bar{x}_i = \frac{1}{T} \sum_{t=1}^T x_{i,t}$) from every variable observed over time t , ($x_{i,t} - \bar{x}_i = \ddot{x}_{i,t}$), we get its time-demeaned observation. Firm-specific effects are solved out (see Equation (4.3)), and coefficients remain unchanged. We also add year fixed effects ($Y_{i,t}$) for variable intercepts ($\beta_Y * Y_{i,t}$) as least squares dummy variables (LSDV).²⁰

$$\ddot{L}ev_{i,t} = \beta_Y * Y_{i,t} + \beta_{ASY} * A\ddot{S}Y_{i,t-1} + \sum \beta_C \ddot{C}_{i,t} + \ddot{\epsilon}_{i,t} \quad (4.3)$$

We apply White's correction to account for heteroscedasticity from firmwise differencing.²¹ Table 4.5 gives estimation results for Equation (4.3), using our information asymmetry indexes and a restricted model. If information asymmetries are a driver of corporate debt policy, we expect a positive and significant coefficient. Note that we explicitly do not include both indexes of information asymmetry ($ASY_{i,t}$, $\sigma_{ASY_{i,t}}$) in one model, because of high collinearity. Both indexes should measure the same informational content, and thus have a correlation coefficient of $\rho = 0.95$ (see Table 4.15).

²⁰Excluding year effects yields estimation results with only minimal changes.

²¹The sample size is large, which justifies White heteroscedasticity robust t-values.

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Table 4.5: Effect of Information Asymmetries on Leverage

	Panel A: $Lev_{i,t}^B$			Panel B: $Lev_{i,t}^M$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ASY_{i,t-1}$		0.009** (7.90)			0.009** (6.19)	
$\sigma_{ASY_{i,t-1}}$			0.008** (6.58)			0.009** (6.01)
$Size_{i,t-1}$	0.03** (14.61)	0.03** (15.39)	0.03** (15.36)	0.04** (22.06)	0.05** (21.28)	0.05** (21.32)
$M2B_{i,t-1}$	0.01** (4.40)	0.003* (1.74)	0.00** (2.62)	0.07** (19.93)	0.06** (16.02)	0.06** (16.55)
$Profit_{i,t-1}$	-0.14** (-12.40)	-0.11** (-9.59)	-0.11** (-9.95)	-0.17** (-16.34)	-0.14** (-13.31)	-0.14** (-13.58)
$Coll_{i,t-1}$	0.07** (6.34)	0.06** (5.11)	0.06** (5.13)	0.09** (7.18)	0.07** (5.85)	0.07** (5.81)
$Tax_{i,t-1}$	-0.03** (-4.64)	-0.02** (-3.20)	-0.02** (-3.40)	-0.03** (-3.98)	-0.02** (-2.73)	-0.02** (-2.82)
$Uni_{i,t-1}$	0.00** (8.17)	0.00** (8.69)	0.00** (8.55)	0.00** (4.78)	0.00** (4.92)	0.00** (4.84)
$Ind_{i,t-1}$	0.57** (14.35)	0.53** (12.30)	0.54** (12.43)	0.65** (20.02)	0.56** (14.30)	0.56** (14.35)
Obs	20,095	17,651	17,651	20,095	17,651	17,651
SER	0.009	0.008	0.008	0.012	0.011	0.011
\tilde{R}^2	0.06	0.06	0.06	0.195	0.187	0.186
FE_Y	Yes	Yes	Yes	Yes	Yes	Yes
FE_F	Yes	Yes	Yes	Yes	Yes	Yes

The table gives results for the "Full" sample from 1992 through 2008. Estimation results with year and firm fixed effects (FE_Y, FE_F) are shown, where we regress book leverage (Panel A: $Lev_{i,t}^B$) and market leverage (Panel B: $Lev_{i,t}^M$) on our year-by-year information asymmetry indexes ($ASY_{i,t}$, $\sigma_{ASY_{i,t}}$), as described in subsection 4.3. Control variables are e sales ($Size_{i,t-1}$), market-to-book ($M2B_{i,t-1}$), profitability ($Profit_{i,t-1}$), collaterals ($Coll_{i,t-1}$), uniqueness ($Uni_{i,t-1}$), tax ratio ($Tax_{i,t-1}$) and the time series leverage median for one-digit SIC industry classifications ($Ind_{i,t}$) as actual variable (t) (see Table 4.13).

Below the control variables are the number of observations (obs), the standard errors of regression (SER), and the adjusted goodness-of-fit (\tilde{R}^2). The standard errors and t-statistics, respectively, of the coefficients are White heteroscedasticity corrected and given in parentheses below coefficients. *, and ** denote statistical significance at the 5%, and 1% levels.

We add our liquidity index to models (2), (3), (5), and (6) of Table 4.5.

All exhibit a positive coefficient and are highly significant ($p < 0.01$).²² In

²²Our results are structurally similar to other estimation methods such as POLS, the Fama and MacBeth (1973) method, and firm fixed effects without controlling for year effects.

contrast to Bharath et al. (2009), who report a 0.004 coefficient for market leverage, our coefficient for $(ASY_{i,t})$ is twice as high, with $\beta_{ASY,Lev^M} = 0.009$ (see model (2)). We assume this is a result of our index, which likely contains a higher share of information.

For book leverage, our values are very similar, with $\beta_{ASY,Lev^B} = 0.009$.²³ In terms of economic significance, a reduction of our information asymmetry index by one standard deviation leads to a reduction in market and book leverage of $(1.89 * 0.009)$ 1.7%. Effects for the index based on liquidity risk are similar, however (see models (3) and (6)).

We briefly summarize our main results for conventional leverage control variables in models (2) and (5). The industry factor is the single most powerful predictor of leverage in terms of economic relevance, and is highly significant, as shown by Lemmon et al. (2008). Collaterals and size are also positively related, in line with our previous arguments. Uniqueness shows positive coefficients, but economic significance is unlikely. Investment opportunities (M2B) have a large positive effect on market leverage, but much less of an effect on book leverage.

Note that size and growth opportunities were considered as proxies for information asymmetries in the literature. In fact, $M2B_{i,t}$ becomes insignificant for book leverage, which supports the idea that our index captures a

²³The lower number of 17,651 observations in Table 4.5, as compared to the "Full" sample in Table 4.1, results from the requirement that firms have either three firm-year observations in a row, or a total of four observations. The leverage equation requires control variables and consecutive observations for leverage, while fixed effects estimation requires a minimum of two observations per explanatory and dependent variable.

relevant fraction of informational asymmetries.²⁴ We conclude that liquidity seems to partially capture effects for $M2B_{i,t}$, but the size effect may only be partially justified by information asymmetries, as captured by our indexes. High profitability has a negative, large, and significant coefficient. This confirms the results of, e.g., Fama and French (2002).

All coefficients are significant at the 1% level. Due to the firm fixed effects estimation, the standard errors of the regression (SER) are low at 0.01, as well as the adjusted goodness-of-fit (\tilde{R}^2), which is 0.06 for $Lev_{i,t}^B$ and 0.19 for $Lev_{i,t}^M$.²⁵ Overall, our regression results are very similar structurally to those found in previous studies.²⁶

We use a standard partial adjustment model below, where the speed of adjustment (δ_{Lev^*}) toward leverage targets ($Lev_{i,t}^*$) is estimated as in Hovakimian et al. (2001). Low rates are interpreted as support for the freedom of managers to deviate from targets. Leary and Roberts (2005) pinpoint costs that slow down the speed of adjustment. Note that firms' leverage targets are not observable. As in the actual research, we use the estimated debt ratios from Equation (4.3), see Table 4.5, as a proxy for time-variant targets.²⁷

²⁴This is also the case for estimating the leverage equation with standard liquidity measures (see subsection 4.5.2). The correlations between liquidity measures and M2B range from -0.2 to 0.2, which removes the problem of multicollinearity.

²⁵The small size of goodness-of-fit does not violate any model assumptions of ordinary least squares estimation. The partial interpretation of the effect of liquidity on leverage remains precise because of the large sample size. It implies only that we have not accounted for a large fraction of factors that explain leverage.

²⁶Adding liquidity measures instead of our information asymmetry index does not change our results. Tables are available from the authors upon request.

²⁷The question of whether leverage targets are time-varying is of no interest to us here, but more details can be found in Frank and Goyal (2007).

In Equation (4.4), the observed change in leverage ($\Delta Lev_{i,t} = Lev_{i,t} - Lev_{i,t-1}$) partially absorbs the target leverage change, which is the difference in (estimated) target leverage and lagged leverage ($\Delta Lev_{i,t}^* = Lev_{i,t}^* - Lev_{i,t-1}^*$).²⁸ A positive value for $\Delta Lev_{i,t}^*$ denotes the lagged leverage is below the target. If targets exist, management will increase leverage, while a negative δ_{Lev^*} denotes the opposite. $\delta_{Lev^*} = 1$ implies a full adjustment; $\delta_{Lev^*} = 0$ implies no adjustment.

$$\Delta Lev_{i,t} = \delta_0 + \delta_{Lev^*} * \Delta Lev_{i,t}^* + z_{i,t} \quad (4.4)$$

We estimate Equation (4.4) to give a simple but clear indication of the speed of adjustment of analyzed firms (see Table 4.6). However, more importantly, we can test the relevance of our instrument, distance from target leverage, for realized changes in leverage, which we apply in the subsequent subsection.

For our purposes, $Cov(\Delta Lev_{i,t}^*; \Delta Lev_{i,t}) \neq 0$ is a necessary condition to identify a relevant instrument. For POLS, we observe mean reversion rates of about 11%-15% per year, depending on the sample, the inclusion or exclusion of year effects, and book or market leverage. If we use fixed effects estimation, estimated adjustment speed increases to 36%-53%. Furthermore, significance is well below 1%, independent of the sample or method used.

²⁸By transformation, the adjustment model can also be written as an equation, where actual leverage is a weighted average of lagged and target leverage:

$$Lev_{i,t} = (1 - \delta_{Lev^*}) * Lev_{i,t-1} + \delta_{Lev^*} * (\beta_0 + \beta_{ASY} * ASY_{i,t-1} + \sum \beta_C * C_{i,t} + \epsilon_{i,t}) + z_{i,t}$$

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Table 4.6: Leverage Adjustment of Firms

Method	Panel A: $Lev_{i,t}^B$				Panel B: $Lev_{i,t}^M$			
	(1) POLS	(2) POLS _Y	(3) FE _F	(4) FE _Y	(5) OLS	(6) OLS _Y	(7) FE _F	(8) FE _Y
Full								
δ_0	0.00** (5.36)	-0.01** (-4.42)			0.01** (14.15)	-0.02** (-6.68)		
$\Delta Lev_{i,t}^*$	0.15** (26.26)	0.15** (26.33)	0.47** (71.97)	0.47** (43.80)	0.12** (19.25)	0.11** (18.08)	0.51** (68.26)	0.46** (41.54)
<i>Obs</i>	17,651	17,651	17,651	17,651	17,651	17,651	17,651	17,651
<i>SER</i>	0.009	0.009	0.006	0.006	0.013	0.012	0.009	0.008
<i>FE_Y</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>R</i> ²	0.06	0.07	0.23	0.23	0.03	0.11	0.21	0.23
exNASDAQ								
δ_0	0.00 (1.45)	-0.01** (-3.87)			0.01** (6.76)	-0.03** (-5.81)		
$\Delta Lev_{i,t}^*$	0.13** (17.39)	0.13** (17.38)	0.47** (46.08)	0.46** (30.05)	0.11** (12.62)	0.09** (11.26)	0.53** (45.86)	0.46** (28.25)
<i>Obs</i>	6,890	6,890	6,890	6,890	6,890	6,890	6,890	6,890
<i>SER</i>	0.006	0.006	0.004	0.004	0.012	0.011	0.008	0.008
<i>FE_Y</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>R</i> ²	0.06	0.08	0.24	0.24	0.03	0.14	0.23	0.26
Survivors								
δ_0	0.00 (-0.65)	-0.01** (-2.51)			0.00 (2.16)	-0.02** (-3.38)		
$\Delta Lev_{i,t}^*$	0.15** (15.84)	0.15** (15.77)	0.35** (29.96)	0.35** (21.73)	0.17** (13.64)	0.15** (12.78)	0.45** (32.46)	0.38** (19.87)
<i>Obs</i>	4,096	4,096	4,096	4,096	4,096	4,096	4,096	4,096
<i>SER</i>	0.006	0.006	0.005	0.005	0.011	0.009	0.009	0.008
<i>FE_Y</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>R</i> ²	0.07	0.09	0.18	0.19	0.06	0.17	0.20	0.24

The table gives estimation results for the "full," "exNASDAQ," and "Survivors" samples by rows from 1989 through 2008. Shown are results for partial adjustment regressions of book leverage (Panel A: $Lev_{i,t}^B$) and market leverage (Panel B: $Lev_{i,t}^M$), where we estimate Equation (4.4). $\Delta Lev_{i,t}^*$ is the difference between the fitted value of Equation (4.3) (see also Table 4.5), and the leverage observed in the previous period ($t - 1$). Estimation methods are pooled OLS (POLS) and firm fixed effects (FE_F), excluding and including year effects (POLS_Y, FE_Y), as indicated by columns. The number of observations (Obs), standard errors of regression (SER), and an indication for year effects (Year) and adjusted goodness-of-fit (R^2) are given for every estimation. Standard errors and t-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. Statistical significance at the 1% (5%) level is indicated by two (one) asterisks.

The results are structurally very similar to previous findings by Huang and Ritter (2005), who find 8%-15% for POLS and 25%-75% for fixed effects, as well as Fama and French (2002), Flannery and Rangan (2006), Lemmon et al. (2008) or Xu (2007).

Our conclusion is threefold. First, in support of Myers (1984), we find that market leverage is a linear function of information asymmetries. Other factors driving leverage are industry effects, profitability, size, and collaterals. Second, firms adjust toward capital structure targets, although the speed and thus the interpretation are in dispute (see, e.g., Shyam-Sunder and Myers, 1999; Fama and French, 2002; Frank and Goyal, 2007; Lemmon et al., 2008). Third, $\Delta Lev_{i,t}^*$ is a useful instrument for explaining variation in leverage ($\Delta Lev_{i,t}$), and thus for analyzing feedback effects on information asymmetries to avoid endogeneity problems.

4.4.2 Feedback Effects of Capital Structure Decisions

Now we turn to the main question: Are capital structure decisions anticipated by capital markets? In contrast to authors who have studied the effects on returns of exchange offer announcements (Shah, 1994), debt-to-equity swaps (Campbell et al., 1991), share repurchases (Vermaelen, 1981; Erwin and Miller, 1998), and seasoned equity offers (Korajczyk et al., 1991),²⁹ we analyze feedback effects on our index based on liquidity.

²⁹For a detailed review of relevant papers see Klein et al. (2002).

In comparison to leverage adjustment regressions (see Equation (4.4)) we determine target leverage changes ($\Delta Lev_{i,t}^*$) effect on changes in our information asymmetry index ($\Delta ASY_{i,t} = ASY_{i,t} - ASY_{i,t-1}$) (see Equation (4.5)), which results in a two-stage least squares estimation. In the previous subsection, we already demonstrated the relevance of our instrument. We now add changes in control variables ($\Delta C_{i,t}$) to our empirical model. Because returns already represent changes in stock prices, we do not use first differencing here.³⁰

$$\Delta ASY_{i,t} = \gamma_0 + \gamma_{Lev^*} * \Delta Lev_{i,t}^* + \sum \gamma_C \Delta C_{i,t} + \epsilon_{i,t} \quad (4.5)$$

We believe this approach is appealing on both an economic and an econometric level. Economically, we are able to map the impact of "targeted actions" of management on the market, which represents signalling effects. As we noted in the previous subsection, the imperfect information between insider managers and remaining owners that is represented in liquidity drives corporate financial decision making. But we need to consider a feedback effect. Ross (1977) argues that more profitable firms can afford high levels of debt. Hence, corporate debt policy reveals information to the market about firm prospects. If this holds, a firm's tendency toward leverage targets should impact any measure that reliably proxies for informational asymmetries such as our index. Moreover, we assume that market participants anticipate management efforts, and use data on the informational and incentive environment of the firm. From an economic standpoint, this would

³⁰The error term ($\epsilon_{i,t}$) is required to satisfy instrument exogeneity, $Cov(\Delta C_{i,t}; \epsilon_{i,t}) = 0$.

justify the use of leverage targets as instruments, because they are known in advance of real capital structure changes.

Econometrically, we find that, if all else remains equal, two stocks priced at U.S. \$1,000 and U.S. \$1 should have similar relative spreads. We do not expect to find any relationship between absolute prices and measures of liquidity. However, Brennan and Subrahmanyam (1996), Stoll (2000) and Chordia et al. (2000) have all found significant negative relationships between prices and relative spreads. Using an instrument circumvents such endogeneity problems, which are rooted in hidden factors that probably drive liquidity and equity prices and thus market leverage.

First differencing in Equation (4.5) offers another advantage. If we examine liquidity measures over time, we find non-stationarity, or a decrease over time, which is very obvious for observed spreads, the Amihud (2002) liquidity measure, and the proportion of zero returns.³¹ A main rationale are technological advances as they reduce information and transaction costs while increasing the number of market participants. This drives our index as well. Gallant et al. (1992) propose alleviating this problem by using a linear transformation of liquidity measures based on market capitalization time series for each firm.

However, we also find a high level of autocorrelation for balance sheet items (despite GDP deflation), profits, and Altman and Saunders's (1998)

³¹The firm variable mean of autocorrelation in $S_{i,t}$ is 0.61, for the $ALM_{i,t}$ it is 0.57 and the $LOT_{i,t}$ it is 0.60. Augmented Dickey-Fuller unit root test are on average highly significant in rejecting stationarity for our survivor sample. Tables can be provided by the authors upon request.

Z'' -scores. Here, a market capitalization-based transformation seems inadequate. It would likely result in biased coefficients in POLS and Fama and MacBeth (1973) regressions, which do not converge to true population estimates (Chordia et al., 2009). By first-differencing the high values of autocorrelation (about 0.5 on average), we can reduce them immediately to between -0.1 and 0.1.

Finally, our approach also reduces complexity and makes our calculations traceable, obviating the need to use several transformations for different control variables. Our approach is a regular instrumental variable and two-stage least squares estimation. We assume $E(\epsilon_{i,t}|Lev_{i,t}^*) = 0$, which implies no correlation between the error term in the information asymmetry Equation (4.5) and the target leverage change. We use an industry variable to control for omitted actual variables, thus impacting liquidity (and our index).³²

$$\Delta A\ddot{S}Y_{i,t} = \gamma_Y Y_{i,t} + \gamma_{Lev^*} * \Delta L\ddot{e}v_{i,t}^* + \sum \gamma_C \Delta \ddot{C}_{i,t} + \ddot{\epsilon}_{i,t} \quad (4.6)$$

Table 4.7 gives results for a within-fixed effects estimation of Equation (4.6). Our index, based either on liquidity measures (panel A) or liquidity risk measures (panel B), is the dependent variable. We also control for year effects. The restricted models (1) and (6) exclude any measures of (target) leverage. Target changes in book, models (3) and (8), and market leverage,

³²We estimate a simultaneous model, where changes in actual control variables and leverage instruments can impact the changes in our index. However, endogeneity between the strictly exogenous control variables and our index may exist and can affect our estimation results. We believe future research should consider using a three-stage least squares approach (Zellner and Theil, 1962), or a model incorporating seemingly unrelated regressions (Zellner, 2010).

models (5) and (10), are explanatory. We also give results for realized changes in leverage, models (2), (4), (7), and (9).

Adding realized changes of market leverage ($\Delta Lev_{i,t}^M$) to explain changes in our liquidity and liquidity risk index, models (4) and (9), leads to positive results that are large and highly significant, similar to Frieder and Martell (2006). But for book leverage, coefficients are negative and significant (see model (2) for $ASY_{i,t}$) and model (7) for $\sigma_{ASY_{i,t}}$).

We assume the results for observed changes in book and market leverage are contradictory, presumably because of endogeneity. A decrease in market leverage might be driven by an increase in market prices (positive returns), instead of by actual management decisions. As already discussed in this subsection, higher prices are related to higher spreads and illiquidity. This could explain the positive coefficient for realized changes in market leverage on our information asymmetry index.

For target leverage changes ($\Delta Lev_{i,t}^*$), the picture is clearly different (see models (3), (5), (8), and (10)). The expected changes in leverage all exhibit a negative coefficient. This not only supports Ross's (1977) conclusions, where changes in capital structure indicate future firm profitability, but it also extends the signalling hypothesis. Our analysis reveals that capital markets anticipate financial policies based on available fundamental firm data that is reflected in our index of information asymmetry and liquidity.

Independent of the leverage ratio and of index composition, we observe results that are significant at the 1% level. We believe the small standard

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errors signal that $\Delta Lev_{i,t}^*$ is a reliable instrument for our purposes. The size of the feedback effect, moreover, is economically significant.

For example, a large positive distance from target leverage leads to the expectation of an increase in debt. This would be taken as a signal of the predictability of future cash flows. A positive target leverage change of, say, 10%, would indicate that the firm's debt ratio is 10% below the target. Because we would thus expect an adjustment toward target leverage, we can observe a clear reduction of the index by -2.5 to -2.9% (book leverage), and by -4.9 to -5.9% (market leverage).³³ Note that, for original measures of liquidity, trading volume would then increase by 3.5% for book leverage and 6% for market leverage, and the price impact would be reduced by roughly 3% and 5% from the previous year (see columns 4 and 8 in Table 4.10 in subsection 4.5.2).

Next, we briefly interpret results for the control variables. Liquidity is commonly driven by transaction costs or inventory risk, which we control for. The positive coefficient of equity volatility (ΔV_t) confirms the findings of Stoll (1978), Ho and Stoll (1981), Amihud and Mendelson (2008) and Lesmond et al. (2008), where an increase in inventory risk and information-based trading increases information asymmetries. But it contradicts the arguments of Frieder and Martell (2006) that advanced competition of speculators provides liquidity, which would lead to a decrease in our index.

³³Results for subsamples and indexes excluding spreads are structurally similar, and are available from the authors upon request.

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Table 4.7: Feedback Effect of Leverage Changes and Target Leverage Changes

Dep. Variable Leverage Model	Panel A: Liquidity Index ($ASY_{i,t}$)			Panel B: Liquidity Risk Index ($\sigma_{ASY_{i,t}}$)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta Lev_{i,t}$		-0.20** (-2.82)		0.70** (6.36)			-0.17** (-2.39)		0.49** (4.84)	
$\Delta Lev^*_{i,t}$			-0.25** (-4.26)		-0.49** (-7.45)			-0.29** (-5.10)		-0.59** (-9.58)
$R_{i,t}$	0.02** (2.79)	0.02** (3.11)	0.02** (2.89)	0.03** (4.39)	0.01* (1.66)	0.14** (18.96)	0.15** (19.20)	0.14** (19.07)	0.15** (19.46)	0.13** (17.47)
$\Delta V_{i,t}$	2.17** (32.10)	2.23** (30.50)	2.19** (32.24)	1.77** (17.23)	2.23** (32.43)	2.67** (41.87)	2.72** (39.21)	2.70** (42.05)	2.39** (25.21)	2.74** (42.41)
$\Delta AV_{i,t}$	-1.40** (-17.84)	-1.49** (-17.01)	-1.44** (-18.14)	-0.89** (-6.99)	-1.49** (-18.63)	-1.16** (-15.21)	-1.23** (-14.42)	-1.21** (-15.62)	-0.81** (-6.81)	-1.27** (-16.29)
$\Delta Z''_{i,t}$	0.00 (1.02)	0.00 (0.69)	0.00 (1.05)	0.00 (1.56)	0.00 (1.13)	0.00 (0.99)	0.00 (0.79)	0.00 (1.02)	0.00 (1.21)	0.00 (1.14)
$\Delta Profit_{i,t}$	-0.88** (-13.17)	-0.91** (-13.41)	-0.89** (-13.35)	-0.83** (-12.47)	-0.88** (-13.21)	-0.56** (-8.81)	-0.58** (-9.12)	-0.58** (-9.07)	-0.53** (-8.27)	-0.56** (-8.87)
<i>Obs</i>	17,651	17,651	17,651	17,651	17,651	17,651	17,651	17,651	17,651	17,651
<i>SER</i>	0.43	0.43	0.43	0.43	0.43	0.39	0.39	0.39	0.39	0.39
\hat{R}^2	0.18	0.18	0.18	0.19	0.19	0.29	0.29	0.30	0.30	0.30
<i>LM-p</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>F_{EY}</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>F_{EF}</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The data consist of the "Full" sample from 1992 through 2008. Panel A shows estimation results with year and firm fixed effects (FEX , FEP), where we regress changes in the liquidity indexes ($ASY_{i,t}$) in panel A on changes in book ($\Delta Lev^B_{i,t}$) and market leverage ($\Delta Lev^M_{i,t}$), or on changes in target book and target market leverage ($\Delta Lev^*_{i,t}$, $\Delta Lev^*_{i,t}$). In Panel B, the dependent variable is $\sigma_{ASY_{i,t}}$ (see subsection 4.3 for the calculation). The estimated (target) leverage change $\Delta Lev^*_{i,t} = Lev^*_{i,t} - Lev^*_{i,t-1}$ is the difference between the fitted value of Equation (4.3) and the leverage observed in the previous period ($t-1$), either for book or market leverage. Control variables include equity returns, changes in equity volatility, asset volatility, Z^* -score, and profit ($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z''_{i,t}$, $\Delta Profit_{i,t}$).

Below the control variables we indicate the number of observations (obs), standard errors of regression (SER), Durbin-Watson statistics (DW), adjusted goodness-of-fit (\hat{R}^2), and indicators for the inclusion of fixed effects and heteroscedasticity robust Lagrange-Multiplier statistic probabilities (LM-p). Standard errors and t-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. *, and ** denote statistical significance at the 5%, and 1% levels.

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In contrast, note that an increase in firm risk ($\Delta AV_{i,t}$) increases liquidity (and leads to a decrease in our index). Equity is a contingent claim on firm value. Thus, higher riskiness increases the value of the option, which in turn attracts investors. The results for the original measures of liquidity are not reported here, but all had the same direction. We interpret this as strong support of our view.³⁴

Stock prices have also been shown to impact liquidity. Controlling for returns ($R_{i,t}$), or price changes, we observe positive coefficients that are mostly significant at a 1% level. This again highlights the problem of endogeneity, which we encounter by our system estimation. The economic significance is minor, however. A 10% increase in returns would result in only a 0.2% increase in our index.³⁵ And the changes in distance to bankruptcy, measured by the Z'' -score, have no impact on our analysis.

Increases in profitability lead to a highly significant and economically relevant reduction in the index. This finding underlines the link between liquidity and information asymmetries regarding firm profitability. An increase in profits would ease investors' problems in evaluating true firm value. We also argue that higher profits attract traders, thereby providing more liquidity.

Our conclusion thus far is that information asymmetries, measured in equity liquidity, determine the level of debt. But any change in capital struc-

³⁴Tables are available from the authors upon request.

³⁵We assume the positive coefficient stems primarily from the ALM measure, which by calculation is positively related to returns and is a main driver of our index (see Table 4.4).

ture also has a feedback effect on informational asymmetries between managers and owners. Any measure that characterizes this principal-agent relationship – such as our information asymmetry indexes – should reflect this. However, endogeneity between liquidity and market prices (and thus market leverage) makes the use of system estimation inevitable. The “target leverage changes” we introduce here can solve this problem.

We take the latter as a signal of the anticipation of an adjustment process of firms’ capital structures. Market participants can use information about a firm’s fundamentals to build expectations about managers’ financial policy decision making. The identified negative and economically significant relationship between target leverage changes and changes in our information asymmetry index support the signalling hypothesis of Ross (1977). Thus, higher expected levels of debt reveal information about the predictability of future cash flows. Our finding that realized increases in profits take effect in the same direction confirms this view.

4.5 Robustness

4.5.1 Structural Changes in Capital Structure

One might argue that previous results are driven by small but irrelevant changes in capital structure, and that small changes in leverage could occur unintentionally rather than by management mandate. For example, consider maturing bonds, for which follow-up financing is not arranged or is just not

available due to market conditions. Market leverage in this case could be driven by small changes in equity prices rather than by clear management decisions. We therefore analyze solely those firms undergoing substantial changes in capital structure, as in Lesmond et al. (2008) or Xu (2007).

Our results could also come from firms that are close to bankruptcy. In both cases, changes in liquidity indexes or unclear effects in traditional measures of liquidity may be driven by other factors. We control for these effects by interrelating a dummy variable with changes in (target) leverage ($D * \Delta Lev_{i,t}; D * \Delta Lev_{i,t}^*$) in estimating Equation (4.7). The dummy variable is equal to 1 if true leverage changes exhibit real shocks of more than $\pm 5\%$ and $\pm 10\%$. In a third specification, we require further that firms have a Z'' -score larger than 2. This explicitly excludes marginal changes in capital structure and close to bankrupt firms, but facilitates an investigation of panel data.

$$\Delta A\ddot{S}Y_{i,t} = \gamma_Y * Y_{i,t} + \gamma_{Lev^*} * D * \Delta L\ddot{e}v_{i,t}^* + \sum \gamma_C \Delta \ddot{C}_{i,t} + \ddot{e}_{i,t} \quad (4.7)$$

Table 4.8 shows estimated values for our general sample and for the exNASDAQ and survivor subsamples. For the sake of conciseness, we do not display full results for the control variables, which are structurally very similar to those in Table 4.7.

The coefficients of realized changes in book leverage are strictly negative. They increase in absolute terms and in significance by imposing more

Table 4.8: Feedback Effect of Structural Leverage Changes on the Liquidity Index ($ASY_{i,t}$)

Dummy	Panel A: $\Delta Lev_{i,t}^B$			Panel B: $\Delta Lev_{i,t}^M$				
	(1) N_0 $ \Delta Lev > 0.05$ $Z'' > 2$	(2) $ \Delta Lev > 0.05$ $Z'' > 2$	(3) $ \Delta Lev > 0.05$ & $Z'' > 2$	(4) $ \Delta Lev > 0.1$ & $Z'' > 2$	(5) N_0 $ \Delta Lev > 0.05$ $Z'' > 2$	(6) $ \Delta Lev > 0.05$ $Z'' > 2$	(7) $ \Delta Lev > 0.05$ & $Z'' > 2$	(8) $ \Delta Lev > 0.1$ & $Z'' > 2$
Realized: $D * \Delta Lev_{i,t}$								
All $n = 17,651$	-0.20** (-2.82)	-0.22** (-3.00)	-0.23** (-3.00)	-0.31** (-3.62)	0.70** (6.36)	0.55** (5.04)	0.35** (3.87)	0.15* (1.65)
exNASDAQ $n = 6,890$	-0.39** (-3.87)	-0.40** (-3.87)	-0.44** (-4.34)	-0.47** (-4.19)	0.27* (2.07)	0.19 (1.51)	0.02 (0.20)	-0.19* (-1.65)
Survivors $n = 4,096$	-0.80** (-5.38)	-0.81** (-5.44)	-0.83** (-5.34)	-0.93** (-5.33)	0.05 (0.21)	0.00 (-0.01)	-0.03 (-0.16)	-0.37* (-1.94)
Targeted: $D * \Delta Lev_{i,t}^*$								
All $n = 17,651$	-0.25** (-4.26)	-0.29** (-3.62)	-0.25** (-2.79)	-0.17 (-1.44)	-0.49** (-7.45)	-0.52** (-6.11)	-0.47** (-5.48)	-0.46** (-4.47)
exNASDAQ $n = 6,890$	-0.23** (-2.79)	-0.31** (-2.70)	-0.29** (-2.51)	-0.33* (-2.03)	-0.41** (-4.67)	-0.45** (-3.96)	-0.46** (-4.19)	-0.50** (-3.75)
Survivors $n = 4,096$	-0.41** (-3.86)	-0.64** (-3.95)	-0.60** (-3.49)	-0.80** (-3.14)	-0.50** (-4.35)	-0.74** (-4.67)	-0.68** (-4.26)	-0.81** (-4.03)

The data consist of the "Full", "exNASDAQ", and "Survivors" samples for 1992 through 2008. The table shows the estimation results of Equation (4.7) with firm and year fixed effects (FE_Y, FE_F). We regress the information asymmetry index ($ASY_{i,t}$) on changes in leverage or target leverage interacted with a dummy (D), which is equal to 1 if specified conditions are met as described in row "dummy" implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index is described in subsection 4.3. Panel A depicts values for book leverage ($\Delta Lev_{i,t}^B$), while panel B shows values for market leverage ($\Delta Lev_{i,t}^M$). Coefficients for the control variables return, equity volatility, asset volatility, Altman and Saunders's (1998) Z' -score, and profitability ($R_{i,t}, \Delta V_{i,t}, \Delta AV_{i,t}, \Delta Z'_{i,t}, \Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Equation (4.3) and the leverage observed during the previous period ($t - 1$). Standard errors and t-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. *, and ** denote statistical significance at the 5%, and 1% levels.

restrictions. However, we cannot draw the same conclusions for market leverage (see panel B). Here, we observe some positive coefficients, as in Lesmond et al. (2008). Note that the effect of small realized changes in market leverage on liquidity could stem from the positive link between liquidity and market price dynamics, rather than from active management decisions conveying information to the public. This could explain why imposing restrictions leads to a reduction in coefficients and significance (see columns 6 to 8).

By excluding NASDAQ firms, we observe even lower coefficients and a reduction in significance. Both suggest a NASDAQ bias, where exaggerated measures of liquidity for NASDAQ firms seem to drive results for market leverage in our general sample. Overall, the positive relationship between market leverage and our index disappears if we require structural capital changes and exclude firms that are close to bankruptcy. We also obtain a negative relationship when concentrating solely on survivors and exNASDAQ firms.

For target leverage changes, the picture is very distinct. We find strong support for our view that the distance from leverage targets has an effect on liquidity. All coefficients, independent of the sample, dummy restrictions, or the leverage ratio, are strictly negative and significant, most at the 1% level. The NASDAQ effect, if observable at all, only slightly amplifies coefficients. We also find that "Survivors" firms show considerably larger (negative) coefficients, particularly for book leverage. Market participants' perceptions of information asymmetries are impacted more strongly by anticipated changes in capital structure for more profitable, higher collateralized firms with fewer

business opportunities, although their speed of leverage adjustment is not clearly lower.

Table 4.9 gives results for estimating Equation (4.7) for our index based on measures of liquidity risk ($\sigma_{ASY_{i,t}}$), which are structurally very similar to the previous table.³⁶ It is interesting to note the lower coefficients for realized changes in capital structure on the index for both leverage ratios, where market leverage is again mostly insignificant. For target leverage changes, the results are highly significant and the coefficients are almost unanimously higher.

In summary, we observe a clear impact of changes in book leverage on liquidity. Capital structure decisions reveal information to the public. On the contrary, however, the empirical link between liquidity and stock prices, and thus market leverage, leads to endogeneity and distorts results. By requiring structural changes in capital structure, we find that this formerly positive link partially disappears. Furthermore, a system estimation using target leverage changes greatly improves our results, and leads to a consistently negative relationship between leverage and changes in our indices. This is independent of the sample, any size requirements for the capital structure change, the leverage ratio, and the information asymmetry index.

The NASDAQ effect also seems to affect our results somewhat, as does the survivorship bias. Overall, the robustness checks in this subsection con-

³⁶Estimation results for indexes constructed without spreads or spread volatility show structurally similar patterns. Tables are available from the authors upon request.

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Table 4.9: Feedback Effect of Structural Leverage Changes on the Liquidity Risk Index ($\sigma_{ASY_{i,t}}$)

Dummy	Panel A: $\Delta Lev_{i,t}^B$			Panel B: $\Delta Lev_{i,t}^M$				
	(1) N_o	(2) $ \Delta Lev > 0.05$	(3) $ \Delta Lev > 0.05$ & $Z'' > 2$	(4) $ \Delta Lev > 0.1$ & $Z'' > 2$	(5) N_o	(6) $ \Delta Lev > 0.05$	(7) $ \Delta Lev > 0.05$ & $Z'' > 2$	(8) $ \Delta Lev > 0.1$ & $Z'' > 2$
$D * \Delta Lev_{i,t}$								
All $n = 17,651$	-0.17** (-2.39)	-0.16* (-2.19)	-0.18** (-2.40)	-0.23** (-2.72)	0.49** (4.84)	0.36** (3.66)	0.20* (2.30)	0.09 (1.08)
Ex NASDAQ $n = 6,890$	-0.30** (-2.43)	-0.30** (-2.43)	-0.40** (-3.30)	-0.40** (-2.98)	-0.09 (-0.59)	-0.17 (-1.08)	-0.18 (-1.37)	-0.22* (-1.69)
Survivors $n = 4,096$	-0.52** (-3.38)	-0.57** (-3.67)	-0.58** (-3.70)	-0.64** (-3.69)	0.26 (1.28)	0.19 (0.94)	0.12 (0.65)	-0.07 (-0.37)
$D * \Delta Lev_{i,t}^*$								
All $n = 17,651$	-0.29** (-5.10)	-0.37** (-4.88)	-0.40** (-4.76)	-0.28** (-2.63)	-0.59** (-9.58)	-0.57** (-7.20)	-0.56** (-6.99)	-0.51** (-5.40)
Ex NASDAQ $n = 6,890$	-0.34** (-3.86)	-0.45** (-3.77)	-0.50** (-4.06)	-0.47** (-2.84)	-0.62** (-6.53)	-0.67** (-5.20)	-0.65** (-5.20)	-0.58** (-3.85)
Survivors $n = 4,096$	-0.46** (-4.51)	-0.64** (-4.35)	-0.66** (-4.19)	-0.86** (-3.76)	-0.59** (-5.52)	-0.64** (-4.30)	-0.65** (-4.48)	-0.61** (-3.24)

The data consist of the "Full", "exNASDAQ", and "Survivors" samples for 1992 through 2008. The table shows the estimation results of Equation (4.7) with firm and year fixed effects (FE_Y, FE_T). We regress the information asymmetry index ($\sigma_{ASY_{i,t}}$) on changes in leverage or target leverage interacted with a dummy (D), which is equal to 1 if specified conditions are met as described in row "dummy" implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index is described in subsection 4.3. Panel A depicts values for book leverage ($\Delta Lev_{i,t}^B$), while panel B shows values for market leverage ($\Delta Lev_{i,t}^M$). Coefficients for the control variables return, equity volatility, asset volatility, Altman and Saunders's (1998) Z'-score, and profitability ($R_{i,t}, \Delta V_{i,t}, \Delta AV_{i,t}, \Delta Z'_{i,t}, \Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Equation (4.3) and the leverage observed during the previous period ($t-1$). Standard errors and t-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coef ($\sigma_{ASY_{i,t}}$) on changes in leverage or target leverage interacted with a dummy (D), which is 1 if specified conditions are met as described in row "Dummy" implying structural changes in capital structure. Calculation of the year-by-year information asymmetry index $ASY_{i,t}$ is described in subsection 4.3. Panel A depicts values for book leverage ($\Delta Lev_{i,t}^B$) while panel B shows values for market leverage ($\Delta Lev_{i,t}^M$). Coefficients for control variables return, equity volatility, asset volatility, Altman and Saunders (1998) Z'-Score, and profitability ($R_{i,t}, \Delta V_{i,t}, \Delta AV_{i,t}, \Delta Z'_{i,t}, \Delta Profit_{i,t}$) are suppressed. The target leverage change is the fitted value of Equation (4.3) and the leverage observed in the previous period ($t-1$). Standard errors, t-statistics respectively, of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. *, **, and *** denote statistical significance at the 5%, and 1% levels.

firm our results from subsection 4.4.2 that the capital markets anticipate financial policy by using target leverage changes ($\Delta Lev_{i,t}^*$).

4.5.2 Results for Original Measures of Liquidity

This subsection discusses estimation results for traditional measures of liquidity to determine whether our results could be driven by the construction methodology of our index. We thus begin by estimating Equation (4.3) to derive our leverage targets. All coefficients for the liquidity measures and the control variables are significant at the 1% level, and show similar directions as those previously found except for $M2B_{i,t}$, which loses significance. The regression results are structurally similar to those in section 4.4.1. The adjusted R-squared of 0.071 is the highest for $ALM_{i,t}$, which also holds for market leverage ($\tilde{R}^2 = 0.192$).

For the sake of brevity, we do not show full second-stage results here, where we estimate the effect of target leverage changes on liquidity measures. The control variables showed structurally the same coefficients as for our liquidity index estimations. For trading volume, which is a measure of liquidity, not illiquidity, we expect to find the opposite signs in the coefficients. Our calculation method shows that the returns exhibit a positive and significant sign in estimating changes in $ALM_{i,t}$ (see model (3)).³⁷ However, in terms of economic significance, we doubt any impact of returns on liquidity. Equity

³⁷As a ratio of returns to trading volume, higher returns must lead to an increase.

volatility, asset volatility, and profits are highly economically and statistically significant.

For $TV_{i,t}$, $ALM_{i,t}$, $LOT_{i,t}$, target changes in leverage show the expected direction, and are highly significant at the 1% level. In terms of economic significance, an expected increase in leverage of, say, 10% would result in a 3.5% growth in trading volume ($TV_{i,t} = \exp 0.345 * 0.1 * TV_{i,t-1}$). The price impact is reduced by roughly 3% ($ALM_{i,t} = \exp -0.297 * 0.1 * ALM_{i,t-1}$), and the number of days with zero returns is reduced by 0.1%.

All models show improved economic power by adding target leverage changes, again except for the Roll (1984) measure. The coefficient is not significantly different from zero, nor is the model jointly significant. Effects of target leverage changes on spreads are indistinguishable from zero, and round-trip transaction costs have the opposite sign.

The results are the same for market leverage, and thus are not provided here. We believe survivorship bias is the probable explanation. If we inspect the results for survivors that are not reported here, we find mostly insignificant results, with larger coefficients ($\beta_{Lev^*,All} < \beta_{Lev^*,Survivor}$). This implies that the liquidity of younger firms, where information asymmetries are even higher, is impacted more strongly by management behavior toward capital structure. The coefficients for liquidity risk measures are mostly negative and are not shown here. We found that increases in leverage lead to a reduction in liquidity risk measures.

Although proven biased, we estimate pooled ordinary least squares (POLS) and Fama and MacBeth (1973) (FM) results for comparison with other studies. For the sake of conciseness, we again do not show the tables here.³⁸ Instead, we provide an overview of the estimated coefficients and the White heteroscedasticity robust t-statistics in Table 4.10 for the signalling effect (see Equation (4.5)).

We find that pooled POLS and FM coefficients show the expected negative (positive for $TV_{i,t}$) signs, independent of the capital structure or liquidity measure used. The Amihud (2002) measure, trading volume, and the ratio of zero returns all exhibit stable coefficients also for fixed effects estimation that are strongly significant at the 1% level. The difference in t-values is driven solely by the coefficients, which indicates the bias of using regular OLS.

In contrast, FM results show varying coefficients and standard errors. One reason may be our relatively short sample period of twenty years. The results for the measures of transaction costs remain unclear. Coefficients for $S_{i,t}$ and $ROLL_{i,t}$ become indistinguishable from zero, while a change in signs is obvious for $RTC_{i,t}$. It may follow from this that transaction cost-based liquidity measures are driven less by information asymmetries than others. But the NASDAQ effect and survivorship bias could also play a role.

³⁸Measures of liquidity all show highly significant coefficients, with the expected sign on the first stage and both ratios of leverage. Results are available from the authors upon request.

Table 4.10: Comparison of Results for Measures of Liquidity by Estimation Methodology

Method	Panel A: $\Delta Lev_{i,t}^B$			Panel B: $\Delta Lev_{i,t}^M$				
	(1) POLS	(2) FM	(3) FE _F	(4) FE _F	(5) POLS	(6) FM	(7) FE _F	(8) FE _F
$\Delta S_{i,t}$	-0.003** (-4.67)	-0.004** (-3.04)	0.001 (0.58)	0.000 (0.33)	-0.005** (-3.84)	-0.006** (-3.51)	0.001 (0.27)	0.001 (0.58)
Obs	19,181	1,199	18,307	18,307	19,181	1,199	18,307	18,307
$\Delta TV_{i,t}$	0.057* (1.87)	0.099* (2.20)	0.296** (4.83)	0.351** (5.80)	0.438** (5.89)	0.357** (5.20)	0.350** (4.07)	0.595** (6.60)
Obs	21,030	1,168	20,146	20,146	21,030	1,168	20,146	20,146
$\Delta ALM_{i,t}$	-0.131** (-4.29)	-0.130** (-3.22)	-0.245** (-3.93)	-0.297** (-4.87)	-0.486** (-7.10)	-0.343** (-5.74)	-0.160* (-1.93)	-0.471** (-5.40)
Obs	21,030	1,168	20,146	20,146	21,030	1,168	20,146	20,146
$\Delta ROLL_{i,t}$	-0.025** (-3.69)	-0.020* (-2.14)	0.026* (1.92)	0.016 (1.21)	-0.032* (-1.92)	-0.023 (-1.54)	0.031* (1.68)	0.012 (0.65)
Obs	20,464	1,137	19,613	19,613	20,464	1,137	19,613	19,613
$\Delta LOT_{i,t}$	-0.010** (-4.19)	-0.017** (-5.14)	-0.007 (-1.41)	-0.012** (-2.52)	-0.025** (-3.87)	-0.032** (-5.90)	-0.036** (-5.46)	-0.040** (-5.79)
Obs	21,030	1,168	20,146	20,146	21,030	1,168	20,146	20,146
$\Delta RTC_{i,t}$	-0.001* (-2.28)	-0.001** (-3.31)	0.004** (5.21)	0.004** (5.15)	-0.002* (-1.99)	-0.002** (-4.90)	0.007** (5.18)	0.008** (5.87)
Obs	20,989	1,166	20,105	20,105	20,989	1,166	20,105	20,105
FE _F	No	-	No	Yes	No	-	No	Yes
FE _F	No	-	Yes	Yes	No	-	Yes	Yes

The data consist of the "Fulllex" sample from 1990 through 2008. For spreads, it is the "Full" sample. The table shows estimation results where changes in liquidity were regressed on changes in target book (Panel A: $\Delta Lev_{i,t}^B$) and market leverage (Panel A: $\Delta Lev_{i,t}^M$) and other controls. The methods used are pooled ordinary least squares (POLS), Fama and MacBeth (1973) regressions (FM), and firm and year fixed effects (FE_F, FE_F), sorted by column. Liquidity measures are indicated by rows, and include spread ($\Delta S_{i,t}$), trading volume ($\Delta TV_{i,t}$), the Amihud (2002) liquidity measure ($\Delta ALM_{i,t}$), the Roll (1984) liquidity measure ($\Delta ROLL_{i,t}$), the ratio of zero trades ($\Delta LOT_{i,t}$), and round trip transaction costs based on market returns ($\Delta RTC_{i,t}$). Control variables are return p.a., changes in equity volatility, asset volatility, Altman and Saunders's (1998) Z^o-score, and profits ($R_{i,t}$, $\Delta V_{i,t}$, $\Delta AV_{i,t}$, $\Delta Z_{i,t}^o$, $\Delta Profit_{i,t}$). Results of the first stage estimation and coefficients of controls are suppressed for the sake of brevity, but are structurally very similar to the results found in Tables 4.5 and 4.7. The estimated (target) leverage change $\Delta Lev_{i,t}^* = Lev_{i,t}^* - Lev_{i,t-1}$ represents the difference between the fitted value of Equation (3) and the leverage observed during the previous period ($t - 1$). For FM estimation, obs does not reflect the total number but rather the time series mean of yearly observations. Standard errors and t-statistics of coefficients are White heteroscedasticity corrected and presented in parentheses below coefficients. We also provide an indicator for year and firm fixed effects (FE_F, FE_F). *, and ** denote statistical significance at the 5%, and 1% levels.

4.6 Conclusion

In summary, we analyzed the impact of expected (targeted) capital structure decisions on information asymmetries, which we measured in equity liquidity. The link between capital structure and liquidity is based on the assumption, that managers are a subset of informed traders. As liquidity is driven by information asymmetries it is a viable, although imperfect, proxy for moral hazard problems between managers and owners. Few researchers have shed light on this endogenous interdependence.

Our results are twofold: 1) Market participants can form expectations on target capital structure of listed firms based on available fundamental data and the firms' informational environment (liquidity). 2) Deviations from these leverage targets – denoted as "target leverage changes" – reveal information. An expected increase in debt is a reliable market signal about the true profitability of the firm, and it thus reduces informational asymmetries (increases liquidity). The denoted feedback effect supports Ross's (1977) signalling hypothesis.

To test our hypotheses, we construct a year-by-year information asymmetry index as per Bharath et al. (2009) for U.S.-listed firms from 1990 through 2008. We use six measures of liquidity (trading activity, trading costs, and price impact of order flow) as well as two measures of capital structure. Accounting for the endogeneity of liquidity and equity prices, and thus market leverage, we find that an expected 10% increase in leverage is

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accompanied by a 3.5% increase in trading volume and a 3% decrease in price impact compared to the previous year.

Our findings are robust to differently constructed information asymmetry indexes, e.g., excluding spreads, and for replacing the index with most of the original liquidity measures. In contrast, liquidity risk measures and an index based thereupon reveal mixed results. Accounting for the survivorship bias and the NASDAQ liquidity effect, results remain stable.

As another robustness check, we analyze structural capital changes, which even amplifies the signalling effect. For feedback effects on our index, we control for equity returns, volatility, asset volatility, bankruptcy Z -scores, and profitability. For further robustness we employ several estimation methods including pooled OLS, Fama and MacBeth (1973) and fixed effects estimation.

Overall, we conclude that liquidity is an excellent source from which to derive insights into corporate finance. It also confirms the views of contract theories, where informational imbalances significantly drive the decision making of market participants and managers. An avenue for further research may shed light on how issuance policy, such as seasoned equity offerings or mezzanine capital, affect informational asymmetries. Another important question is how specific market liquidity shocks, such as those occurring during the latest crises in 2008 and 2009, might impact corporate finance. Finally, we would also recommend conducting an event study on the signalling effect of capital structure on liquidity, which could increase understanding about this subject.

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Appendix A: Further Information on the Data

Table 4.11: Data Definitions for Variables from Databases

Source	Mnemonic	Name	Item
<i>S&P Compustat</i>	at	Total Assets	A6
	ACT	Current Assets - Total	A4
	DP	Depreciation and Amortization	A14
	DT	Total Debt	A9 + A34
	EBIT	Operation Income After Depreciation	A178
	INVT	Inventories - Total	A3
	ITCB	Investment Tax Credit	A208
	LCT	Current Liabilities - Total	A5
	OIBDP	Operating Income Before Depreciation	A13
	PI	Pretax Income	A170
	PPENT	Property, Plant & Equipment net	A8
	PSTK	Preferred Stock - Par Value	A130
	PSTKL	Preferred Stock - Liquidating Value	A10
	PSTKRV	Preferred Stock - Redemption Value	A56
	RE	Retained Earnings	A36
	SALE	Sales (Net)	A12
	SEQ	Stockholders Equity	A216
	TXDB	Deferred Taxes	A74
	TXT	Income Taxes - Total	A16
XRD	Research and Development Expense	A46	
<i>CRSP</i>	Ask	Ask, End of Period	ask
	Bid	Bid, End of Period	bid
	CUSIP	CUSIP	ncusip
	EX	Exchange Code	exched
	P	Price, End of Period	prc
	PERMCO	PERMCO	permco
	R	Returns, Daily	ret
	SC	Share Code	shrcd
	ShROUT	Shares Outstanding	shr
	SIC	SIC Code	siccd
	Vol	Volume Total	vol

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Table 4.12: Data Definitions for Variables Calculated

Abbrev.	Name	Calculation
Panel A: Measures of Absolute Liquidity		
$ALM_{i,t}$	Adjusted Amihud (2002) Liquidity Measure (Daily Avg.)	$\ln(10^6 * \frac{ R_{i,t} }{TV_{i,t}})$
$ASY_{i,t}$	Information Asymmetry Index based on measures of liquidity	PCA - section 4.3
$LOT_{i,t}$	Lesmond et al. (1999) Ratio of Zero Returns	$\frac{{}^n R_{i,t=0} + n \# P}{T_{i,t}}$
$ROLL_{i,t}$	Roll (1984) Liquidity Measure	$\sqrt{-Cov(R_{i,t}, R_{i,t-1})}$
$RTC_{i,t}$	Lesmond et al. (1999) Round Trip Transaction Costs	$ \alpha_{i,t}^u + \alpha_{i,t}^d $
$S_{i,t}$	Spread (%) (Daily Avg.)	$2 * \frac{(Ask_{i,t} - Bid_{i,t})}{P_{i,t}}$
$TV_{i,t}$	Trading volume (Daily Avg.)	$\ln Vol_{i,t} * P_{i,t}$
Panel B: Measures of Liquidity Risk		
$\sigma_{ALM_{i,t}}$	Standard deviation of monthly Avg. ALM	$std(ALM_{i,t}^m)$
$\sigma_{ASY_{i,t}}$	Information Asymmetry Index based on measures of liquidity risk	PCA - section 4.3
$\sigma_{LOT_{i,t}}$	Standard deviation of monthly Avg. LOT	$std(LOT_{i,t}^m)$
$\sigma_{ROLL_{i,t}}$	Standard deviation of monthly Avg. ROLL	$std(ROLL_{i,t}^m)$
$\sigma_{RTC_{i,t}}$	Standard deviation of 100 bootstrapped RTC	$std(RTC_{i,t}^{Sim})$
$\sigma_{S_{i,t}}$	Standard deviation of monthly Avg. S	$std(S_{i,t}^m)$
$\sigma_{TV_{i,t}}$	Standard deviation of monthly Avg. TV	$std(TV_{i,t}^m)$
Panel C: Other Data		
$AV_{i,t}$	Asset Volatility	$\frac{V * ME}{at}$
$BE_{i,t}$	Book Equity	$SEQ + TXDB + ITCB - PFS$
$Coll_{i,t}$	Collateral	$\frac{INVT + PPENT}{at}$
$Lev_{i,t}^B$	Book Leverage	$\frac{DT}{at}$
$Lev_{i,t}^M$	Market Leverage	$\frac{DT}{ME + DT}$
$M2B_{i,t}$	Market-to-Book	$\frac{ME + PFS - ITCB - TXDB + DT}{at}$
$ME_{i,t}$	Market Equity	$P * Shrout$
$PFS_{i,t}$	Preferred Stock	1. PSTKRV; 2. PSTKL; 3. PSTK
$Profit_{i,t}$	Profitability	$\frac{OIBDP}{at}$
$R_{i,t}$	Return p.a.	$\frac{P_y^{at}}{P_{y-1}} - 1$
$Tax_{i,t}$	Tax Rate	$100 * \frac{TXT}{PI}$
$Uni_{i,t}$	Uniqueness	$\frac{XRD}{at}$
$V_{i,t}$	Volatility p.a.	$std(R) * \sqrt{250}$
$Z''_{i,t}$	Altman and Saunders (1998) Z''-Score	$3.25 + 6.56 * \frac{ACT - LCT}{at} + 3.26 * \frac{RE}{at} + 6.72 * \frac{EBIT}{at} + 1.05 * \frac{BE}{DT}$

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Table 4.13: Industry Factor Over Time

SIC	Agri, For 100-999	Min, Cons 1000-1999	Manul 2000-2999	Manu2 3000-3999	Utility 4000-4999	Trade 5000-5999	Ser1 7000-7999	Ser2 8000-8999
Panel A: $Lev_{i,t}^B$								
1989	0.08	0.24	0.22	0.22	0.37	0.27	0.18	0.15
1990	0.23	0.30	0.24	0.21	0.31	0.26	0.15	0.16
1991	0.30	0.29	0.21	0.18	0.28	0.24	0.13	0.15
1992	0.38	0.23	0.16	0.23	0.23	0.23	0.11	0.17
1993	0.18	0.22	0.16	0.16	0.29	0.22	0.09	0.14
1994	0.40	0.21	0.17	0.15	0.25	0.23	0.13	0.15
1995	0.37	0.23	0.19	0.17	0.28	0.23	0.11	0.17
1996	0.37	0.23	0.18	0.16	0.20	0.23	0.09	0.23
1997	0.19	0.23	0.19	0.15	0.19	0.22	0.10	0.22
1998	0.19	0.27	0.23	0.18	0.24	0.25	0.10	0.19
1999	0.30	0.26	0.23	0.19	0.28	0.25	0.14	0.23
2000	0.20	0.23	0.22	0.20	0.31	0.25	0.09	0.19
2001	0.09	0.20	0.19	0.17	0.14	0.23	0.06	0.14
2002	0.12	0.24	0.20	0.17	0.25	0.19	0.09	0.13
2003	0.15	0.20	0.22	0.17	0.23	0.18	0.12	0.14
2004	0.03	0.23	0.19	0.14	0.17	0.16	0.11	0.14
2005	0.03	0.16	0.18	0.14	0.15	0.19	0.11	0.13
2006	0.14	0.15	0.18	0.14	0.14	0.19	0.11	0.13
2007	0.30	0.14	0.20	0.15	0.10	0.16	0.12	0.14
2008	0.25	0.14	0.26	0.16	0.13	0.20	0.16	0.21
Panel A: $Lev_{i,t}^M$								
1989	0.07	0.19	0.18	0.22	0.21	0.36	0.14	0.10
1990	0.34	0.33	0.20	0.26	0.22	0.35	0.15	0.22
1991	0.36	0.24	0.14	0.17	0.18	0.21	0.10	0.15
1992	0.40	0.23	0.11	0.16	0.23	0.18	0.07	0.08
1993	0.25	0.20	0.09	0.12	0.24	0.17	0.05	0.06
1994	0.29	0.22	0.13	0.12	0.20	0.24	0.08	0.11
1995	0.26	0.22	0.11	0.11	0.18	0.27	0.06	0.12
1996	0.26	0.19	0.09	0.10	0.20	0.21	0.05	0.15
1997	0.16	0.22	0.11	0.10	0.21	0.20	0.05	0.13
1998	0.13	0.34	0.14	0.15	0.16	0.22	0.05	0.17
1999	0.30	0.24	0.16	0.14	0.28	0.26	0.05	0.23
2000	0.40	0.18	0.13	0.16	0.33	0.32	0.08	0.11
2001	0.17	0.18	0.12	0.14	0.21	0.20	0.04	0.07
2002	0.18	0.23	0.17	0.15	0.22	0.21	0.08	0.10
2003	0.17	0.17	0.13	0.11	0.11	0.15	0.06	0.08
2004	0.03	0.15	0.10	0.10	0.13	0.12	0.06	0.07
2005	0.03	0.11	0.10	0.10	0.15	0.14	0.06	0.06
2006	0.06	0.12	0.11	0.10	0.07	0.13	0.06	0.08
2007	0.33	0.13	0.12	0.10	0.09	0.15	0.10	0.10
2008	0.55	0.17	0.23	0.19	0.16	0.24	0.17	0.22

The table shows time series medians of book ($Lev_{i,t}^B$) and market leverage ($Lev_{i,t}^M$) for SIC one-digit industry classification ranges for the "Full" sample from 1992 through 2008.

Appendix B: Measures of Liquidity

Trading activity is often measured as simple trading volume ($TV_{i,t}$), where we assume that stocks with a high trading volume (defined as the volume of traded stocks ($V_{i,t}$) times the actual price ($P_{i,t}$) can be sold within very short periods and at literally no price impact. As Foster and Viswanathan (1993) propose, trading volume is a function of information asymmetries on an asset value.

The proportion of zero returns is another variable that tries to capture this aspect of liquidity. Lesmond et al. (1999) argue that informed traders only trade only if new information yields higher profits than transaction costs (Kyle, 1985). We calculate ($LOT_{i,t}$) as the ratio of zero returns ($n_{R_{i,t}=0}$) and CRSP estimated mid-prices (which indicate that no real transactions occurred ($n_{\neq P_{i,t}}$) to trading days per year ($T_{i,t}$).

Both measures ignore trading book orders because of a deviation from bid and ask prices. But transactions could be enforced if price discounts (premiums) were accepted (paid). The relative bid-ask spread is the mostly common used measure (e.g. Amihud and Mendelson, 1986). We can calculate $S_{i,t}$ as the ratio of the difference between ask ($P_{i,t}^{Ask}$) and bid price ($P_{i,t}^{Bid}$) to mid price ($P_{i,t}^{Mid}$).

Roll (1984) proposes the "effective spread" (Hasbrouck, 2009) be calculated as the first-order autocorrelation of stock returns (see Equation (4.8c)). In efficient markets, stock prices ($P_{i,t}^*$) fluctuate randomly (see Equation

(4.8a)), where trading costs (c) lead to negative serial autocorrelation in observed stock returns.

$$P_{i,t}^* = P_{i,t-1}^* + u_{i,t} \quad (4.8a)$$

$$P_{i,t} = P_{i,t}^* + cd_{i,t} \quad (4.8b)$$

$$\Leftrightarrow c_{i,t} = \sqrt{-Cov(\Delta P_{i,t}, \Delta P_{i,t-1})} \quad (4.8c)$$

The final trading price $P_{i,t}$ is the efficient price plus some c as the half bid-ask spread, where $d_{i,t}$ is a dummy variable equal to +1 for a buy and -1 for a sell with equal probability (see Equation (4.8b)). However, empirically and depending on the observation period, we randomly observe positive return autocovariance for some stocks. We follow Harris's (1990) proposition and set those values to zero.³⁹ We face further problems for the previous transaction cost measures if no trades are observed over one day. In this case, mid-prices would be disclosed in CRSP. We are either unable to infer any transaction costs, or we potentially underestimate true transaction costs.

The "round-trip transaction costs" (RTC) proposed by Lesmond et al. (1999) account for this fact, and can be calculated by using only return series in a limited dependent variable model (see Tobin, 1958; Rosett, 1959 and Equation (4.9a)). This methodology also offers an asymmetric consideration of buy and sell orders. True returns $R_{i,t}^*$ are driven by market returns

³⁹We prefer this over dropping observed prices, which in turn is likely to lead to heteroscedasticity because of multiperiod observations. Hasbrouck (2009) assumes a Bayesian approach to this problem, resulting in the Gibbs measure.

$(R_{BM,i,t})$, where informed investors trade only if transaction costs are exceeded. This results in measured returns $R_{i,t}$. The RTC are the sum of $|\alpha_{i,t}^u|$ and $|\alpha_{i,t}^d|$, calculated by yearly regressions of positive and separately negative observed stock returns on market returns..⁴⁰

$$R_{i,t}^* = \beta * R_{BM,i,t} + \epsilon_{i,t} \quad (4.9a)$$

$$R_{i,t} = R_{i,t}^* - \alpha_{i,t}^d \quad \text{if } R_{i,t}^* < \alpha_{i,t}^d \quad (4.9b)$$

$$R_{i,t} = 0 \quad \text{if } \alpha_{i,t}^d < R_{i,t}^* < \alpha_{i,t}^u \quad (4.9c)$$

$$R_{i,t} = R_{i,t}^* - \alpha_{i,t}^u \quad \text{if } R_{i,t}^* > \alpha_{i,t}^u \quad (4.9d)$$

Previous measures have ignored the potential price impact. Amihud (2002) proposes calculating the daily ratio of the absolute value of observed returns to trading volume to account for price changes implied by order size. Holding everything else equal, higher daily returns would proxy for a strong price impact. Hasbrouck (2009) finds a 0.67 correlation between ALM and Kyle's (1985) λ , and a correlation of 0.61 between ALM and effective costs as the difference between transaction price and previous mid-price. Both are derived from intraday data. We use a transformed version to reduce extreme skew.

In our estimation, we need only one yearly observation. For spreads ($S_{i,t}$), trading volume ($TV_{i,t}$), and the Amihud (2002) liquidity measure, we use averages of daily observations ($S_{i,t} = \frac{1}{D_i} \sum_{d=1}^{D_i} S_{i,d}$). $LOT_{i,t}$, $ROLL_{i,t}$, $RTC_{i,t}$ are yearly values by calculation method. Liquidity risk measures are stan-

⁴⁰We also use the Fama and French (1993) three-factor models; we find the descriptions and the coefficients in the regressions are the same. The correlation is about 0.99.

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dard deviations of monthly averages of $S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, $LOT_{i,t}$, and the risk measures of round-trip transaction costs stem from bootstrap simulations. Thus, we draw a 100 times 25% of all observed positive and negative stock returns, and we calculate regressions as in Equations (4.9). The standard deviation of the resulting distribution of round-trip transaction costs is $\sigma_{RTC_{RM,i,t}}$.

Table 4.14 provides descriptions. The average trading volume is 9.83, which is approximately U.S. \$18,600 per day, while the median (in parentheses) is about U.S. \$25,800. The lowest 5% quantile shows a trading volume of only U.S. \$125 per day. The spread is on average 3.09% (1.93%), which is lower than the roughly 6% (5%) round-trip transaction costs. The average price impact is 21.2% (13.4%) per U.S. \$ million in trading volume. All measures of illiquidity and liquidity risk are right-skewed; the opposite is true for absolute trading volume. This indicates that, especially for firms above the 75% quantile (e.g., trading volume below the 25% quantile), liquidity is a serious matter.

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Table 4.14: Cross Sectional Data on Liquidity Measures

<i>Measure</i>	Mean	Std	Skew	Kurt	95% Quant	Median	5% Quant	Obs
$S_{i,t}$	3.01	3.61	3.15	20.27	9.66	1.85	0.13	26,396
$TV_{i,t}$	10.00	2.50	-0.56	3.28	13.76	10.25	5.34	29,687
$ALM_{i,t}$	3.02	2.49	0.56	2.23	7.61	2.57	0.08	29,687
$ROLL_{i,t}$	0.23	0.21	0.38	1.89	0.60	0.22	0.00	29,687
$LOT_{i,t}$	0.17	0.18	1.85	7.73	0.50	0.13	0.01	29,687
$RTC_{i,t}$	6.63	4.06	1.77	8.08	14.42	5.67	2.25	29,687
$ASY_{i,t}$	0.00	1.90	1.15	4.96	3.63	-0.42	-2.40	26,396
$\sigma_{S_{i,t}}$	1.58	1.99	5.20	70.83	5.05	0.97	0.12	26,396
$\sigma_{TV_{i,t}}$	1.51	1.11	1.35	3.70	4.07	1.04	0.50	29,687
$\sigma_{ALM_{i,t}}$	3.39	2.87	0.49	2.02	8.47	2.85	0.05	29,687
$\sigma_{ROLL_{i,t}}$	0.23	0.04	-0.40	3.18	0.29	0.23	0.15	29,687
$\sigma_{LOT_{i,t}}$	0.08	0.04	0.43	2.89	0.15	0.07	0.01	29,687
$\sigma_{RTC_{i,t}}$	0.85	0.56	2.67	18.29	1.87	0.71	0.28	29,687
$\sigma_{ASY_{i,t}}$	0.00	1.70	1.34	5.84	3.33	-0.46	-2.01	26,396

The table shows cross-sectional data on liquidity for the "FullexS" sample from 1989 (1992 for spreads) through 2008. The measures, all daily averages, include percentage spread ($S_{i,t}$), natural logarithmic trading volume ($TV_{i,t}$), and the Amihud (2002) liquidity measure ($ALM_{i,t}$). The proportion of zero returns ($LOT_{i,t}$) per year, the Roll (1984) measure ($ROLL_{i,t}$), and the round-trip transaction costs ($RTC_{i,t}$) (see Table 4.12). Liquidity risk measures are standard deviations of monthly averages of $S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, $LOT_{i,t}$. The risk measures of round-trip transaction costs stem from bootstrap simulations. We draw a 100 times 25% of all observed positive and negative stock returns, and we calculate regressions as in Equations (4.9). The standard deviation of the resulting distribution of round-trip transaction costs is $\sigma_{RTC_{i,t}}$. $ASY_{i,t}$ and $\sigma_{ASY_{i,t}}$ indicate the first principal component in liquidity measures and liquidity risk measures, respectively.

Table 4.15: Correlation of Liquidity Measures

	ASY	σ_{ASY}	ASY.xS	$\sigma_{ASY.xS}$	S	TV	ALM	ROLL	LOT	RTC	σ_S	σ_{TV}	σ_{ALM}	σ_{ROLL}	σ_{LOT}		
Panel A: Pearson Correlation, Pairwise, $n = 29, 687$ or $26, 396$																	
ASY	1																
σ_{ASY}	0.94	1															
ASY.xS	0.99	0.93	1														
$\sigma_{ASY.xS}$	0.93	0.98	0.93	1													
S	0.80	0.74	0.75	0.69	1												
TV	-0.91	-0.87	-0.93	-0.89	-0.60	1											
ALM	0.92	0.91	0.92	0.91	0.77	-0.87	1										
ROLL	0.68	0.53	0.68	0.53	0.57	-0.50	0.59	1									
LOT	0.70	0.67	0.66	0.61	0.78	-0.60	0.72	0.43	1								
RTC	0.71	0.69	0.69	0.66	0.80	-0.47	0.69	0.45	0.49	1							
σ_S	0.72	0.79	0.68	0.66	0.77	-0.56	0.70	0.43	0.57	0.71	1						
σ_{TV}	0.77	0.80	0.77	0.83	0.67	-0.79	0.84	0.50	0.75	0.46	0.55	1					
σ_{ALM}	0.89	0.89	0.89	0.89	0.76	-0.82	0.99	0.59	0.72	0.69	0.69	0.83	1				
σ_{ROLL}	0.00	0.04	0.00	0.02	-0.08	-0.01	0.01	0.00	-0.07	-0.06	-0.01	-0.06	0.02	1			
σ_{LOT}	0.56	0.63	0.50	0.58	0.62	-0.45	0.65	0.41	0.59	0.42	0.50	0.62	0.66	0.05	1		
σ_{RTC}	0.58	0.64	0.58	0.63	0.59	-0.41	0.54	0.26	0.37	0.86	0.60	0.35	0.53	-0.01	0.27	1	
Panel B: Spearman Rank Correlation, Pairwise, $n = 29, 687$ or $26, 396$																	
ASY	1																
σ_{ASY}	0.95	1															
ASY.xS	1.00	0.95	1														
$\sigma_{ASY.xS}$	0.94	0.99	0.94	1													
S	0.64	0.65	0.64	0.63	-0.55	1											
TV	-0.94	-0.91	-0.94	-0.91	0.83	-0.87	1										
ALM	0.89	0.89	0.89	0.89	0.50	-0.48	0.53	1									
ROLL	0.64	0.49	0.65	0.50	0.88	-0.50	0.77	0.45	1								
LOT	0.56	0.59	0.57	0.59	0.70	-0.45	0.68	0.39	0.50	1							
RTC	0.60	0.61	0.62	0.62	0.70	-0.45	0.68	0.39	0.50	0.50	1						
σ_S	0.70	0.71	0.70	0.68	0.89	-0.61	0.83	0.46	0.71	0.74	0.73	1					
σ_{TV}	0.73	0.80	0.74	0.82	0.78	-0.73	0.90	0.42	0.78	0.57	0.73	0.73	1				
σ_{ALM}	0.87	0.88	0.87	0.88	0.84	-0.83	0.99	0.53	0.79	0.68	0.83	0.91	0.83	1			
σ_{ROLL}	0.12	0.12	0.09	0.09	0.06	-0.08	0.08	0.08	0.02	0.01	0.09	0.03	0.08	0.01	1		
σ_{LOT}	0.52	0.59	0.47	0.55	0.82	-0.43	0.68	0.40	0.85	0.43	0.68	0.69	0.70	0.07	0.63	1	
σ_{RTC}	0.55	0.59	0.56	0.60	0.53	-0.43	0.56	0.27	0.33	0.92	0.63	0.47	0.56	0.02	0.28	0.28	1

The table indicates pairwise Pearson (panel A) and Spearman rank (panel B) correlations for the "Full" sample from 1992 through 2008. Variables are the information asymmetry indexes ($ASY, \sigma_{ASY}, \sigma_{ASY.xS}, \sigma_{ASY.xS}$) (see section 4.3), liquidity measures ($S, TV, ALM, ROLL, LOT, RTC$), and liquidity risk measures ($\sigma_S, \sigma_{TV}, \sigma_{ALM}, \sigma_{ROLL}, \sigma_{LOT}, \sigma_{RTC}$) (see Table 4.12).

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Table 4.16: Time Series of Leverage and Liquidity Measures

Year	Firms	$Lev_{i,t}^B$		$Lev_{i,t}^M$		$S_{i,t}$		$TV_{i,t}$		$ALM_{i,t}$		$ROLL_{i,t}$		$LOT_{i,t}$		$RTC_{i,t}$	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
1989	946	0.25	0.19	0.27	0.23			10.50	2.95	3.99	2.29	0.26	0.23	0.40	0.24	6.66	3.91
1990	1,214	0.25	0.19	0.32	0.26			9.99	3.11	4.36	2.54	0.24	0.25	0.38	0.26	8.16	5.23
1991	1,128	0.22	0.17	0.24	0.23			10.31	3.06	3.81	2.53	0.23	0.24	0.33	0.25	7.50	4.70
1992	1,194	0.21	0.17	0.22	0.21	4.98	5.64	10.28	3.10	3.69	2.61	0.28	0.23	0.28	0.18	7.62	5.04
1993	1,572	0.20	0.16	0.18	0.19	5.06	4.55	10.34	2.73	3.60	2.51	0.30	0.23	0.26	0.14	7.67	4.78
1994	1,729	0.20	0.17	0.20	0.20	5.13	4.45	10.06	2.67	3.69	2.50	0.32	0.23	0.26	0.14	7.53	4.80
1995	1,792	0.21	0.17	0.20	0.21	4.70	4.34	10.25	2.57	3.32	2.45	0.28	0.23	0.24	0.13	7.16	4.58
1996	1,939	0.21	0.18	0.19	0.20	4.34	4.00	10.32	2.44	3.11	2.36	0.24	0.22	0.22	0.13	7.14	4.16
1997	2,115	0.21	0.18	0.18	0.20	3.98	3.72	10.19	2.40	3.10	2.37	0.25	0.21	0.19	0.13	6.93	3.97
1998	2,020	0.22	0.19	0.22	0.22	3.54	3.12	10.08	2.39	3.22	2.40	0.21	0.21	0.17	0.13	7.39	3.95
1999	1,784	0.23	0.19	0.23	0.24	3.28	3.02	9.99	2.47	3.11	2.45	0.22	0.20	0.16	0.13	7.49	3.85
2000	1,717	0.22	0.19	0.26	0.27	3.06	2.83	10.24	2.48	2.91	2.46	0.21	0.20	0.13	0.13	8.70	3.93
2001	1,650	0.20	0.19	0.20	0.23	2.37	2.52	9.73	2.60	3.12	2.61	0.18	0.19	0.10	0.13	7.11	3.46
2002	1,515	0.20	0.18	0.22	0.22	2.08	2.23	9.61	2.56	3.05	2.62	0.23	0.19	0.08	0.12	6.25	3.01
2003	1,292	0.20	0.17	0.17	0.18	1.15	1.44	9.95	2.24	2.31	2.31	0.18	0.17	0.06	0.09	4.61	2.11
2004	1,303	0.19	0.17	0.15	0.16	0.84	1.14	9.86	1.99	2.01	2.08	0.17	0.17	0.05	0.07	4.33	1.94
2005	1,264	0.19	0.17	0.15	0.17	0.72	0.96	9.64	1.86	1.91	2.05	0.17	0.17	0.05	0.07	3.99	1.85
2006	1,176	0.19	0.17	0.15	0.17	0.60	0.83	9.40	1.80	1.87	2.09	0.14	0.16	0.05	0.06	3.87	1.61
2007	1,253	0.20	0.19	0.18	0.19	0.60	0.90	9.44	1.75	1.68	2.02	0.19	0.17	0.04	0.05	3.95	1.71
2008	1,084	0.22	0.18	0.27	0.24	1.02	1.74	9.38	1.84	2.00	2.27	0.21	0.17	0.03	0.05	5.60	2.38

The table shows time series means and standard deviations of leverage and liquidity measures for the "Full" sample from 1992 through 2008. The first two columns show the year and the number of observed firms. Columns 3 to 6 show average book leverage ($Lev_{i,t}^B$), and average market leverage ($Lev_{i,t}^M$). Columns 7 to 18 give absolute liquidity measures ($S_{i,t}$, $TV_{i,t}$, $ALM_{i,t}$, $ROLL_{i,t}$, $LOT_{i,t}$, $RTC_{i,t}$) (see Table 4.12 for calculation methods).

Chapter 5

Summary and Outlook

Overall, this doctoral thesis aims at improving the general understanding of factors which drive key investment objectives, namely *performance*, *investment risk*, and *liquidity* in the institutional investment process. The work at hand sheds light on the the following questions:

- *Which investment choice – strategic asset allocation, tactical allocation or security selection – is the main driver of investment performance?*
- *Do institutional investors offer a reduction of harmful risk-taking conducted by investment managers as shown for mutual funds?*
- *Do investors use fundamental data to anticipate firms' financing policy, which drives equity liquidity?*

The first essay, "*Investment Choice in Multi-Manager Accounts*" (chapter 2), analyzes the value contribution of investment choices in institutional

investments. Hence, it explicitly investigates investment strategy, portfolio construction and trading employing sound performance analysis (steps 3 to 5) in the investment process (see section 1.1). The knowledge on the overwhelming importance of the strategic asset allocation and the potential for outperformance of the security selection has several consequences.

Results provide an indication of how to apply scarce resources. In accordance with Table 2.4, utilizing 75% to 90% of all available time and money for the strategic asset allocation appears to be reasonable. If public investors decide to rely on financial service providers, they need to explicitly ask for strategic allocation and manager selection skills. Some of the institutional investor's managers yield an outstanding outperformance of up to 14% p.a. (see Table 2.11). But this upside comes at a cost of -0.21% p.a., which is notably fairly low in comparison to other studies.

Attributing active management performance to its components, neither institutional investors nor their appointed managers were able to provide any significant timing capabilities. Importantly, the largest share of outperformance is contributed by security selection. It is therefore suggested to select investment products which foreclose tactical allocation. The average positive alpha underpins this view. If we consider symmetric risk, none of the active investment choices has proven any significant impact. Future research could emphasize investment choices' impact on downside risks. Insurances for example are clearly concerned with avoiding extreme losses (see Funke et al., 2006).

What can the money management industry learn from the previous findings? Asset managers, investment consultants, banks or insurance corporations may screen their offered services for their unique value proposition and build up competence in the relevant investment choices. Finally, regulatory authorities should, rather than limiting access to investment vehicles, better spare no effort to increase comparability of investment services by requiring a clear but perspicuous performance attribution.

In the essay "*Risk-Taking in Institutional Investments*" (chapter 3), a specific agency problem known from the mutual fund literature is analyzed. Brown et al. (1996) suggest that medium term "loser" fund managers increase risk relatively to their peers towards the end of the year, while "winners" decrease risk to lock in previously achieved returns. Both behaviors result in a higher turnover but do not maximize risk-adjusted returns (favored by investors).

However, none is known about the tournament behavior in multi-manager accounts. Chapter 3 closes this research gap. It extends the knowledge on the portfolio construction and trading behavior of investment managers and institutional investors' capabilities for "effective governance" conducted in steps 4 and 5 of the investment process (see section 1.1).

This is important, as institutional investors are specialists who provide services to their beneficiaries – the general investing public. The value proposition is based on higher financial sophistication, investment experience and more frequent monitoring. These features allow for "effective governance" and enable to react immediately to risk-adjusted performance measures of ap-

pointed managers, such as market-model alpha (see Table 3.6). The outlook to lose AuM due to low performance mitigates potential harmful behavior (see Table 3.9).

The failure to provide evidence for tournament behavior sheds new light on the average negative outperformance shown in chapter 2 (see Table 2.6). Public investors must deliberate about their willingness to pay a small fee of e.g. 20 basis points to mitigate agency conflicts in general and harmful tournament behavior in particular. Two findings are related to this consideration. Institutional investors' overall risk strategy drives the risk of single mandates, while enforcing risk limits is easier for bond mandates coinciding with Lakonishok et al. (1992). Information on governance abilities might improve public investors decision to rely on investment specialists.

From a regulatory perspective, the results are encouraging. Institutional investors' skills to reduce or even impede harmful risk-taking, affirms the diverging regulatory regime. In this specific case private governance seems more efficient than governance by law.

Interestingly, entrusting larger shares of the portfolio to one manager enlarges the leeway for risk increases. Further, applied methods yield relatively low explanatory power in explaining changes in active risk (tracking error), compared to volatility. Both allows for further research.

Finally, the essay "*Anticipated Capital Structure and Equity Liquidity*" (chapter 4) documents step 2 of the investment process. Investors systematically use firms' fundamental data, to forecast firms's debt policy, which

affects equity liquidity, a proxy for information asymmetries. While the role of information asymmetries on capital structure has largely been discussed since the pioneering works of Modigliani and Miller (1958) and Myers (1984) little is known on feedback effects of expected changes in capital structure on information asymmetries.

Table 4.10 shows that an expected increase of a firms' book leverage by 10% is accompanied by an increase in trading volume of 3.5% and a reduction of price impact of 3%. Noteworthy, several other contemporaneous factors drive equity liquidity (see Table 4.7). An increase in firms' profitability by e.g. 21% (one standard deviation in our sample see Table 4.3) leads to a raise in trading volume by roughly 25%, while the price impact is reduced by about 24%. Equity volatility takes effect in the opposite direction. A change of one standard deviation (which is 0.35) reduces the trading volume by 0.35%, while the price impact increases by roughly 75%.

Future research could use findings in this thesis to develop sound forecasts of equity liquidity. Hereby investors can 1) earn a liquidity premium (see, e.g., Amihud and Mendelson, 1986; Acharya and Pedersen, 2005), 2) consider predicted liquidity in the portfolio construction process (see, e.g., Davis and Norman, 1990; Dumas and Luciano, 1991; Longstaff, 2001; Browne et al., 2003; Lo et al., 2003; Vath et al., 2007), 3) meet risk management requirements,¹ and 4) model future values of assets. Overall, an understanding of drivers of liquidity helps institutional investors to meet the liabilities vis-à-vis their beneficiaries at all times.

¹See MaRisk, from the 15th of December 2010, BTR 3.1., where banks and insurances need to demonstrate their ability to manage future asset liquidity.

CHAPTER 5. SUMMARY AND OUTLOOK

Further, understanding the link between information asymmetries and liquidity may improve the governance process between investors ("outsiders") and firms' managers ("insiders"). Especially institutional investors which hold larger shares of the firm may profit thereof. Simple measures such as trading volume or the price impact ratio proposed by Amihud (2002) can help to identify firms systematically, where increased monitoring and control is needed to limit firm managers' leeway. This would also be in the best interest of their beneficiaries.

Summarizing, this thesis analyzes the achievement of target objectives in institutional investments from three alternative perspectives. It reveals valuable information for public investors, the money management industry as well as regulatory authorities.

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