Equity Style Indices and Liquidity in Europe

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Betreuer:

Prof. Dr. Niklas Wagner

vorgelegt von

Elisabeth Winter

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Erstgutachter: Prof. Dr. Niklas Wagner

Zweitgutachter: Prof. Dr. Gertrud Moosmüller

Abstract

Contributing to the still scarce European evidence this thesis examines in detail different aspects of equity styles and systematic liquidity in Europe and their role with respect to European stocks and mutual funds. First, a consistent set of European style indices is outlined from which risk factors like market excess return, size, valuation and momentum, but also novel idiosyncratic risk and systematic liquidity factors are derived. The daily 2002 to 2009 time period examined contains the recent financial crisis. As based on a stochastic discount factor GMM based analysis, liquidity is found to be help to price European stocks and a decrease in common liquidity during the recent period of market stress reveals the role of liquidity as a state variable of hedging concern to investors. Moreover, the risk factors including liquidity and idiosyncratic risk are found to be relevant in mutual fund performance evaluation as indicated by significant risk exposures of a set of mutual funds with European investment focus. However, regarding different models the risk-adjusted net performance of these funds is mainly found to be indistinguishable from zero, being in line with equilibrium models of fund performance. Furthermore, the dynamic abilities of fund managers with respect to liquidity and risk factor timing are examined by conducting unconditional as well as time-varying analyses based on a Kalman filter approach. The results reveal dynamics in the risk exposures of mutual funds, but evidence on daily risk factor timing is weak with respect to established risk factors as well as liquidity. Finally, the evidence that both liquidity and idiosyncratic risk affect the cross-section of asset returns suggests that both risk factors capture different return characteristics. As motivated by models of price discovery processes, liquidity might capture transaction costs, while idiosyncratic risk seems to capture effects of price discovery.

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List of Symbols

a	Regression constant; estimator of Kalman filter state vector
α	Risk-adjusted return; Kalman filter state vector
$AILLIQ$	Average of Amihud measure
$AVOLE$	Average of Euro trading volume
β	Risk factor sensitivity
b	Regression coefficient; parameter in stochastic discount factor
c	System vector
χ^2	Chi-square distribution
δ	Timing coefficient in Treynor-Mazuy model
d	System vector
D	Number of days
Div	Dividend
e	Idiosyncratic part of regression
ε	Idiosyncratic part of regression; disturbance term
f	Risk factor
F	Innovation covariance matrix
g_T	Moment condition
γ	Timing coefficient in Henriksson-Merton model
H	Covariance matrix
η	Disturbance term
I	Indicator Function; identity matrix
$ILLIQ$	Amihud measure
J_T	GMM target function
λ	Risk factor premium
m	Stochastic discount factor, pricing kernel
$\#moments$	Number of moments
$N(0,1)$	Standard normal distribution
NID	Normally and independently distributed
Ω	Information set
P	Price; estimation error covariance matrix of Kalman filter
$\#param$	Number of parameters
Q	Covariance matrix
R	Return; Kalman filter system matrix
R^2	Coefficient of determination
R_f	Riskless rate-of-return
S	Covariance matrix of pricing errors
$SIZE$	Size factor
σ	Standard deviation
σ^2	Variance

T	Kalman filter system matrix
u	Pricing error
υ	Idiosyncratic part of regression
VAL	Valuation factor
$VOLE$	Euro trading volume
VIF	Variance inflation factor
W	Weighting matrix
ξ	Idiosyncratic part of regression; disturbance term
y	Signal
z	Instrument
Z	Kalman filter system matrix

List of Abbreviations

adj.	Adjusted
AIC	Akaike information criterion
APT	Arbitrage Pricing Theory
augm.	Augmented
avg.	Average
b.p.	Basis point
cap	Capitalization
CAPM	Capital Asset Pricing Model
coeff.	Coefficient
const.	Constant
CTA	Commodity trading advisor
dec. / D.	Decile
detr.	Detrended
dev.	Deviation
div.	Dividend
e.g.	Exempli gratia
et al.	Et alii
exc.	Excess
exp.	Exposure
e.V.	Eingetragener Verein
E.-w.	Equal-weighted
FF	Fama and French
FFLI	Four factor model with liquidity and idiosyncratic risk
FFMI	Four factor model with momentum and idiosyncratic risk
FFML	Four factor model with momentum and liquidity
GDP	Gross domestic product
geom.	Geometric
GMM	Generalized Method of Moments
HAC	Heteroskedasticity and autocorrelation consistent
HML	High minus low
HR	Hansen and Richard
idios.	Idiosyncratic risk
i.e.	Id est
illiqu.	Illiquidity
kurt.	Kurtosis
LTCM	Long Term Capital Management
Ltd.	Limited
LSE	London Stock Exchange
max.	Maximum

med.	Medium
min.	Minimum
mom.	Momentum
mut.	Mutual
NASDAQ	National Association of Securities Dealers Automated Quotations
neg.	Negative
NYSE	New York Stock Exchange
obs.	Observation
OLS	Ordinary least squares
p.	Page
p.a.	Per annum
P/B	Price-to-book
p.d.	Per diem
P/E	Price-to-earnings
PIGS	Portugal, Italy, Greece, Spain
PIN	Probability of informed trading
portf.	Portfolio
pos.	Positive
pp.	Pages
q.e.d.	Quod erat demonstrandum
quint. / Q.	Quintile
QLR	Quandt likelihood ratio
ret.	Return
S & P	Standard and Poor's
SBC	Schwarz Bayesian criterion
SDF	Stochastic discount factor
sect.	Section
signif. / sig.	Significant, significance
SMB	Small minus big
stat.	Statistic
std.	Standard
UCITS	Undertakings for the Collective Investment in Transferable Securities
UK	United Kingdom
unexp.	unexpected
U.S.	United States
valuat.	Valuation
var.	Varying
VIF	Variance inflation factor
vs.	Versus

1 Introduction

1.1 Introduction and motivation

Investment strategies like the so called equity styles have increasingly received attention during the last years. As a prominent example, mutual fund managers classify their investment products into different style categories in order to signalize a specific investment strategy to mutual fund investors. The most widely used categories include those on market capitalization as well as value and growth. The importance of styles and style investing is emphasized by the findings of Boyer (2011) that mutual fund managers even trade their stocks rather based on style labels than fundamentals. The style classifications common in asset and mutual fund management also call for specific style indices which serve as benchmarks in performance evaluation. In line with this, numerous index providers like MSCI, Russell or Stoxx offer different kinds of indices which reflect not only different market, industry and geographic sectors but also investment styles. These indices can be interpreted as portfolios which reflect the performance of related trading strategies.

According to Barberis and Shleifer (2003) assets in a style usually share common characteristics. Then, investors allocating funds among such asset classes reflecting styles implement style investing. These investment or respectively equity styles can also be understood as cross-sectional anomalies in asset prices which can often not be explained by standard theoretical asset pricing models. However, recent research (see e.g. Liew and Vassalou (2000), Vassalou (2003)) is looking for a risk based explanation of investment styles which emphasizes the role of styles not only in performance analysis as benchmarks but also as determinants of asset prices.

However, the style classifications usually common in index construction as well as asset management ignore novel theoretical as well as empirical findings on cross-sectional regularities in asset pricing. The October 1987 market crash documented that an important influencing factor on asset prices is liquidity risk. As illustrated by Pastor and Stambaugh (2003), this crisis could be linked to an extreme deterioration of overall stock market liquidity. The perception of investors that capital markets may suddenly dry up imposes securities to an undiversifiable risk which may quickly result in a decrease of asset prices. In 1998, the breakdown of the liquidity sensitive Long-Term Capital Management (LTCM) hedge fund after the decrease of market-wide liquidity caused by the Russian debt crisis further illustrates the importance of liquidity risk. In addition to the link to crises, investors fear times of high market illiquidity as their flexibility in trading on assets is strongly diminished. However, liquidity as a systematic risk factor in asset pricing only has received attention during the last years. Thus, liquidity is still relatively unexplored and its role as an investment style as well as in performance evaluation is still unknown. Motivated by this missing knowledge on the respective role of liquidity, liquidity risk also should be a useful measure to conceive style indices which may then serve as liquidity risk factor mimicking portfolios. As one expects that the importance of liquidity as a risk factor has risen during the current 2007 / 2008 financial crisis which has started from the subprime crisis in the U.S. and which has spread to Europe and the rest of world, this issue is worth to be addressed in this thesis.

While the evidence on investment styles and liquidity is vast for the U.S., empirical evidence on styles and liquidity for Europe is rather scarce. Thus, an investigation of European data is motivated. An analysis of other countries than the U.S., which is still the most extensively investigated capital market, is useful as these results can not always be extrapolated to other regions, see e.g. Heston et al. (1999). Due to capital market integration across countries, risk factors must not only impact asset prices within but also across countries. The increasing integration of the European stock market is a prerequisite for a deeper empirical investigation of equity styles and liquidity with respect to the rather unexplored European region. Taking a cross-border perspective has been enabled by several recent regulatory initiatives like e.g. the Investment Services Directive or the Undertakings for the Collective Investment in Transferable Securities (UCITS) Directive, see e.g. Demarchi and Foucault (2000). These initiatives helped to, among others, facilitate cross-border stock broking and trading and to consolidate accounting standards, see e.g. Licht (1997), Baele et al. (2004) or Hanhardt and Ansotegui (2009), and legal aspects have also been harmonized. Moreover, the European Monetary Union eliminates currency risk and, overall, pan-European portfolio diversification and inter-European raising of capital are facilitated. Increased European financial market integration has been found among others by Fratzscher (2002), Baele et al. (2004) or Berben and Jansen (2005). Hence, in the following, investigating pan-European data in the context of for example performance evaluation like e.g. in Otten and Bams (2002) is feasible. The focus on Europe in this thesis should bring new insights on the issues of equity styles, liquidity and their role in asset pricing, performance measurement and risk factor timing, which are still quite unexplored with respect to Europe.

In the next section, an overview on the structure of this thesis is given.

1.2 Overview

This thesis investigates different aspects of equity styles, style indices and liquidity in Europe. The importance of style investing is demonstrated in Barberis and Shleifer (2003) who show that style investing can even cause asset prices to covary more than induced by fundamental value. So, related literature and theory on investment styles is outlined in Chapter 2 which also gives a brief overview on the theory of multifactor models of returns. These models help to provide for an understanding of equity styles from a theoretical perspective as well as serve as a theoretical background for the following chapters. Then, in Chapter 3, a consistent family of style indices is outlined which covers well-known but also novel equity styles. This family of equity style indices displays investment styles like the widely used size, value / growth and momentum effects but also novel styles like idiosyncratic risk and liquidity. The data set based on this style index family offers not only to analyze the performance of trading strategies based on equity styles but also to construct risk and benchmark factors which may be part of e.g. multifactor models of performance analysis. As argued above, the focus on a European data universe is motivated by the facts that this region is rather unexplored in empirical financial studies, that recent developments in financial market integration render a pan-European analysis feasible and that the financial crisis impacts Europe severely as demonstrated by the recent crises and market turmoil rising from the PIGS states.

Investment styles are not only important to investors and asset managers following specific investment strategies as well as for performance evaluation purposes. There are also risk-based explanations which link equity styles to underlying risks which are of hedging concern to investors. In this way, investment styles as a kind of risk factor proxies may play a role in asset pricing as recent research interpreting styles as risk factor mimicking portfolios emphasizes. A prominent example is the three factor model of Fama and French (1992, 1993) which found its way in asset pricing and mutual fund performance evaluation. In line with such a risk-based explanation, liquidity as a systematic risk immanent on the equity market is of special interest. Stocks are usually considered to be liquid assets but recent evidence strongly suggests that there arise market-wide, undiversifiable liquidity risks in equity markets. This proposes liquidity to play a role as a state variable affecting investors' investment opportunity sets. This is why, in Chapter 4, an investigation of systematic liquidity risk and its pricing implications on asset returns is conducted, contributing to the European empirical evidence on liquidity. Furthermore, the role of liquidity risk in the recent financial crisis is interesting as periods of crisis are often associated with increased levels of market illiquidity, like the examples of the October 1987 stock market crash or the Long Term Capital Management breakdown suggest.

As already mentioned, equity styles are relevant for the availability of adequate benchmarks in the analysis of investment performance, like e.g. with respect to mutual funds. This is confirmed by Barberis and Shleifer (2003) who emphasize that style investing is not only important with respect to trading or allocation strategies but also helps in performance attribution and measurement. In the context of performance evaluation of mutual funds as well as hedge funds, it is useful to control for styles as one does not want to reward managers for simply exploiting such widely known anomalies, see Bollen and Busse (2001). The importance of adequate methods of performance measurement is underpinned by a press release of the German association of mutual funds, i.e. the BVI Bundesverband Investment und Asset Management e.V., at www.bvi.de. The BVI states that, at the end of 2009, more than 800 billion Euro have been invested in mutual funds only with respect to Germany. Hence, appropriate models of performance measurement are needed to control whether this huge amount of assets under management is well invested. So, in Chapter 5, the family of equity style indices is examined in the context of unconditional performance evaluation of mutual funds. The empirical evidence in this chapter also enlarges the empirical findings on novel multifactor performance models including liquidity and idiosyncratic risk in comparison to widely used standard evaluation models.

In addition to static performance evaluation methods, this thesis also examines dynamic methods of performance analysis as asset managers need to quickly react to new information and to dynamics in the capital markets. Motivated by this observation, Chapter 6 relaxes the assumption of a static performance analysis and analyzes dynamics in the risk factor exposures of mutual funds and the timing abilities of asset managers. A dynamic perspective has become even more important as the financial crisis starting in 2007 / 2008 documented that changes in market as well as risk factors can evolve very quickly, which one expects to also lead to adequate changes in risk factor exposures by fund managers. As such dynamic investment strategies are especially relevant to hedge funds, the evidence in Chapter 6 is not only based on mutual funds but also backtested regarding hedge funds. Finally, Chapter 7 concludes.

2 Multifactor models and investment styles

2.1 Multifactor models

Multifactor models have become widely applied in empirical studies, e.g. in the areas of asset pricing or performance measurement. Hence, this chapter aims to give a brief overview on some of the most important multifactor models like the Intertemporal Capital Asset Pricing Model (ICAPM) or the Arbitrage Pricing Theory (APT), which contain several risk factors and not only the market excess return as in the Capital Asset Pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966). Moreover, regularities in asset pricing, the so called investment styles, are outlined which can either be interpreted as exceptions to these models or as systematic risk factors in these models.

In the ICAPM of Merton (1973), in equilibrium, investors are compensated for bearing systematic market risk and the risk of unfavorable aggregate shifts in the investment opportunity set. Risk premia arise which are associated with the covariance between asset returns and such unanticipated changes in state variables proxying for the time variation in the investment opportunity set. In the ICAPM, with the market risk premium λ_M and the risk premia λ_s on $s = 1, \ldots, m$ state variables, the unconditional, expected risk premium of an asset i, i.e. $E(R_i) - R_f$, can be written in the following way

$$E(R_i) - R_f = \beta_{i,M}\lambda_M + \sum_{s=1}^{m} \beta_{i,s}\lambda_s, \tag{2.1}$$

see e.g. Brennan et al. (2004) or Ozoguz (2009). Assets whose returns covary more with future investment opportunities possess higher expected returns and higher risk premia due to their reduced hedging ability in case of worsening investment opportunities. However, the ICAPM does not specify the identity of the state variables which has been criticized to give a lot of freedom of interpretation, see e.g. Breeden (1979). Examples given are wage incomes and consumption goods whose relative prices are changing over time, technological change or the real interest rate, see Merton (1973), Cox et al. (1985) and Brennan et al. (2004).

Breeden (1979) shows in his Consumption CAPM that the dynamic multi-beta pricing equation of Merton (1973) presented above can be reduced into a single-beta equation, where the expected excess return on any security is proportional to its covariance with respect to only aggregate consumption. In this model, the risk corrections to asset prices are driven by the covariance of asset payoffs with marginal utility and consumption, see Cochrane (2001) pp. 149. As investors prefer stable consumption streams over time, they favor assets which have high payoffs in negative states of nature, i.e. recessions, and vice versa. Thus, a security shall provide for a hedge against adverse movements in consumption, see Breeden (1979), and such a relationship also exists between factor risk premia and consumption, where risk premia are negative if the consumption is developing into the opposite direction of the state variable, see Cox et al. (1985). However, consumption based models like those of Rubinstein (1976) or Breeden (1979) are rather difficult to be empirically tested as it is challenging to appropriately estimate aggregate consumption. Furthermore, consumption-based models rather do not work well empirically, see e.g. Cochrane (2001) pp. 44, Lengwiler (2006) pp. 172 as well as an overview on respective literature in Lettau and Ludvigson (2001), and usually consumption data are not available at a daily frequency. However, Cochrane (2001) pp. 149 as well as Singleton (2006) p. 290 argue that the factors in multifactor models of returns may be interpreted as proxies for and reduced-form representations of the agents' marginal rate of substitution.

In the empirically more widely used APT of Ross (1976) a linear multifactor return generating process arises by modeling the tendency of returns to move together, without the model being based on a theoretical equilibrium nor preference based model where intertemporal consumption and investment decisions are optimized. The APT does not give a special role to the (unobservable) market portfolio and is thus a testable alternative. Moreover, the APT is not based on as many assumptions as the CAPM nor is it restricted to one period. Using mainly assumptions like the returns being described by a linear multifactor structure and assuming absence of arbitrage leads to the derivation of the APT, see Roll and Ross (1980). The multiple factors in the APT arise by a factor analysis of the covariance matrix, see also Cochrane (2001) pp. 173. The final APT relation provides for a framework to test whether the respective factors are priced due to the following multifactor relation

$$E(R_i) - R_f = \beta_{i,1}\lambda_1 + \ldots + \beta_{i,m}\lambda_m. \tag{2.2}$$

In Equation 2.2, if one assumes m factors to influence returns, this leads to the expected excess return of the asset i depending on m risk premia λ_k, taking into account the respective factor loadings $\beta_{i,k}$ with respect to risk factor k. However, as with the ICAPM, the identity of the factors is not clear. Instead of a statistical factor analysis program which is often used to identify the risk factors, e.g. Chen et al. (1986) investigate pre-specified macro-economic variables in the context of the APT. As Brennan et al. (2004) note, in the ICAPM the priced factors are not only any set of factors correlated with returns like in the APT, but are the innovations in state variables that predict future returns.

Most researchers prefer to focus on risk-based explanations for factors, but motivating expected return beta models by the above outlined theoretical models has received some criticism as the identity of the respective risk factors in the models is not fully clear. Fama (1991) notes that these models provide for a kind of fishing license for only empirically motivated factors which are correlated with returns. Overall, the main implication for the empirical use of the multifactor beta models is that, in these models, the expected returns are linearly dependent on betas, i.e. factor loadings, and on factor returns, i.e. factor risk premia.

In the next section, an overview on investment styles, which can be seen as anomalies to these theoretical models, is given.

2.2 Investment styles

2.2.1 Overview

Investment styles are often understood either as empirical anomalies to the above mentioned theoretical models or as risk factors being part of these models. In the following, I briefly outline investment styles like the size effect, the value / growth and the momentum anomalies.

Well-known styles like size, growth and value are meant to capture regularities in asset prices, see a broad overview in Ziemba (1994), and have been considered in many multifactor asset pricing studies and also by almost all index providers. The consideration of size is suggested by the empirical findings in Banz (1981), Reinganum (1981) and Schwert (1983) that assets with smaller market capitalization (small cap stocks) have higher returns in the cross-section of returns than large cap stocks. Moreover, studies like Reinganum (1981) or Keim (1985) find a value vs. growth effect where e.g. stocks with high book-to-market or low price-to-earnings ratios have higher returns in the cross-section of returns than stocks with opposite characteristics. Some empirical studies even show that models including these variables can help to explain the cross-sectional variation in asset returns better than traditional asset pricing models like the CAPM, see e.g. the three factor model of Fama and French (1992 and 1993) which contains a size factor and the book-to-market ratio –as a proxy for the growth and value anomaly– in addition to the market excess return. Therefore, it has become common to consider such anomalies in asset pricing tests, performance evaluation or in index construction. Furthermore, there also exists a momentum anomaly which corresponds to the 'hot hands effect' of sustained superior short-run performance of e.g. Hendricks et al. (1993). The momentum anomaly has become popular in multifactor models of performance evaluation, see the widely used four factor model of Carhart (1997) which augments the Fama and French (1992, 1993) three factor model by a momentum factor. Grinblatt et al. (1995) confirms that focusing on momentum, i.e. winner over loser stocks, brings better performance.

Style anomalies and style investing are also relevant with respect to European data. Additionally to the above mentioned U.S. evidence, e.g. Fama and French (1998) give international evidence on the explanatory power of the size and book-to-market factors in the cross-section of stock returns and find the value vs. growth premium to be evident in several European countries. Heston et al. (1999) find for internationally diversified portfolios comprising stocks from 12 European countries that average stock returns are negatively related to size. In a similar data set, Rouwenhorst (1998) shows that a momentum effect can be found. Arshanapalli et al. (1998) conclude that value vs. growth are also cross-sectional determinants of stock returns in Europe. Hence, investment styles are also important with respect to Europe.

Next, rational explanations for investment styles are addressed.

2.2.2 Rational explanations

Investment styles refer to asset specific characteristics which lead to differences in returns. There are several possible rational explanations for the existence of such individual stock characteristics as regularities in asset prices. First, capital markets are typically not semi-strong form efficient. That is why active trading strategies based on styles or other asset return regularities may provide for abnormal returns, see for example Schlater et al. (1980) or Haugen and Baker (1996). Second, Berk (1995) shows that individual asset characteristics like e.g. size will and must explain that part of the cross-section of expected returns left unexplained by an incorrectly specified asset pricing model. The market portfolio may be mismeasured leading to other factors than the market factor having explanatory power, see e.g. Fama and French (2004). Third, investment styles based on firm characteristics may be important in asset pricing as they possess different sensitivities to systematic risk factors and thus mimic these risks, see Campbell et al. (1997) p. 239, being in line with the theoretical models in Section 2.1 which only refer to systematic risks as determinants of asset prices. As argued in Cochrane (2001) p. 449, anomalies in asset prices may be explained by time-varying risk premia as this leads to future cash flows being discounted at a higher rate which may cause e.g. the small firm effect. However, neither linear multifactor models like the APT nor the ICAPM specify which risk factors are to be included and, hence, empirical researchers have some empirical freedom to interpret the risks behind the respective return anomalies.

In this sense, recent research focuses on whether characteristic-based factors like e.g. size or momentum may capture the cross-sectional variation in asset returns as they proxy for exposures to macroeconomic risk factors, see an overview in Aretz et al. (2010). Fama and French (1992) as well as Fama and French (1996) suggest that their three factor model is an equilibrium pricing model and can be interpreted as a three-factor version of the ICAPM of Merton (1973) or the APT of Ross (1976) and that their SMB and HML factors proxy for underlying risk factors or state variables of special hedging concern to investors. A similar explanation is provided by Petkova (2006) and Aretz et al. (2010) on the book-to-market, size and momentum factors. Such macroeconomic factors may be expected economic growth, inflation or the term structure of interest rates, see Liew and Vassalou (2000), Kelly (2003), Vassalou (2003) or Hahn and Lee (2006). Other studies also find the default risk to be an explanatory factor, see Vassalou and Xing (2004) who suggest that the SMB and HML factors contain some default-related information. Fama and French (1998) argue that the value premium in their three factor model is due to relative distress, see also some research by Petkova (2006) and Gharghori et al. (2007).

In the next section, behavioral and other alternative explanations for investment styles are outlined.

2.2.3 Behavioral and alternative explanations

There are also explanations for the size, value / growth and momentum anomalies which are unrelated to a risk based explanation, but related to behavioral finance. For example, Barberis and Shleifer (2003) and Chen and De Bondt (2004) believe that due to many investors trying to chase past winners styles and avoiding past loser styles as well as due to the popularity of style investing, style returns are able to help to explain the cross-section of expected returns for individual stocks. Chen and De Bondt (2004) suggest that there are predictable and lasting biases similar to waves of optimism and pessimism in how investors interpret macroeconomic data. Similar explanations with respect to suboptimal investor behavior like e.g. misinterpretation of information or misvaluation which forestall market efficiency are given by Lakonishok et al. (1994), Chan et al. (1999) or Hou and Moskowitz (2005).

Empirical deficiencies like the look-ahead bias or data snooping might distort the results of empirical studies on styles, see Haugen and Baker (1996) or Conrad et al. (2003). Look-ahead bias can arise when accounting data are only available to the investor later on in the year and, thus, one misleadingly assumes an investor to forecast e.g. future reported earnings without error. For example, van Dijk (2011) explains that the size effect may be caused by sorting methodologies which are influenced by data snooping or which may lead to biased results, see Lo and MacKinlay (1990) as well. Furthermore, sample dependent effects like outliers in Knez and Ready (1997) or ex-post-selection and survivorship bias may arise when the data base examined ignores companies which are not viable anymore due to e.g. bankruptcy, see Banz and Breen (1986). Daniel and Titman (1997) show that the covariances in book-to-market stocks are rather due to other similar characteristics of the firms, like e.g. similar industries. The evidence in Doukas and Li (2009) shows that value stocks are associated with higher idiosyncratic risk, which forestalls a prompt price adjustment to new information with respect to value stocks. Thus, overall, a quite large number of alternative explanations may be valid as well.

Explanations with respect to the momentum anomaly are also quite challenging as rational and risk based explanations are rather missing. According to Cochrane (2001) pp. 446, momentum is only an ad hoc factor related to a mechanical strategy and can rather be interpreted as a performance attribution or evaluation factor. Behavioral models of momentum are given by Barberis et al. (1998), Daniel et al. (1998), Lee and Swaminathan (2000) or Chan et al. (2000) who address e.g. over- and underreaction with respect to information or herding by investors. Hwang and Rubesam (2008) argue that the momentum effect mainly existed because of the bull market in the nineties, but that after the high-tech boom this anomaly rather has disappeared. Fundamentally based explanations are provided by e.g. Johnson (2002) that recent performance is correlated with levels of expected growth rate which is then also monotonically related to risk, or by Avramov and Chordia (2006) that there may be an undiscovered, systematic risk factor related to the business cycle. Sadka (2003) shows that seemingly profitable momentum strategies are associated with high levels of transaction costs and low levels of liquidity, leading to momentum not being fully arbitraged away.

Hence, this assortment of literature shows that there are quite many rational, behavioral as well as alternative explanations for the existence of style effects in the cross-section of stock returns. As suggested by the empirical evidence on return anomalies being proxies for systematic risks, it seems viable to include style effects in multifactor models of returns.

In addition to these well-known investment styles, the next section introduces novel risk factors, i.e. liquidity and idiosyncratic risk.

2.3 Liquidity and idiosyncratic risk

2.3.1 Liquidity

In the recent past, liquidity has been suspected to be a risk factor determining asset prices as it has been shown that more illiquid securities offer higher returns, see e.g. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and an overview in Amihud et al. (2005). Thereby, liquidity is defined as the ease of trading a security on the capital market. If a security is not liquid, a considerable risk may arise as there may result problems or additional costs in situations that make it necessary to close a given trading position. Liquidity is linked to exogenous transaction costs (like e.g. brokerage fees) which hamper the ease of trading a security, but it is also part of models where market makers face private information, inventory risk or demand pressure, see an overview in Amihud et al. (2005). A more detailed overview on liquidity follows in Chapter 4.

In addition to a liquidity effect in individual stock returns, Chordia et al. (2000) and Huberman and Halka (2001) are among the first to show that there may exist an aggregate effect of commonality in liquidity and a market-wide risk of liquidity concerning all stocks which, thus, impacts asset prices. For example, Pastor and Stambaugh (2003) find a positive interrelation between liquidity risk and expected stock returns and conclude that liquidity is a state variable in asset pricing. Acharya and Pedersen (2005) develop an asset pricing model including three additional risk factors due to liquidity besides the well-known market risk factor. Furthermore, Watanabe and Watanabe (2008) investigate time variation in liquidity betas and liquidity risk premia. Then, liquidity risk is priced because shocks in liquidity make the consumptions of investors more volatile which is disliked by investors who, hence, demand more risk premium. In line with this, Watanabe and Watanabe (2008) find that the liquidity risk premium is larger during periods of higher return sensitivity towards systematic liquidity. Liu (2006) finds that there is a highly negative correlation between liquidity and the market factor which reflects the state nature of systematic liquidity as an indicator of the investment opportunity set. This means that the market is less liquid when it is in a downturn state which causes rational investors to require higher returns for such less liquid states. Recent evidence given by Naes et al. (2011) states that aggregate stock liquidity is time-varying and has a business cycle component. They even find evidence that when market liquidity worsens, this is followed by a significant downturn in economic growth. Furthermore, Gibson and Mougeot (2004) find that the liquidity risk premium is influenced by an estimate of the probability that the economy will be in a future recession phase. Hence, liquidity may be an important risk factor in asset pricing which has until the recent past not thoroughly been considered in multifactor models.

The aspect of aggregate liquidity on the European capital market offers an interesting field of further research. It has not been thoroughly investigated until now as studies like Stahel (2005), Liang and Wei (2006) or Karolyi et al. (2007) investigate commonality in liquidity and the relationship between liquidity risk and expected return for some European countries, but they either do not separately study aggregate European liquidity or do not explicitly examine aggregate liquidity across all European countries. To my knowledge, the idea of a liquidity index which uses a sophisticated illiquidity measure in order to select stocks from an index universe is new as well. Usually, index providers only consider free-float market capitalization as a measure of selecting the most liquid stocks, thus neglecting more sophisticated approaches to measure liquidity. This motivates to construct an aggregate European liquidity risk factor based on a sophisticated liquidity measure which later on helps to bring further insights on European liquidity.

In the next section, idiosyncratic risk as another novel risk factor is introduced.

2.3.2 Idiosyncratic risk

In addition to liquidity, the role of idiosyncratic risk in Europe is also an issue worth to be more closely investigated. Traditional asset pricing models like the CAPM or the Arbitrage Pricing Theory (APT) of Ross (1976) assume that only systematic risk matters in determining asset prices. However, exceptions to this are still an ongoing issue in the asset pricing literature, where idiosyncratic risk has increasingly received attention.

There are many possible explanations for idiosyncratic risk playing a role in asset pricing. First, one may assume the firm's equity to be a call option on total assets if the firm is levered, see Goyal and Santa-Clara (2003) or Johnson (2004). So, according to option pricing models, the price of the firm's equity rises with higher asset variance. Second, Levy (1978) introduces an extended version to the CAPM in which investors hold undiversified portfolios. In line with this, Malkiel and Xu (2004) find that idiosyncratic risk can be a very important variable in explaining cross-sectional expected return differences in case of under-diversification when e.g. not every investor is able to effectively hold the market portfolio. Such a situation of not perfectly diversified portfolios may arise because of e.g. transaction costs that hinder full diversification, see Statman (1987) and Malkiel and Xu (2004). Third, Xu and Malkiel (2003) relate idiosyncratic volatility to the increased importance of institutional investors which simultaneously change their sentiment. They propose that the coordinate behavior of institutional traders will have a greater impact on individual volatility as the arrival of information on individual stocks is much more frequent. Fourth, companies likely to expect high future growth rates and pursuing unique investment projects are likely to exhibit high idiosyncratic volatility, see Xu and Malkiel (2003). Fifth, Campbell et al. (2001) find that the components of volatility and hence also idiosyncratic risk move counter-cyclically and may proxy for business cycle fluctuations. Sixth, private information may motivate investors to hold large positions in single securities, see Goyal and Santa-Clara (2003), as well as institutional investment managers who willingly accept idiosyncratic risk in order to gain extraordinary returns compared to a benchmark, see Malkiel and Xu (2004).

Last, in the model of Merton (1987), each investor knows only about a subset of the available securities which hinders some investors to hold the market portfolio. In contrast to an ideal setting where everyone would hold the market portfolio, this then also forestalls the remaining investors from holding the market portfolio and results in idiosyncratic risk being priced. Thus, according to Merton (1987), expected returns depend on both market risk as well as total return variance. A more general, but similar explanation is given by Malkiel and Xu (2004), where some constrained investors are not able to hold the market portfolio due to various restrictions. There will be oversupply for the stocks investors can rarely hold. Hence, the prices of these stocks are low and investors are compensated with respect to these stocks by higher risk premia. Investors use the available market portfolio which is less diversified than the theoretically optimal market portfolio to price assets. Risk premia will be higher and firms sensitive to idiosyncratic risk shocks will have higher expected returns. This is also in line with the empirical evidence in Spiegel and Wang (2006) who find that portfolios long in stocks with high residual volatility and short in stocks with low residual volatility generate a significant risk-adjusted return. Under specific assumptions, the more general model of Malkiel and Xu (2004) collapses to the Merton (1987) model, but both models show that expected returns are not only influenced by the conventional market risk factor, but also by a market wide undiversified idiosyncratic risk premium.

Empirical cross-sectional evidence with respect to the U.S. regarding the relationship between idiosyncratic risk and return is steadily increasing. Malkiel and Xu (2004) find that idiosyncratic risk in the U.S. (and Japan) can be a very important variable in explaining cross-sectional expected return differences even after accounting for other factors like book-to-market ratios, etc. The findings of Fu (2009) document a positive relation between idiosyncratic risk and expected returns, even after controlling for liquidity and other factors like size or momentum. The importance of idiosyncratic risk is also emphasized by Campbell et al. (2001) and Xu and Malkiel (2003) who find a dramatic increase in the idiosyncratic volatility of stock returns over the past decades. Ang et al. (2006) find that stocks with high idiosyncratic volatility have low average returns, but Fu (2009) and Huang et al. (2010) claim this to be caused by return reversals immanent in their measure of idiosyncratic volatility. For the UK, there are two studies by Angelidis and Tessaromatis (2008) and Angelidis and Andrikopoulos (2010) which investigate idiosyncratic volatility and its predictive power for future stock market returns. Ang et al. (2009) study whether idiosyncratic volatility is related to expected returns in the cross-section of international stock returns, including Europe, but rather find that stocks with high idiosyncratic volatility in Europe have low expected returns. As European evidence on the idiosyncratic risk return relationship is still relatively scarce and ambiguous, the relevance of investigating the role of idiosyncratic risk in this thesis and as a part of European style indices is emphasized.

Next, the relationship between liquidity and idiosyncratic risk is addressed.

2.3.3 Relationship between liquidity and idiosyncratic risk

The evidence in Sections 2.3.1 and 2.3.2 motivates an investigation of a market-wide measure of idiosyncratic risk in addition to a market-wide liquidity risk factor. To my knowledge, the combined importance of idiosyncratic risk and liquidity has not explicitly been investigated on the European capital market. That is why, now, I would like to briefly review the theoretical and empirical literature which links liquidity and idiosyncratic risk.

First, a theoretical link between idiosyncratic risk and liquidity can be motivated by inventory control models which predict that liquidity should be inversely related to idiosyncratic risk. In the argumentation of Spiegel and Wang (2006) the specialist in an inventory model of market making must trade off capital gains from trading and his willingness to hold an unbalanced position.[1] If the specialist has a higher probability to miss his end of day target he may become less willing to offer liquidity, which is influenced by the variance of the security i concerned. If the security is exposed to e.g. the risk of the market M, then its variance σ_i^2 can be splitted into systematic and unsystematic risk the following way

$$\sigma_i^2 = \beta_{i,M}^2 \sigma_M^2 + \sigma_{i,idios}^2. \tag{2.3}$$

As the specialist may be able to hedge systematic risk factors like the market risk, see the argumentation in Spiegel and Wang (2006), only the idiosyncratic part $\sigma_{i,idios}^2$ remains.

[1] With respect to the London Stock Exchange, Deutsche Boerse and Euronext - additionally to the electronic order book - markets makers provide for additional liquidity, if necessary, to support the liquidity in these European exchanges. Hence, market makers are important liquidity providers which underpins the empirical relevancy of market maker models.

Hence, higher levels of idiosyncratic risk may lead to lower liquidity offered by the specialist. According to the inventory based microstructure literature, see Stoll (1978) and Ho and Stoll (1980), one expects trading activity and hence liquidity to be low as inventory risks are in high volatility states higher. Such inventory models of market making have occupied researchers for a long time. Benston and Hagerman (1974) find that, in contrast to systematic risk for which a dealer is compensated by higher expected return, unsystematic risk in the form of residual variance is associated with spreads as it is influenced by the dealers' costs of portfolio diversification, inventory risks and costs of trading with insiders. Ho and Stoll (1980) link the bid-ask spread to the variance of the stock's return, because market makers require a higher compensation –reflected in higher bid ask spreads– for taking a position in more volatile assets. If part of the volatility is idiosyncratic, this links idiosyncratic risk and liquidity at the asset level.

Chordia et al. (2002) examine market-wide order imbalances between buyer and seller initiated orders which may be a signal of private information. These imbalances cause price pressures which affect returns and, then, increasing return fluctuations cause a widening of the bid-ask spread due to increased inventory risk. They find a strong contemporaneous association between these order imbalances and market-wide liquidity. Liquidity falls following market declines which is consistent with inventory risk increasing during periods of large price fluctuations. In line with this, Chordia et al. (2005a) find that liquidity and volatility shocks are often systemic in nature and that increasing volatility in a market tends to decrease a market's liquidity, which they argue to be consistent with increased inventory risk. Furthermore, Brunnermeier and Pedersen (2009) argue that market liquidity is correlated with volatility as trading more volatile assets requires higher margin payments. In their model, mutually reinforcing liquidity and volatility spirals may arise, as higher volatility leads to lower market liquidity due to funding problems and lower market liquidity again leads to higher volatility. Brunnermeier and Pedersen (2009) understand the traders' volatility –as proxied by the VIX– as a state variable which influences market liquidity and risk premia.

Second, in addition to an inventory-based explanation, Spiegel and Wang (2006) show that there exists a theoretical relationship between idiosyncratic risk and liquidity in the context of the Merton (1987) model. They derive from this model that expected returns decrease if the stock's liquidity increases and that this effect is larger for firms with higher idiosyncratic risk. In the Merton (1987) model, in contrast to e.g. the CAPM, each investor knows only about a subset of the available securities and, hence, there is incomplete information. In this model, expected returns are, among others, higher on lesser-known firms with relatively smaller investor bases, which is likely related to the liquidity of the asset, see also Merton (1987). This is confirmed by Kadlec and McConnell (1994) with respect to listings on the NYSE, who find that both investor recognition as well as liquidity improve with listing. Hence, expected returns should be a decreasing function of liquidity and an increasing function of illiquidity.

In line with this, Easley et al. (2002) show that stocks which have a higher probability of being traded with private information have higher expected returns because uninformed investors are unable to infer information from prices. In their model, individual investors with differential information being not fully revealed rationally choose to hold idiosyncratic risk. This is linked to liquidity as the probability of informed trading may also be a useful proxy measure of liquidity, see e.g. Amihud et al. (2005), and as it is positively correlated with bid-ask spreads. However, the effect of PIN (probability of informed trading) is still positive in the cross-section of stock returns when controlling for the bid-ask spread which is a prominent liquidity measure. In addition, Kelly and Ljungqvist (2012) analyze the importance of information asymmetry with respect to asset prices in the context of coverage terminations. They find that prices fall in such cases due to expected returns becoming more sensitive to liquidity risk based on the Acharya and Pedersen (2005) model.

A rational explanation of both liquidity and idiosyncratic risk simultaneously influencing the cross-section of returns may be related to price discovery processes. As Kamara et al. (2008) argue, liquidity is associated with the price discovery process and, hence, it may affect the systematic and idiosyncratic volatility of stock returns. This is underpinned by the model of O'Hara (2003), where, in an asymmetric information equilibrium, both informed and uninformed investors hold idiosyncratic risk. Informed investors willingly hold specific assets in order to gain from mispricing, while, in equilibrium, the uninformed investors end up holding those stocks the informed investors do not want to hold, which leads to idiosyncratic risk not being dissipated. Thus, information as well as price discovery risk may provide for an explanation for idiosyncratic risk playing a role in asset pricing and liquidity may also be an influencing factor on this price discovery process. However, according to O'Hara (2003), price discovery is more complex than liquidity, which is linked to the transaction costs of trading, as it also covers the inclusion of information in asset prices. The concept in O'Hara (2003) with its asymmetric information setting differs also from the models including incomplete information of e.g. Merton (1987). In these models, both uninformed and informed investors agree on the price of an asset they know about, but ability of risk diversification is reduced as there is less trading in the remaining assets less investors know about. The intuition in O'Hara (2003) has received some empirical confirmation as trading on private information provides for abnormal returns as, for example, the capital market is not efficient for insider trading, see Fama (1991). Despite the implications by the model of O'Hara (2003) and the argumentation in Easley et al. (2002), Chordia et al. (2000) find no direct evidence that asymmetric information itself has common determinants, hence leaving open why price discovery may be systematic.

Further empirical evidence on jointly considering liquidity and idiosyncratic risk is given by Pastor and Stambaugh (2003) and Fujimoto (2004) who both find that aggregate liquidity is low when market volatility is high. Pastor and Stambaugh (2003) argue that this is sensible as the compensation required by liquidity providers for a given level of order flow is higher when volatility is higher. Chordia et al. (2005b) give evidence on the existence of cross-effects driving liquidity and volatility in the stock market. Ang et al. (2006) control for a liquidity risk factor similar to Pastor and Stambaugh (2003) with respect to the cross-sectional pricing of idiosyncratic volatility in stock returns and find that both seem to capture different risks. Fu (2009) finds that liquid firms tend to have higher idiosyncratic volatilities than illiquid firms. In a time-series context, Goyal and Santa-Clara (2003) and Bali et al. (2005) address liquidity and idiosyncratic risk. Moreover, different cases of asymmetric information like less information disclosure due to poor future earnings prospects, high dispersion in analyst's earning forecasts as well as value characteristics which are all associated with higher idiosyncratic risk as well as illiquidity are investigated in Jiang et al. (2009), Leippold and Lohre (2009) and Doukas and Li (2009).

More evidence on the specific link between idiosyncratic risk and liquidity is given by Malkiel and Xu (2004) who find that the explanatory power of idiosyncratic risk is not diminished by considering liquidity. Angelidis and Tessaromatis (2008) conclude that idiosyncratic risk is not a proxy for liquidity risk in the UK. The empirical results in Spiegel and Wang (2006) suggest that both liquidity and idiosyncratic risk are highly interrelated as high idiosyncratic risk firms tend to be those which are most illiquid. However, when idiosyncratic volatility and liquidity are simultaneously used to explain the cross-sectional variation in stock returns rather only idiosyncratic risk has explanatory power, which may be due to imperfect approaches to measure liquidity. Angelidis and Andrikopoulos (2010) show that volatility can be predicted by shocks in illiquidity.

Overall, it is not clear by this assortment of evidence whether liquidity and idiosyncratic risk influence or dominate each other when simultaneously considered in multifactor models and how this relationship looks like for a European data set. Hence, both should be considered in more detail when conceiving and analyzing the class of equity style indices and risk factors, which are going to be introduced next.

3 Construction of equity style indices

3.1 Introduction

In this chapter, a set of European equity style indices based on the Stoxx Europe 600 universe which reflect the above mentioned cross-sectional regularities in asset prices is outlined. These equity style indices do not only cover well-known styles like size, value / growth or momentum but also novel equity styles like liquidity and idiosyncratic risk, as first presented in Wagner and Winter (2013). Idiosyncratic risk and liquidity have received increasing attention in the recent empirical literature, but have not explicitly been considered yet in index construction.

This new index family contributes to the equity style literature in the following ways. First, it comprises a consistent set of equity styles in the form of style indices for the European capital market, which are characterized by a straightforward way of index construction. Second, it covers well-known equity styles, but also takes into account recent findings in the empirical asset pricing literature. For instance, aggregate idiosyncratic risk and liquidity indices are introduced. Third, the liquidity index displays aggregate market illiquidity which in this form is new in the empirical literature with respect to Europe. In this context, a sophisticated illiquidity measure based on the price impact measure of Amihud (2002) is used to derive the liquidity indices. Fourth, the indices take into account sophisticated procedures of index providers, i.e. free-float weighting in comparison to standard value weighting that is often used in the context of, for example, Fama and French factor portfolios. Fifth, one can calculate difference, i.e. zero investment portfolios in the sense of the Fama and French SMB or HML factor portfolios. Hence, the indices also qualify for the derivation of risk factors being part of multifactor asset pricing models as of Section 2.1 as well as benchmark models in performance evaluation.

In the next section, the index universe from which the equity style indices are calculated and the weighting methodology are described.

3.2 Equity style indices

3.2.1 Index universe and weighting methodology

The Stoxx Europe 600 index has been chosen as the index universe as it is one of the main European stock indices, whose constituent stocks are characterized by relatively good data availability, as they do not comprise too illiquid stocks. At the same time this data universe covers a quite large part of the free-float market capitalization in Europe. This index is covering the 600 largest stocks in the Stoxx Europe total market index according to a quarterly selection procedure and as derived from free-float market capitalization, see the detailed index methodology of Stoxx Ltd. at www.stoxx.com. The fixed number of 600 index components in the Stoxx Europe 600 represents large, mid and small capitalization companies across 18 countries of the European region. The Stoxx Europe 600 index is considered as a data universe in e.g. Stotz et al. (2010).

As, in the following, mainly market capitalization weighting with an additional free-float adjustment as well as equal-weighting is considered, both weighting methods as well as alternative weighting schemes are briefly outlined. First, market capitalization weighting is discussed, which is motivated by the fact that the individual index constituent stocks contribute to the index performance according to their relative importance in the stock market as measured by the market value of the outstanding shares. Market capitalization weighting is usually the most common weighting methodology, as it is the case with well-known indices like e.g. the S&P 500. However, it is based on the assumption that there is a fair pricing of stocks in the capital market. If the market is not efficient, market value weighting is no longer optimal, see Chen et al. (2007). In the case of mispricing, like e.g. bubbles, overpriced stocks would receive a larger weight in the index as the error distribution is skewed to the right, see Treynor (2005), leading to more being invested in over- than in underpriced stocks. However, this is solved by capping the index weights of single stocks to a free-float weight of 20 percent, see www.stoxx.com, which avoids that single stocks dominate the index, especially when index tracking companies increase demand on such stocks.

Second, an alternative and also quite frequent weighting scheme is the equal-weighting of the stocks in an index. This methodology represents a more diversified view on the market as stocks with small market capitalization contribute to the overall index performance in the same way as large company stocks. Unfortunately, this may not only lead to an over-emphasis on smaller stocks, see Treynor (2005), but it also results in an ongoing rebalancing need in order to maintain the constant equal weights, which may induce higher transaction costs. Moreover, this method ignores the information of relative market values which is included in market capitalization weighted indices and may overemphasize stocks which are almost not investable. This is the reason why, according to practical experience, free-float weighted indices are more widely used than equal-weighted indices.[2] Other alternatives would be fundamental index weighting (see e.g. Arnott et al. (2005)) based on fundamental firm variables like e.g. gross sales, the method in Chen et al. (2007) trying to infer fundamental values from past prices or the equally weighted risk contributions portfolios of Maillard et al. (2009), but these methods may result in new biases like e.g. a value bias for fundamental index weighting.

However, Wilshire Atlas, the data base and software system used to construct the equity style indices only supports free-float and equal-weighting as these are still the most commonly used weighting approaches. By considering free-float market capitalization weights the style indices are adjusted in order to only consider that part of a company's outstanding market capitalization that is available for trading and not held for strategic long-term purposes, as suggested by the methodology of Stoxx at www.stoxx.com. Overall, a combination of free-float weighting with equal-weighting seems to be a sophisticated procedure in order to minimize the above mentioned flaws of both methods.

The next section describes in detail the equity style indices.

3.2.2 Style indices

The equity style indices are constructed by using Wilshire Atlas which enables to create portfolios according to different trading rules based on price data and other asset specific characteristics. As such, the style indices are not indices in the classical sense as they do not specifically consider index basing and linking technologies like it is the case with Paasche and Laspeyres indices. However, they provide investors with insights into the performance evolution of portfolios constructed based on specific rules. The respective data used to construct the style indices are provided by Wilshire Atlas as well.

The selection criteria, as proposed in Wagner and Winter (2013), in order to classify the stocks into the different style indices are applied at the point of time of each rebalancing, i.e. quarterly and monthly. In the following, mainly the quarterly rebalanced indices are analyzed as this rebalancing frequency is advantageous with respect to transaction costs and corresponds to the methodology of well-known indices, like e.g. the Stoxx index family. Additionally, semiannually rebalanced momentum indices are constructed

[2]Thus, in the following empirical analyses, a focus is set on examining free-float weighted indices, whereas equal-weighted indices are rather considered in robustness tests.

in order to consider that the performance of momentum strategies may depend on the length of the holding period, see Jegadeesh and Titman (1993).

Now, the different style indices are going to be characterized in detail. First, size indices based on market capitalization criteria are constructed, as documented by Banz (1981), Reinganum (1981) or Fama and French (1992), because size has received increasing attention in index construction. The small cap index consists of stocks in the 0-20%-percentile while the remaining stocks are part of the large cap index. These classification criteria ensure that both portfolios are characterized by a large enough and relatively balanced number of constituents, similar to e.g. those of the Russell indices.[3] A possible alternative would have been the median to split the small and large cap stocks. As objective cut-off-rates and limits for the classification criteria are not available, the setup of rules in order to guarantee sub portfolios which are diversified in a sufficient way is chosen as a compromise.

Second, growth and value are not only well-known investment styles but are also widely used to construct benchmark indices for performance evaluation purposes, see e.g. Elton et al. (1996a). The classification criteria considered are the price-to-book (P/B) and the price-to-earnings (P/E) ratios which take into account the market value in relation to fundamental factors in order to get a sense of over- or undervaluation of a stock in the stock market, as shown in Reinganum (1981) or an overview in Ziemba (1994) and which are consistent with Fama and French (1992 and 1993). Moreover, dividend yield is also considered as Fama and French (1993) confirm that low dividend yield stocks show the return characteristics of growth stocks, whereas high dividend yield stocks show those of financial distress / value stocks, see also Keim (1985) for the interrelation between asset returns and dividend yield. The P/E (price-to-earnings) ratio equals here the ratio of a firm's closing stock price and its trailing 12 months' earnings per share, while the dividend yield is the indicated dividend rate divided by the current price. The trailing 12-month earnings and indicated dividends per share considered in Wilshire Atlas are provided by Interactive Data Corporation. The P/B (price-to-book) ratio equals the ratio of a firm's closing stock price and its fiscal year-end book value per share, with the data for the P/B ratio available in Wilshire Atlas being obtained from the individual company disclosures as well as from Worldscope.

The aggregate value and growth indices in the style index family are constructed according to a multivariate procedure which should avoid that an outlier regarding one crite-

[3] One has to keep in mind that the bottom market cap index is not a small cap index for the overall European market but just in that prespecified index universe. However, considering the constituent stocks of the Stoxx Europe 600 index to derive style indices ensures data availability.

rion results in a misclassification, see e.g. Lakonishok et al. (1994). A multidimensional approach is more reliable than a one-dimensional approach as growth / value characteristics are not only restricted to book-to-market ratios, see Fama and French (1993) and an overview in Ziemba (1994). A multivariate approach can also be applied in case when some accounting data, like e.g. book values, are not reliably available for single stocks. Two out of three of the following criteria have to be fulfilled for a stock to be classified to the value index. These are (i) the dividend yield is falling into the 75-95%-percentile, (ii) the price-to-earnings ratio is part of the 5-25%-percentile, (iii) the price-to-book ratio is falling into the 5-25%-percentile.[4] Thus, value stocks are characterized by a high dividend yield and small price-to-book and price-to-earnings ratios. The growth index consists of stocks fulfilling two out of three of the following criteria. These are (i) the dividend yield is falling into the 0-20%-percentile of the overall group, (ii) the price-to-earnings ratio is part of the 75-95%-percentile, (iii) the price-to-book ratio is falling into the 75-95%-percentile. In case of the growth index, the dividend yield criterion has been chosen to consider stocks that are falling into the 0-20%-percentile of the overall group. This means that stocks which do not pay dividends at all have not been ignored. The reason why the lowest and highest 5%-percentiles are ignored is that extreme outliers in one of the factors, data errors or potential misvaluations in market measures like e.g. returns should not have an influence on the performance of the style indices. In the case of the dividend yield criterion this decision rule ignores for example that proportion of constituent stocks that have paid a special dividend in order to avoid distortions in the style classification.[5]

Third, strong and weak momentum indices are conceived which reflect the 'hot and icy hands effects' of sustained, superior and inferior short-run performance of Hendricks et al. (1993). Thus, they consider that there might be a reversal in momentum performance, see e.g. monthly effects in Jegadeesh (1990) or the one week reversals in Lehmann (1990). Moreover, Hwang and Rubesam (2008) identify a structural break around 2000 after which, according to their empirical results, the profitability of momentum strategies has disappeared. The design of the momentum indices is derived from Jegadeesh and Titman (1993) who conceive portfolios based on past one to four quarter returns. A longer-term performance persistence is reflected by the past six month total return. The

[4]According to Puttonen and Seppae (2007), the multivariate style index methodology as proposed by Stoxx at www.stoxx.com which is applied to form value and growth categories for the Stoxx indices seems to lead to style indices which behave close to each other. Hence, it is useful to conceive here a different modeling approach in constructing value and growth indices.

[5]As cutting off the highest and lowest 5%-percentiles may ignore the most informative data points and may seem to be ad hoc, robustness tests later on refer to 1%- and 99%-cut-off-rates as well.

top six month momentum index consists of stocks where the past six month performance falls into the 75-95%-percentile, whereas the past six month performance of the bottom six month momentum index falls into the range of the 5-25%-percentile. Similar indices have been constructed from past three month total returns which take into account a shorter-term performance persistence.

Fourth, the recent findings about the importance of idiosyncratic risk in asset pricing, see e.g. Malkiel and Xu (2004) and the literature on idiosyncratic risk in Section 2.3.2, motivate the construction of European idiosyncratic risk indices. Following the direct decomposition approach the idiosyncratic risk measure is calculated from the residuals of an asset pricing model, as suggested in Xu and Malkiel (2003) or Malkiel and Xu (2004). The residuals from the univariate market model are taken into account, as this is supported by Wilshire Atlas. The individual excess return of the stock i over the risk-free rate R_f is related to the excess return of the market M, i.e. the Stoxx Europe 600, in a one factor model of the following form

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}. \tag{3.1}$$

Then, the measure of idiosyncratic risk is derived from the standard deviation of the regression residuals $\varepsilon_{i,t}$. The three month Euribor is considered as the risk-free rate R_f, see www.euribor.org. The calculations are based on rolling monthly regressions of historical returns from which the estimates of residual variance are derived. Each regression is estimated from 60 months of historical total returns which take into account price returns as well as dividends, because no daily data are available before September 2002. Regression parameters based on a time-period of five years should not be biased by different market cycles. In case a stock enters the data set, a minimum of twelve months is required for estimation of the variables in (3.1) and, hence, for inclusion in one of the idiosyncratic risk indices. Then, the top idiosyncratic risk index covers stocks with the standard deviation of the residuals being part of the 75-95%-percentile. The bottom idiosyncratic risk index is based on a selection of stocks characterized by a standard deviation of the residuals in the 5-25%-percentile.

The next section describes the way how the illiquidity proxy measure and the methodology to construct the liquidity indices have been designed.

3.2.3 Construction of liquidity indices

Recent evidence as outlined in Section 2.3 has been in favor of taking into account liquidity as a systematic factor in asset pricing. That is why indices are constructed which mimic the behavior of liquid vs. illiquid portfolios.

As it is not possible to directly measure illiquidity, one has to use proxy measures. According to Kyle (1985), there are three dimensions of liquidity. First, tightness refers to the cost of turning around a position over a short period of time. Second, depth is related to the size of the order flow innovation which is required to change prices a given amount. Third, resiliency is the speed at which prices recover from a random uninformed shock. Hence, liquidity is a multidimensional issue which is not easy to measure. In the following, the illiquidity measure of Amihud (2002) as a proxy is used as it is widely used and characterized by good data availability in comparison to microstructure data like e.g. the bid-ask spread in Amihud and Mendelson (1986), see Acharya and Pedersen (2005) or Hou and Moskowitz (2005). As Hasbrouck (2009) and Goyenko et al. (2009) find in several comparisons with e.g. the effective spread measure estimated from intraday data, that the Amihud measure is an adequate illiquidity measure, the European liquidity indices are based on this measure.

Amihud (2002) measures illiquidity as the absolute dollar price change per (dollar or Euro) trading volume in order to detect illiquidity in the form of a price impact. If the percentage price change for the respective security is large compared to the corresponding trading volume, one assumes that the security is rather illiquid. The concept behind the Amihud measure is to proxy for the Kyle (1985) lambda. In the Kyle (1985) model, λ measures the price impact of a unit of trade size and is larger for less liquid stocks. Thus, the Amihud measure displays the price impact of trading, i.e. the response of price to order flow in Kyle's concept of illiquidity, where it is an increasing function of the probability of facing an informed trader as the market maker does not know whether the order flow results from informed traders or from noise traders. One has to be aware that the Amihud measure cannot distinguish between an absolute price change due to informational events, which result in large price changes combined with still small trading volumes, and a price change due to illiquidity, see e.g. Porter (2003), which may lead to illiquidity being slightly overstated. However, this shortcoming and the problems of extreme outliers, missing data and maybe erroneous data should be mitigated by calculating monthly and quarterly averages of the illiquidity measure. Other alternative measures would for example have been the illiquidity measure taking into account return reversals based on order flow of Pastor and Stambaugh (2003) or turnover, i.e. the number of shares traded as a fraction of the number of shares outstanding, as in Datar et al. (1998).[6] As the Amihud measure is widely used and as it can be implemented with given data, this

[6] A broad overview on different measures of illiquidity is given in Amihud et al. (2005).

measure qualifies as an applicable selection criterion regarding the liquidity indices.

First, the Amihud measure is calculated for the individual stocks before the final aggregation to an index, see also Wagner and Winter (2013). The daily Amihud measure for each stock i is calculated as

$$ILLIQ_{idt} = \frac{|R_{idt}|}{VOLE_{idt}}, \tag{3.2}$$

where $|R_{idt}|$ is the absolute daily return of stock i on day t and $VOLE_{idt}$ is the respective daily Euro trading volume. All data used have been converted to Euro as this is the currency the Stoxx Europe 600 index universe is denominated in, see www.stoxx.com. In case of stock prices or volumes not being denominated in Euros the data are converted with exchange rates available in Thomson Datastream. Monthly and quarterly averages of $ILLIQ_{idt}$, $AILLIQ_{imd}$ and $AILLIQ_{iqd}$ are also calculated, respectively

$$AILLIQ_{imd} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{|R_{idt}|}{VOLE_{idt}}, \tag{3.3}$$

$$AILLIQ_{iqd} = \frac{1}{D_{iq}} \sum_{t=1}^{D_{iq}} \frac{|R_{idt}|}{VOLE_{idt}}, \tag{3.4}$$

where D_{im} and D_{iq} denote the number of days for which data are available in the month m and quarter q averaging period. The Amihud illiquidity proxy measure is calculated based on daily closing prices and the total number of shares traded on a security on the current day (the trading volume). The daily trading volume is multiplied by the daily closing price in order to approximate the daily Euro trading volume $VOLE_{idt}$. If neither the daily closing price nor the daily trading volume are available, the data for the security for the respective day have to be ignored. Usually, if at all, only a few days of data are missing. As monthly and quarterly averages of the Amihud measure are used, the problem of missing data should be negligible. The Amihud measure is calculated for the time period July 1, 2002 to September 30, 2009 as this is the time period needed to calculate monthly and quarterly averages in order to obtain the liquidity index selection criteria for the observation period from October 1, 2002 to September 30, 2009.

With the help of information available at www.stoxx.com, all the stocks that have been added to or deleted from the index are taken into account and the data for these constituent stocks are retrieved from Thomson Datastream.[7] In the time period from July 1, 2002 to September 30, 2009, there have been around 882 additions and deletions of stocks to and

[7]Due to unavailability in Datastream, data for 11.6% of the constituent stocks have been complemented from Bloomberg.

from the index which results in a number of around 485 companies. Including the 600 current index members, data for a total number of 1085 companies are needed to calculate the Amihud measures. The data for around 16 companies are not available or are too sparse to be used, but as this amounts to only around 1.5% of the total data universe, the impact on results should be negligibly small. Additionally, a detrended Amihud measure is calculated following the detrending procedure of Wagner (2008) pp. 251 by detrending the trading volume by its moving average over the last 100 observations. This mitigates problems of possible stochastic trends and outliers in the trading volume and, hence, in the Amihud measure and smoothes random fluctuations in these measures.

The liquidity indices have been calculated based on the monthly and quarterly undetrended and detrended Amihud illiquidity measures. The top monthly average illiquidity index comprehends those stocks where the monthly average of the undetrended Amihud measure falls into the 75-95%-percentile. The bottom monthly average illiquidity index consists of stocks with a monthly average of the normal Amihud measure being part of the 5-25%-percentile. This is in line with a larger Amihud measure signalizing a higher illiquidity of the corresponding stocks. The capping of the top and bottom five percent again avoids the problem of extreme outliers or misvaluations. Moreover, top and bottom quarterly average illiquidity indices have been constructed based on quarterly averages of the Amihud measure in order to capture a rather long-term illiquidity effect. Furthermore, top and bottom, monthly and quarterly detrended illiquidity indices are constructed derived from the detrended Amihud measure based on the same rules. As the illiquidity measure is only analyzed at the point of time of each rebalancing, the monthly averages are useful with monthly rebalancing whereas the quarterly averages are useful with quarterly rebalancing.

In the next section, the statistical characteristics of the style indices are discussed.

3.3 The European style indices from 2002 to 2009

3.3.1 Summary statistics: Style indices

This section presents a detailed analysis of the equity style indices for the seven years period from October 1, 2002 to September 30, 2009, resulting in 1809 daily observations considering non-trading days. Therefore, the data set covers the 2007 / 2008 financial crisis which started from the subprime crisis in the United States and then spread to a global crisis.

First graphical examples are displayed in Figures 3.1 and 3.2. There, selected performance results for the free-float and equal-weighted style indices as well as the overall Stoxx Europe 600 indices are given starting from a base value of 100 on October 1, 2002. The charts plot total returns which take into account stock-split adjusted price returns as well as dividend returns and show the results for the quarterly rebalanced indices. The momentum indices displayed here are based on the past six month performance and the liquidity indices are derived from quarterly Amihud averages. In both figures, a considerable co-movement in the time series of the style indices becomes evident. Moreover, they show that the style indices follow the upturn of the market which has been followed by the overall downturn, especially due to the financial crisis. Before the financial crises most of the style strategies offered a considerably good performance, but this has been reversed during the crisis.

This section also displays summary statistics with respect to the free-float indices, see Table 3.1. With respect to all index statistics, daily total logarithmic returns, which again include price changes, dividends and stock splits, are displayed. Means and standard deviations are on a per annum basis and are annualized by assuming 250 trading days per year. The t-statistics and respective p-values are calculated to test the null hypothesis that the mean daily total logarithmic return of an index equals zero. T-statistics and respective p-values which are statistically significant at the 10%-level are labeled with one asterisk, whereas results significant at the 5%-level are labeled with two asterisks, respectively.

In Table 3.1, average per annum returns show the performance of the free-float weighted indices. Overall, the following free-float weighted style indices seem to have performed better than their corresponding counterparts: small cap, value, top six month momentum, top idiosyncratic risk and top illiquidity. This corresponds to what one should expect regarding the different styles, see the literature overview in Chapter 2. However, one has to be aware that none of the indices possesses a statistically significant average daily logarithmic return that is different from zero. This may be linked to the break-down of the performance during the financial crisis whose most negative impact on the style indices has been at the end of 2008. The summary statistics for the equal-weighted indices are given in Table 3.2. Due to their focus on smaller assets and a size effect one expects the equal-weighted indices to possess an overall higher performance, which is confirmed by the summary statistics and the graphical results for almost all style indices. With respect to the equal-weighted indices, the following individual indices show a higher average per annum return than their corresponding counterparts: small cap, value, top idiosyncratic risk and top illiquidity. Again, none of the indices possesses a statistically significant performance.

The per annum standard deviations give a first sense on the overall riskiness of the indices. Here, the free-float weighted value, bottom six month momentum and top idiosyncratic risk indices possess a considerably high standard deviation. The standard deviations regarding the equal-weighted indices are generally smaller, with the bottom six month momentum index displaying the largest volatility. With respect to all indices, the skewness and excess kurtosis are also given to describe the shape of the distribution of the logarithmic returns. The assumption of normality is strongly rejected for all indices.[8] Overall, the skewness numbers are often relatively small signalizing a rather symmetric distribution of the daily logarithmic returns. The excess kurtosis of the daily logarithmic returns is always positive. Therefore, one can assume a leptokurtic distribution with fatter tails. The beta regarding the daily logarithmic returns is derived from

$$\beta_{index} = \frac{Cov(R_{index};R_{market})}{Var(R_{market})}, \tag{3.5}$$

where R_{index} is the return on each style index and R_{market} is meant to be the return on the overall Stoxx Europe 600 index, respectively. Beta captures the sensitivity of the individual indices with respect to R_{market}. The betas of the different style indices are usually quite close to one, where larger deviations from a beta of one occur with the valuation, momentum and idiosyncratic risk indices, see Tables 3.1 and 3.2. Moreover, the number of stocks in each index is given for the last day of the observation period, i.e. September 30, 2009, with the number of stocks in the different indices being quite stable over time. Almost all indices comprise more than 100 stocks and, hence, should be quite well diversified, see e.g. Statman (1987).

With respect to all indices, the autocorrelation coefficient at lag 1, $\rho(1)$, as well as the respective t-statistics and p-values are given. The autocorrelation coefficients are small, as they are not larger (smaller) than 10% (-10%), and only some free-float weighted indices show a significantly negative or positive autocorrelation. Moreover, the results for the autocorrelation at lag 1 of the squared logarithmic returns are given, where the style indices show significantly positive autocorrelations of the squared returns larger than 10% and often even larger than 20%. The results seem to be slightly more pronounced with respect to the free-float weighted indices. This positive dependence in the series of the squared returns can be interpreted to be a sign for volatility clustering in the return series. The correlations between the daily logarithmic returns of all style indices and the overall market index are displayed in Tables A.1 and A.2 in Section A.1 in the appendix. The correlations between the different indices are usually quite high, often even larger than 90%, confirming the co-movement in the time series. This had to be expected because

[8] This is strongly supported by unreported Jarque-Bera statistics regarding the daily logarithmic returns.

all indices have been calculated on the basis of the same data universe and, therefore, there might be systematic influences simultaneously concerning all indices. Overall, the correlations between the equal-weighted indices seem to be even higher than those of the free-float weighted indices.

The equity style indices are also backtested for (i) a monthly rebalancing frequency, (ii) alternative momentum formation periods and rebalancing frequencies, (iii) an alternative outlier detection method and (iv) alternative liquidity indices based on detrended Amihud illiquidity. The main results for the monthly rebalanced indices are given in Table A.3 in Section A.2 in the appendix. They are quite similar to the results with respect to the quarterly rebalanced indices. As quarterly rebalancing is advantageous with respect to smaller transaction costs, this rebalancing frequency is more useful than monthly rebalancing. Major deviations regarding the results occur with respect to the monthly and semiannually rebalanced momentum indices as the performance of momentum depends on the rebalancing frequency. Therefore, for each rebalancing method, summary statistics for the momentum indices based on the past three and six month performance are also given in Table A.4 in Appendix A.2. The results suggest that momentum strategies based on the past three month performance do not seem to be preferable as the bottom momentum index almost always offers a better performance than the top momentum index. This is not the case for the momentum strategy based on the past six month momentum which is more in line with the literature outlined in Section 2.2 which finds a positive return on the momentum strategy. The summary statistics for the momentum indices do not clearly show which rebalancing frequency should be preferred. However, as semiannual rebalancing is too infrequent over a period restricted to seven years and as monthly rebalancing causes higher transaction costs, quarterly rebalancing seems to be the most useful approach. In Appendix A.2, the summary statistics for all liquidity indices are given. The liquidity indices based on monthly and quarterly normal and detrended averages show quite similar results. In Table A.5 in Appendix A.2, the summary statistics of the indices (as well as risk factors, see the next section) are also given for a different outlier detection method considering 1%- and 99%-cut-off-rates instead of 5%- and 95%-cut-off-rates. The results are quite similar to those for the 5%- and 95%-cut-off-rates. However, in order to make sure that no distortions or erroneous data influence the classification of constituent stocks towards the respective top and bottom indices, the 5%- and 95%-cut-off-rates seem to be more sensible. Overall, these backtests also show that variations in the style index construction do not lead to significantly differing results.

Next, the statistical characteristics of the risk factors derived from the style indices are analyzed.

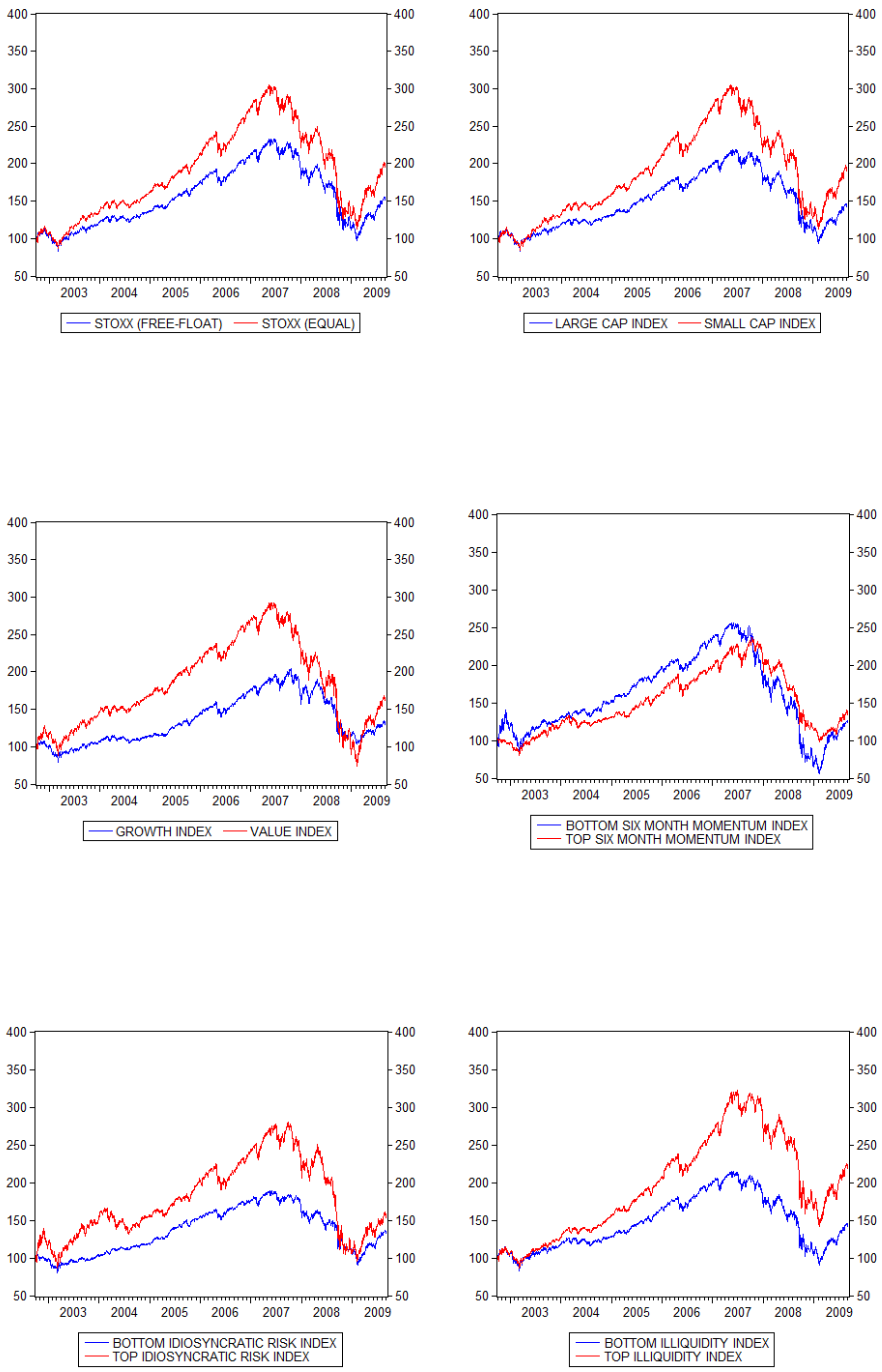

Figure 3.1: Daily performance of free-float weighted style indices

A base value of 100 is invested at the start of the sample period in October 2002. Sample period: October 1, 2002 to September 30, 2009.

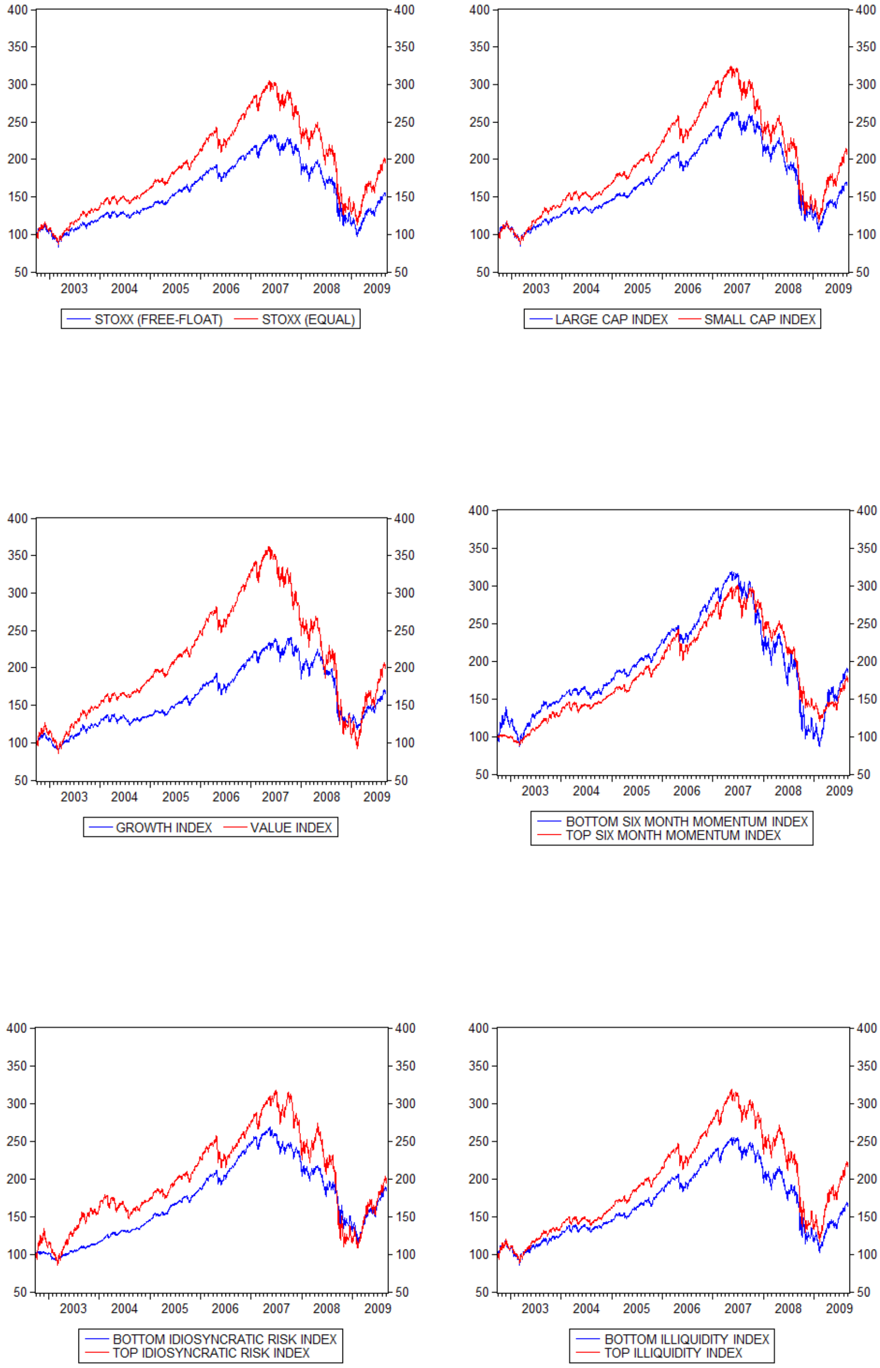

Figure 3.2: Daily performance of equal-weighted style indices

A base value of 100 is invested at the start of the sample period in October 2002. Sample period: October 1, 2002 to September 30, 2009.

Table 3.1: Summary statistics: Free-float weighted indices

Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively.

Free-float weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
Mean p.a.	6.10%	5.33%	9.15%	3.88%	7.20%	3.33%	4.33%	4.38%	6.30%	5.13%	11.33%
T-stat.	0.786	0.677	1.189	0.549	0.679	0.296	0.592	0.640	0.614	0.631	1.499
P-value (t-stat.)	0.432	0.499	0.235	0.583	0.497	0.767	0.554	0.522	0.539	0.528	0.134
Median	0.07%	0.06%	0.12%	0.09%	0.08%	0.06%	0.08%	0.05%	0.08%	0.05%	0.10%
Std. dev. p.a.	20.89%	21.16%	20.73%	19.01%	28.49%	30.32%	19.64%	18.43%	27.60%	21.84%	20.33%
Skewness	-0.034	0.019	-0.238	0.015	0.216	0.078	-0.123	0.007	0.191	0.087	0.078
Excess Kurtosis	7.289	7.563	5.830	6.535	8.504	8.202	5.836	9.589	6.588	8.188	9.205
Beta	1.000	1.010	0.952	0.812	1.287	1.350	0.865	0.852	1.191	1.038	0.923
Number of Stocks in Portfolio	600	193	407	79	102	142	142	127	128	143	142
$\rho(1)$	-0.043	-0.059	0.038	-0.045	0.008	0.023	-0.036	-0.073	-0.012	-0.050	-0.026
T-stat. ($\rho(1)$)	-1.474	-2.091	1.129	-1.597	0.238	0.669	-1.438	-2.564	-0.410	-1.737	-0.949
P-value ($\rho(1)$)	0.141	0.037	0.259	0.110	0.812	0.504	0.151	0.010	0.682	0.083	0.343
$\rho(1)$ of squ. ret.	0.243	0.261	0.190	0.226	0.190	0.198	0.319	0.321	0.227	0.242	0.181
T-stat. ($\rho(1)$ of squ. ret.)	3.109	3.179	3.668	5.647	3.405	4.714	2.902	2.987	4.040	2.869	2.341
P-value ($\rho(1)$ of squ. ret.)	0.002	0.002	0.000	0.000	0.001	0.000	0.004	0.003	0.000	0.004	0.019

Table 3.2: Summary statistics: Equal-weighted indices

Significance at the 1%-, 5%-, 10% is denoted by ***, **, and *, respectively.

Equal weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
Mean p.a.	9.50%	7.30%	10.28%	7.30%	9.93%	8.73%	7.80%	8.70%	9.45%	7.05%	10.98%
T-stat.	1.228	0.925	1.321	1.048	1.032	0.867	1.162	1.377	0.998	0.875	1.411
P-value (t-stat.)	0.220	0.355	0.187	0.295	0.302	0.386	0.245	0.169	0.319	0.382	0.158
Median	0.12%	0.09%	0.12%	0.11%	0.09%	0.09%	0.12%	0.09%	0.14%	0.08%	0.13%
Std. dev. p.a.	20.81%	21.21%	20.95%	18.71%	25.86%	27.10%	18.05%	16.98%	25.48%	21.66%	20.93%
Skewness	-0.218	-0.073	-0.266	-0.450	-0.094	-0.029	-0.437	-0.228	-0.230	-0.002	-0.326
Excess Kurtosis	6.346	7.273	5.840	5.645	6.422	7.059	5.515	9.504	5.616	7.509	6.554
Beta	1.000	0.997	1.001	0.853	1.212	1.257	0.807	0.785	1.196	1.017	0.992
Number of Stocks in Portfolio	600	193	407	79	101	142	142	127	128	143	142
$\rho(1)$	0.035	-0.026	0.064	0.012	0.066	0.078	0.015	0.001	0.049	-0.030	0.076
T-stat. ($\rho(1)$)	1.066	-0.883	1.848	0.380	1.979	2.152	0.534	0.022	1.520	-0.994	2.109
P-value ($\rho(1)$)	0.287	0.377	0.065	0.704	0.048	0.032	0.593	0.982	0.129	0.320	0.035
$\rho(1)$ of squ. ret.	0.196	0.218	0.194	0.189	0.197	0.183	0.233	0.271	0.153	0.208	0.217
T-stat. ($\rho(1)$ of squ. ret.)	3.462	3.181	3.895	4.283	4.355	4.616	2.810	2.953	3.501	2.979	4.047
P-value ($\rho(1)$ of squ. ret.)	0.001	0.002	0.000	0.000	0.000	0.000	0.005	0.003	0.001	0.003	0.000

3.3.2 Summary statistics: Risk factor portfolios

Now, risk factors, see Section 2.1, are derived from the style indices in order to not only consider simple style indices as in Sharpe (1992). These include the market excess return, size, valuation, momentum, idiosyncratic risk and (il-)liquidity, as has been presented in Wagner and Winter (2013). The market excess return is calculated as the difference between the respective Stoxx index and the risk-free rate, i.e. the three month Euribor. The size factor is defined as the small cap minus the large cap index. The valuation factor is the difference between the value and growth indices. The other risk factors are simply calculated as the respective top minus bottom indices. These risk factors are constructed as zero investment portfolios as in Fama and French (1993) or Eckbo and Norli (2007) going long in stocks with e.g. high illiquidity and short in stocks with low illiquidity and displaying the performance of unconstrained long-short investment strategies.

The graphical performance of the free-float and equal-weighted market excess return and the risk factors is illustrated in Figure 3.3. The risk factors based on the style indices are scaled the same way as the market excess return in order to make them comparable. The market excess return shows the highest performance, which, however, has considerably been diminished during the financial crisis, but the figures for some of the other risk factors –like size or free-float weighted illiquidity– show a considerable outperformance as well. The overall performance level is much smaller for the remaining risk factors compared to the market excess return, but still some of the zero investment strategies outperform. Moreover, some of the risk factors suffered a lot during the financial crisis like it is e.g. the case with valuation. This is intuitive as undervalued or distressed stocks probably have been more negatively influenced by market stress caused by the financial crisis. The graphs also show that risk factors like momentum or idiosyncratic risk have been characterized by more volatility and dynamics over the observation period than other risk factors like e.g. size. For both risk factors, positive performance is quickly followed by negative performance, leading to an overall rather neutral performance. However, these figures only give a first impression and have to be complemented by a more detailed statistical analysis.

Tables 3.3 and 3.4 give summary statistics with respect to the risk factors, see also Wagner and Winter (2013). These statistics are calculated the same way as those in Tables 3.1 and 3.2. Regarding the free-float weighted risk factors, average risk factor returns are highest in magnitude for liquidity, followed by market, size and valuation. As the return characteristics of the size and liquidity factors show, there is enough return variation in the constituent stocks of the Stoxx 600 based on size and liquidity characteristics, even if its index universe focuses on the 600 largest stocks by free-float market capitalization. This observation holds for the free-float and equal-weighted risk factors. The results document that risk premia for momentum and idiosyncratic risk are relatively low during the sample period.[9] Only free-float weighted liquidity possesses a significantly positive daily logarithmic return at the 5%-level, with a mean per annum return of 6.20%. None of the other free-float nor equal-weighted risk factors shows a significantly positive average daily logarithmic return. The statistical significance of the liquidity factor also vanishes with equal-weighting. Therefore, with equal-weighting, where a larger emphasis is put on smaller and probably more illiquid stocks, a significantly positive return through a strategy that is long in more illiquid stocks and short in less illiquid stocks is not profitable any more. A reason may be that with free-float weighting bank stocks display a considerable fraction of the Stoxx 600. After the Lehman Brothers bankruptcy, stocks in the financial sector may have been more illiquid than those of other sectors, leading to a higher return of the free-float compared to the equal-weighted risk factor, as induced by a risk return trade-off. Overall, the performance of the equal-weighted risk factors seems to be smaller than that of the free-float weighted risk factors.

I conclude that the positive performance results on size, valuation and liquidity are in line with those of most of the U.S. and European empirical studies in Sections 2.2 and 2.3. The results on idiosyncratic risk are also in line with most of the above mentioned empirical evidence, even if the effect is not very strong as indicated by risk factor performance. However, the positive performance on the idiosyncratic risk strategy is not in line with Ang et al. (2009) who find that, in Europe, stocks with high idiosyncratic volatility have low expected returns. However, their observation period covers the years 1980 to 2003, whereas my observation period also covers the start of the 2007 / 2008 financial crisis and is much more actual. Another explanation may be that their measure of idiosyncratic risk, which is estimated only over the previous month, is less accurate than the construction methodology of the idiosyncratic risk indices where idiosyncratic risk is estimated over 60 months of past data combined with regular rebalancing, see Section 3.2.2. Moreover, the observation that the momentum strategy does not perform well over the overall observation period is consistent with Hwang and Rubesam (2008) that this effect is not so pronounced anymore since the end of the dotcom bubble.

The minimum and maximum numbers suggest that some risk factors are characterized

[9] This is rather inconsistent with both factors being systematic risk factors, but may be caused by the choice of the sample period. As the sample period includes the financial crisis which is characterized by high volatility, where results may not be extrapolated to normal periods, specific robustness tests later on will consider subperiods including and excluding the financial crisis. Extending the sample period further into the past is not useful as well due to incompleteness of European financial market integration.

by extreme positive as well as negative daily returns. These extreme returns especially occurred during the recent financial crisis. Around one sixth of the constituent stocks in the Stoxx 600 belong to the banks, financial services as well as insurance sectors which have been considerably hit by the financial crisis. This may be a sensible explanation for outliers in the graphical risk factor performance which especially occur during autumn 2008 when Lehman Brothers filed bankrupt, see Figure 3.3. Also, outliers with respect to the free-float weighted risk factors are much more pronounced than regarding the equal-weighted risk factors. This may be caused by some large cap constituent stocks which have been strongly influenced by the financial market crisis. Another explanation may be that free-float weighting is much more exposed to misvaluations and over- / understatements of performance, as has been mentioned above.

Some risk factors in Tables 3.3 and 3.4 possess a small standard deviation of less than 10%, i.e. free-float and equal-weighted size and liquidity. This means that these difference portfolios are not so risky as suggested by total risk. Some risk factors are quite skewed and have a quite high excess kurtosis in the sense of leptokurtosis. Particularly under free-float weighting, the risk factors display non-normality.[10] Equal-weighting as compared to free-float weighting tends to be accompanied by higher levels of negative skewness in market excess returns. While size and momentum tend to be negatively skewed, valuation and idiosyncratic risk are characterized by a positive skewness. The results for the liquidity risk factor are ambiguous as, again, equal-weighting tends to be combined with negative skewness in returns. The significant autocorrelations in the squared returns are again a sign of volatility clustering in the return series while the autocorrelations of the normal returns are not always significant. Moreover, the autocorrelations in the risk factor time series are partly negative as well as positive with a magnitude which is rather small.

Table 3.5, as derived from Wagner and Winter (2013), displays the correlations between the risk factors of each weighting methodology, which should be smaller than the correlations of the style indices, as they are derived from difference portfolios. Some free-float weighted risk factors are characterized by a very small correlation, like e.g. free-flow weighted size. In contrast, a quite high positive correlation exists between the market excess return and valuation. A high correlation between risk factors may be a sign for high redundancy and a possible substitutability between these risk factors as both risk factors may serve as proxies for identical underlying systematic risks. The market excess return is also positively correlated with idiosyncratic risk but only slightly correlated with size. A strong negative correlation exists between the market excess return and momentum as

[10]This is again affirmed by unreported Jarque-Bera statistics regarding the daily logarithmic returns.

well as between valuation and momentum. This negative correlation between valuation and momentum is also found by Asness (1997) who provides a rational as well as an irrational explanation for this fact. A rational explanation argues that winner stocks are rather not distressed in contrast to value stocks. With respect to the irrational explanation, investors are uncomfortable in holding stocks which seem to be cheap with respect to their fundamentals but are more comfortable in holding recent winners. The remaining pairs are characterized by relatively small correlation coefficients: size and valuation, liquidity and momentum, idiosyncratic risk and size, and idiosyncratic risk and valuation.

Overall, the results with respect to the free-float versus equally weighted risk factors are rather similar. In detail, the correlations regarding the equal-weighted risk factors show results which are only partly slightly different from those of the free-float weighted risk factors. Quite high positive correlations now exist between the market excess return and valuation as well as idiosyncratic risk. A quite high negative relation can be found between the market excess return and momentum, as well as between valuation and momentum. One notable exception of the equal- vs. the free-float weighted results refers to the correlation between liquidity and size, where the equally weighted liquidity factor exhibits a correlation of 0.75 with the size factor as opposed to a moderate value of 0.24 for the free-float weighted liquidity factor. Hence, increasing weights for smaller stocks seems to cause the free-float weighted liquidity factor to become closer to the size factor. Overall, it seems to be useful to later on control for size when analyzing liquidity in order to capture possible interrelations between both risk factors, but equal-weighted liquidity seems to be unrelated to other risk factors.

Overall, the results of the correlation analysis show that some risk factors show interdependencies, which should be analyzed when investigating the cross-section of stock or mutual fund returns.

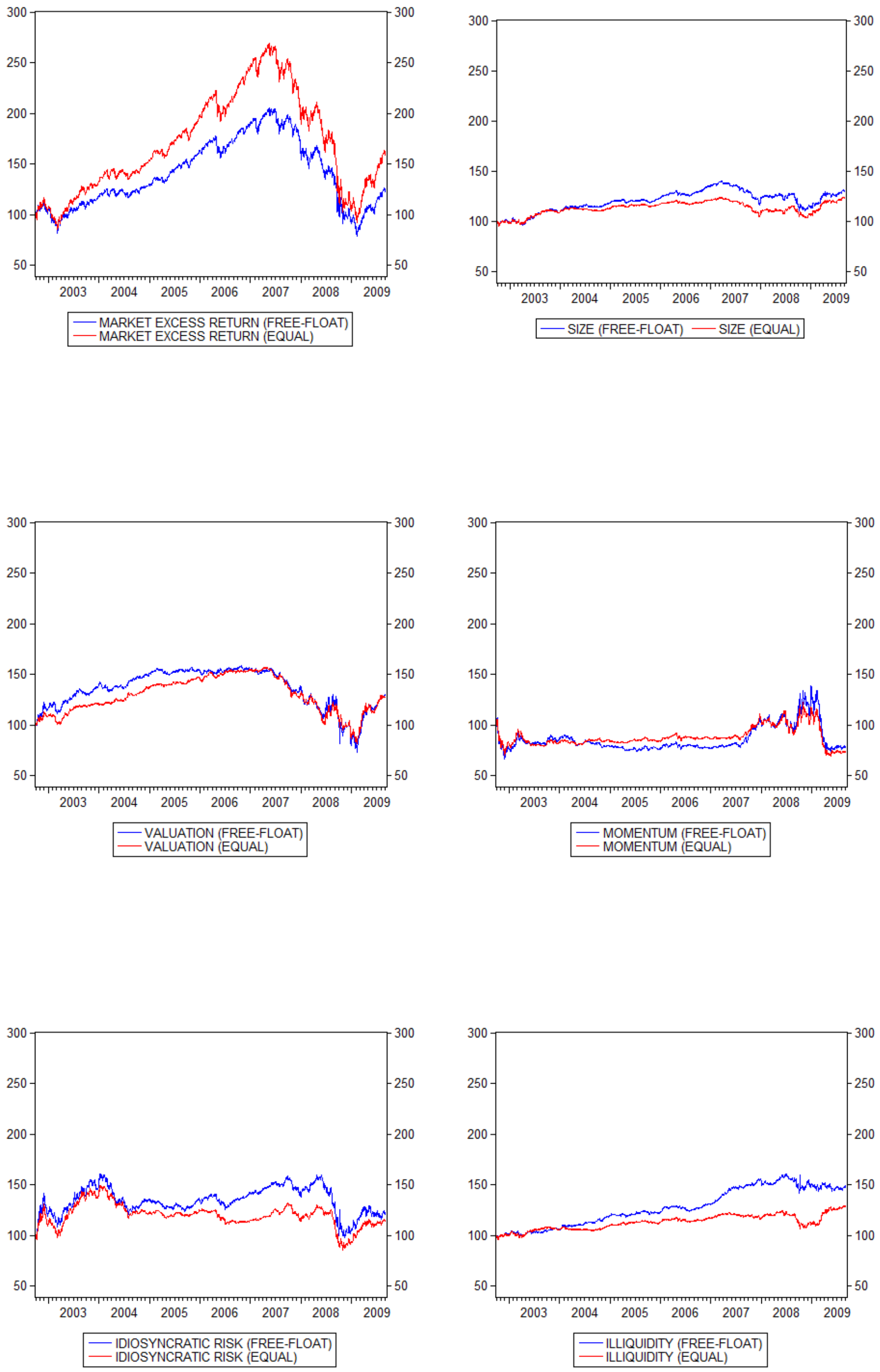

Figure 3.3: Daily performance of free-float and equal-weighted risk factors

A base value of 100 is invested at the start of the sample period on October 1, 2002. Sample period: October 1, 2002 to September 30, 2009.

Table 3.3: Summary statistics: Free-float weighted risk factor portfolios

Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. All statistics are calculated based on daily total logarithmic risk factor returns including stock splits and dividends. Means and standard deviations are annualized assuming 250 trading days per year. The t-statistics and p-values test the null hypothesis of a zero mean daily risk factor return. The excess kurtosis is the kurtosis minus the kurtosis of a normally-distributed variable. $\rho(1)$ refers to the autocorrelation coefficient at lag 1. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

Free-float weighted	MARKET EXCESS RETURN	SIZE	VALUATION	SIX MONTH MOM.	IDIOS. RISK	ILLIQUIDITY
Mean p.a.	3.18%	3.83%	3.30%	0.99%	1.92%	6.20%
T-stat.	0.410	1.413	0.478	0.132	0.306	2.047**
P-value (t-stat.)	0.682	0.158	0.633	0.895	0.760	0.041**
Maximum p.d.	9.49%	2.54%	13.48%	8.04%	12.99%	9.24%
Minimum p.d.	-7.96%	-3.03%	-11.32%	-7.85%	-13.21%	-8.22%
Median	0.06%	0.02%	0.02%	0.03%	0.02%	0.02%
Std. dev. p.a.	20.90%	7.30%	18.64%	20.16%	16.88%	8.15%
Skewness	-0.039	-0.284	0.341	-0.467	0.412	0.683
Excess Kurtosis	7.283	4.306	24.608	7.701	29.502	93.355
$\rho(1)$	-0.041	0.037	0.087	0.145	0.070	-0.105
T-stat. ($\rho(1)$)	-1.384	1.207	1.764	4.368	0.971	-1.081
P-value ($\rho(1)$)	0.167	0.228	0.078	0.000	0.332	0.280
$\rho(1)$ of squ. ret.	0.243	0.182	0.533	0.181	0.612	0.535
T-stat. ($\rho(1)$ of squ. ret.)	3.122	3.916	3.648	4.831	4.074	5.195
P-value ($\rho(1)$ of squ. ret.)	0.002	0.000	0.000	0.000	0.000	0.000

Table 3.4: Summary statistics: Equal-weighted risk factor portfolios

Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. All statistics are calculated using daily total logarithmic returns. Means and standard deviations are annualized assuming 250 trading days per year. The t-statistics and p-values test the null hypothesis of a zero mean daily risk factor return. The excess kurtosis is the kurtosis minus the kurtosis of a normally-distributed variable. $\rho(1)$ refers to the autocorrelation coefficient at lag 1. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

Equal weighted	MARKET EXCESS RETURN	SIZE	VALUATION	SIX MONTH MOM.	IDIOS. RISK	ILLIQUIDITY
Mean p.a.	6.58%	3.00%	2.63%	-0.93%	0.76%	3.95%
T-stat.	0.850	1.267	0.543	-0.155	0.162	1.566
P-value (t-stat.)	0.396	0.205	0.587	0.877	0.871	0.118
Maximum p.d.	8.50%	2.06%	5.10%	6.03%	4.55%	2.21%
Minimum p.d.	-8.56%	-2.54%	-4.70%	-6.39%	-4.07%	-2.50%
Median	0.11%	0.02%	0.01%	0.03%	0.02%	0.02%
Std. Dev. p.a.	20.82%	6.36%	13.06%	16.15%	12.59%	6.76%
Skewness	-0.223	-0.282	0.298	-0.611	0.250	-0.392
Excess Kurtosis	6.342	3.566	8.112	7.312	4.358	4.005
$\rho(1)$	0.036	0.016	0.139	0.183	0.142	-0.021
T-stat. ($\rho(1)$)	1.090	0.453	3.452	5.330	4.756	-0.635
P-value ($\rho(1)$)	0.276	0.651	0.001	0.000	0.000	0.525
$\rho(1)$ of squ. ret.	0.196	0.295	0.280	0.184	0.104	0.261
T-stat. ($\rho(1)$ of squ. ret.)	3.474	5.087	5.464	5.127	3.520	3.703
P-value ($\rho(1)$ of squ. ret.)	0.001	0.000	0.000	0.000	0.000	0.000

Table 3.5: Correlations: Risk factor portfolios

Free-float weighted	MARKET EXCESS RETURN	SIZE	VALUATION	SIX MONTH MOM.	IDIOS. RISK	ILLIQUIDITY
MARKET EXCESS RETURN	1.000	-0.168	0.533	-0.502	0.419	-0.296
SIZE	-0.168	1.000	0.076	-0.109	0.136	0.241
VALUATION	0.533	0.076	1.000	-0.721	0.044	-0.345
MOMENTUM	-0.502	-0.109	-0.721	1.000	-0.292	0.178
IDIOSYNCRATIC RISK	0.419	0.136	0.044	-0.292	1.000	0.262
ILLIQUIDITY	-0.296	0.241	-0.345	0.178	0.262	1.000
Equal-weighted	**MARKET EXCESS RETURN**	**SIZE**	**VALUATION**	**SIX MONTH MOM.**	**IDIOS. RISK**	**ILLIQUIDITY**
MARKET EXCESS RETURN	1.000	0.015	0.572	-0.580	0.680	-0.078
SIZE	0.015	1.000	0.138	-0.112	0.153	0.751
VALUATION	0.572	0.138	1.000	-0.760	0.286	0.078
MOMENTUM	-0.580	-0.112	-0.760	1.000	-0.492	-0.052
IDIOSYNCRATIC RISK	0.680	0.153	0.286	-0.492	1.000	0.086
ILLIQUIDITY	-0.078	0.751	0.078	-0.052	0.086	1.000

3.4 Conclusion

In this chapter, innovative style indices for the European capital market have been introduced. The data universe, on which the family of style indices is based, consists of the 600 largest European stocks as represented by the Stoxx Europe 600. The indices display market risk as well as size, valuation, momentum, idiosyncratic risk and liquidity styles from which risk factors are derived. In the following, this new class of equity style indices as well as risk factors will be considered in empirical asset pricing studies as well as multifactor models based on this index family, which may be useful in the performance evaluation, timing and style analyses of mutual and hedge funds. Of special interest in the context of the development of equity style indices are liquidity and idiosyncratic risk as they display novel risk factors. The recent asset pricing literature emphasizes the importance of these risk factors which are considered in more detail in the following chapters.

The interplay between different risk factors is also a field of further analysis. As the correlations between risk factors given in this chapter suggest, some risk factors may be proxies for other risk factors. In line with this, it is of interest to further investigate the role of the idiosyncratic risk and liquidity factors, which have not been characterized by striking levels of correlation, and their relationship to other risk factors. On the other hand, the results imply that some risk factors do not show any interdependencies. Therefore, further research is necessary to thoroughly investigate the equity style indices. In the following chapters, I analyze whether such interrelations can be found in the context of asset pricing as well as static and dynamic performance evaluation. Moreover, it will be of interest to further study the role of certain risk factors especially in the context of the recent global financial market crisis. In this context, liquidity risk plays an important role as is investigated in more detail in the next Chapter for Europe.

4 Liquidity and asset pricing

4.1 Introduction

The extensive impact of liquidity induced crises like the October 1987 stock market crash or the LTCM breakdown motivate a detailed analysis of systematic liquidity with respect to a European data set. This is underpinned by the short literature review emphasizing the relevance of liquidity in Section 2.3.

That is why I now conduct a broad analysis on different aspects of systematic liquidity of European stocks. First, commonality in liquidity of the constituent stocks of the broad European Stoxx 600 stock index is analyzed which enlarges the only poor evidence of commonality in liquidity in Europe. Two of the few studies on this issue are De Jong and Mentink (2005) and Brockman et al. (2009) but their data sets are restricted to 2004 and 2003, respectively, while the data set presented here is much more actual and broad. Second, positive evidence of commonality in liquidity motivates to further investigate the liquidity risk premium, as indicated by the performance of the traded liquidity risk factor in Chapter 3 and by taking into account widely used risk adjustments. Existing studies on this issue refer to single European countries (see Martinez et al. (2005) for Spain or Mazouz et al. (2009) for the London Stock Exchange), but there is no pan-European study on this issue. However, the increase in interrelations between European capital markets, contagious effects and even crises influencing many capital markets simultaneously call for a thorough investigation of systematic liquidity in Europe.

Third, the application of a stochastic discount factor, Generalized Method of Moments based procedure in addition to an analysis of the liquidity risk premium takes into account that, in the case of correlated risk factors, estimates of risk premia may be unreliable, see Cochrane (2001) p. 260. Thus, the analysis based on risk premia as well as stochastic discount factors provides for a broad and robust evidence on the pricing of liquidity risk. Last, the time period analyzed in this empirical study covers the financial crisis. This offers not only to investigate the evolution of systematic liquidity during crises as emphasized by, among others, Pastor and Stambaugh (2003) or Watanabe and Watanabe (2008), but also to examine the role of liquidity as a pricing determinant during periods of market turmoil, when the investment opportunity sets as well as marginal rates of substitution of investors are strongly affected.

The detailed analysis of liquidity is motivated by broad recent evidence which lead researchers to suspect liquidity to be a factor determining asset prices. Thereby, liquidity refers to how easy it is to trade a security on the capital market. For example, Gibson and Mougeot (2004) define liquidity as the time and cost which are associated with the liquidation (or purchase) of a given quantity of financial securities. In traditional equilibrium or arbitrage asset pricing models the aspect of liquidity is either ignored, precluded or the equilibrium even rules out trading, but in several studies it has been shown that more illiquid securities offer higher returns, see e.g. Amihud and Mendelson (1986), Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996) or Datar et al. (1998). Such studies show that illiquid assets as well as assets with high transaction costs trade at low prices relative to their expected cash flows. There exists also a time-series relation between measures of market liquidity and expected market returns, see e.g. Amihud (2002). However, even if the level of liquidity like e.g. the bid-ask spread may be a determinant of stock returns, it is of question whether liquidity is time-varying, systematic and hence priced, see Chacko (2005). As evidence of commonality in liquidity (e.g. Chordia et al. (2000)) as well as liquidity being a systematic risk factor (see e.g. Pastor and Stambaugh (2003) or Acharya and Pedersen (2005)) confirms the systematic nature of liquidity, it seems to be worth to more closely investigate systematic liquidity in Europe.

This chapter is structured as follows. The next section gives an overview on related literature on liquidity. Section 4.3 outlines the empirical research design with respect to the stochastic discount factor approach and the Generalized Method of Moments. Then, in Section 4.4 the data set is described, before in Section 4.5 the empirical evidence on different aspects of liquidity in Europe is given. Section 4.6 concludes.

4.2 Literature review

4.2.1 Liquidity and commonality in liquidity

In addition to a large number of studies documenting a liquidity effect in individual stock returns, see an overview in Amihud et al. (2005)), recent empirical findings give evidence on an aggregate effect determined as commonality in liquidity, where there may be a market-wide, systematic risk of liquidity concerning all stocks. The most prominent studies which show that, on the U.S. market, individual stock liquidity is characterized by comovements with market-wide liquidity include Chordia et al. (2000) and Huberman and Halka (2001). Chordia et al. (2000) argue that commonality in liquidity probably arises if inventory fluctuations are correlated across individual securities as simultaneous large orders may put common pressure on individual securities. This may for example result from institutional funds following a similar investment style which leads to correlated trading patterns. Hence, liquidity could be expected to exhibit a similar comovement and there may be a covariation in liquidity and associated comovements in trading costs, which then influences a stock's expected return. Huberman and Halka (2001) report similar findings, but attribute commonality in liquidity to the presence of noise traders who trade on non-information as if it were information. In contrast, Hasbrouck and Seppi (2001) find a rather small commonality in intra-daily liquidity measures in the constituent stocks of the Dow Jones Industrial index. Another model which offers a theoretical explanation for commonality in liquidity is given by Brunnermeier and Pedersen (2009) which relate this effect to the funding liquidity and the capital as well as the margin requirements of traders.

This evidence on commonality in liquidity has been the corner stone for taking into account liquidity as a systematic risk factor in asset pricing, as is outlined next.

4.2.2 Liquidity and asset pricing

If commonality in liquidity exists and influences a stock's expected return, liquidity may be regarded as a systematic and not only individual risk factor which has to be considered in asset pricing. There is a growing number of studies on this subject. With respect to U.S. data, among others, Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) investigate whether stocks with greater sensitivities towards aggregate liquidity fluctuations earn higher expected returns. This is often measured by liquidity betas, i.e. stocks with higher covariance with market liquidity offer higher expected returns. Evidence for the U.S. that liquidity is a priced state variable is found by Pastor and Stambaugh (2003). Acharya and Pedersen (2005) develop an asset pricing model on the basis of three additional risk factors due to liquidity besides the well-known market risk factor. These are liquidity risk due to commonality in liquidity with market liquidity, return sensitivity to market liquidity as well as liquidity sensitivity to market returns. Acharya and Pedersen (2005) conclude that the risk premia in their liquidity augmented model are significant with respect to U.S. data.

Amihud (2002) finds a positive cross-sectional relationship between stock returns and liquidity on the stock market, finally concluding that liquidity is priced. Gibson and Mougeot (2004) find that liquidity is priced in U.S stocks, that the liquidity premium is time-varying and that systematic liquidity risk even dominates market risk. In addition, Goyenko (2006) concludes that both stock and bond liquidity are priced in the stock market even after controlling for the Fama and French and Carhart factors. Furthermore, Watanabe and Watanabe (2008) detect time variation in liquidity betas and liquidity risk premia. This assortment of evidence shows that liquidity may not only be a cross-sectional determinant of stock returns but also a risk factor even possessing changing characteristics over time. Hence, according to these U.S. studies, liquidity may be an important risk factor in asset pricing which has until the recent years not thoroughly been considered in asset pricing. International evidence on the pricing of liquidity risk is given by the following studies. Chan and Faff (2005) find support of a Fama and French three factor model which has been augmented by a liquidity factor for Australian data. Bekaert et al. (2007) investigate 19 emerging markets and find that liquidity risk is an essential component of expected excess stock returns, being consistent with liquidity being a priced factor.

Multifactor models including liquidity have been considered only in the recent past. For example, Chordia et al. (2001) show that liquidity is not captured by size and book-to-market factors and find that liquidity coexists with the momentum factor. Goyenko (2006) take into account Fama and French and Carhart models with liquidity. In his findings, liquidity is not represented by size and book-to-market factors but dominates the momentum factor in the Carhart four factor model. Pastor and Stambaugh (2003) and Avramov and Chordia (2006) consider Fama and French and Carhart models with liquidity. Brown et al. (2007) investigate the relationship between stock market trading volume as a measure of liquidity and size, price-to-book and momentum trading strategies. Sadka (2003) examines the relationship between liquidity and momentum, where he also considers a liquidity augmented Fama and French model. Sadka (2003) suggests that the liquidity risk premium explains half of the momentum anomaly and that the momentum anomaly persists because liquidity effects –by causing higher transaction costs– inhibit that this anomaly is exploited. Thus, an anomaly may persist if it carries a premium for liquidity risk.

Overall, this line of research shows that there may be interdependences between liquidity risk and other risk factors which should be considered when analyzing liquidity in order to provide for robust results.

Next, European evidence on liquidity is outlined in more detail.

4.2.3 European evidence on liquidity

In addition to the U.S., there is also some evidence of commonality in liquidity for individual European countries, see e.g. Martinez et al. (2005) for Spain or Galariotis and

Giouvris (2007) for the London Stock exchange. However, the aspect of aggregate liquidity on the overall European capital market has still not been thoroughly analyzed, especially for the recent financial crisis, see the overview on related studies on commonality in liquidity in Section 2.3. None of these studies explicitly examines aggregate liquidity across all European countries with a special focus on pan-European liquidity. One of the few advances in this direction is made by Brockman et al. (2009) who investigate commonality in liquidity with respect to 47 stock exchanges, which cover among others 16 European countries as based on intraday data over the time period October 2002 to June 2004. They find that e.g. commonality in liquidity in North America is stronger than in Europe. Another advance in this direction is given by De Jong and Mentink (2005) who analyze the commonality in liquidity in Euro stock markets, as proxied by the Stoxx Euro 50 index, as well as government and corporate bond markets for 2002 to 2003. There are also some studies analyzing the pricing of liquidity risk for some individual European countries, like Martinez et al. (2005) who conclude that market-wide liquidity does not seem to be priced in the Spanish stock market or Mazouz et al. (2009) who find that systematic liquidity is not priced on the London Stock exchange.

However, there seems to be no study on systematic liquidity for the overall European capital market which also covers the time period since the start of the financial crisis, like it is the case with the data set of the European style indices as given in this thesis. Due to the increasing interdependences between the European capital markets liquidity risk may be a pan-European issue. Hence, this is an interesting field of research as not only single European countries, like e.g. in Martinez et al. (2005), are of interest. This has been illustrated by the recent financial crisis where almost all geographic regions and asset classes have been affected by the financial crisis. As, in this chapter, a time period of seven years of daily data is investigated with respect to a pan-European data set, the findings to be presented as well as the aggregate liquidity risk factor as of Chapter 3 contribute to the still rather small empirical evidence on liquidity in Europe. The first results in Section 3.3.2 on the liquidity risk factor have been in favor of the existence of an aggregate liquidity effect in Europe, but it needs to be investigated more thoroughly whether systematic liquidity risk is priced in the European market.

In the next section, the empirical research design is described in detail.

4.3 Methodology and empirical research design

4.3.1 Two factor liquidity model

The role of liquidity may be theoretically motivated by the ICAPM of Merton (1973) as liquidity risk may capture variations in investment opportunities. Hence, in recessions with unfavorable investment opportunities, investors require higher expected returns when holding assets more sensitive to liquidity risk. High-liquidity risk stocks are also unfavorable in low consumption states of the economy, when marginal rates of substitution of investors regarding additional consumption are high, as it is difficult to sell them during such times and, hence, these stocks do not help to smooth consumption, see the consumption CAPM of e.g. Breeden (1979). If investors prefer future immediacy, they lower the current prices of securities covarying more with market liquidity which leads to higher expected returns, see e.g. Gibson and Mougeot (2004). In a continuous time setting, Longstaff (2001) shows that the discount for illiquidity can be substantial and that investors' portfolio choice may be very different from the choice when there is no liquidity constraint. The motivation of liquidity risk in the context of the ICAPM and the consumption CAPM is also in line with the first empirical evidence in Chapter 3 where the market excess return and the liquidity risk factors have been negatively correlated. Hence, both state variable as well as consumption related argumentations seem to be useful when analyzing the pricing of liquidity in Europe.

In the following, a two factor liquidity pricing model is empirically investigated, including the market excess return and a systematic liquidity factor. Such a model is similar to the return generating processes specified in Gibson and Mougeot (2004), Liu (2006) or Liu (2009). It can be interpreted to be a liquidity augmented CAPM and is also similar to the models applied in Martinez et al. (2005) and Vaihekoski (2009). In the classical multifactor beta representation, this model is represented as

$$E(R_i) - R_f = \beta_{M,i}(E(R_M) - R_f) + \beta_{ILLIQ,i}\lambda_{ILLIQ}. \tag{4.1}$$

where the excess return $E(R_i) - R_f$ of an asset i is determined by the sensitivities $\beta_{M,i}$ and $\beta_{ILLIQ,i}$ of asset i to the market excess return $E(R_M) - R_f$ and the liquidity risk premium λ_{ILLIQ}, respectively. It represents a rather parsimonious but economically motivated asset pricing model which, according to Liu (2006), is more theoretically sound than augmenting the Fama and French model as it is not subject to the problem of arbitrary fishing for factors which describe the returns of assets. Its theoretical motivation of liquidity as a state variable and as a market wide risk factor is economically stronger than compared to rather empirically motivated factors like e.g. the Fama and French factors.

This liquidity augmented two factor model refers to a proxy measure of systematic liquidity. In some studies, like Pastor and Stambaugh (2003) or Liu (2009), liquidity risk is proxied by portfolios containing assets with different sensitivities towards market liquidity. Many other studies model liquidity risk directly by forming liquidity factor-mimicking portfolios, see e.g. Chacko (2005), Liu (2006) or Eckbo and Norli (2007). I consider the last procedure as it is similar to the formation of a zero investment portfolio, see the liquidity risk factor as of Section 3.3.2. The so constructed zero investment liquidity portfolio equals a traded factor long in illiquid and short in liquid Stoxx 600 constituent stocks which is interpretable as a risk factor, see e.g. Cochrane (2001) pp. 230.

The next section describes the empirical research methodology into which the analysis of the two factor liquidity CAPM is embedded.

4.3.2 Empirical research design

The theoretical background of the asset pricing model presented in this chapter refers to the stochastic discount factor (SDF) framework which is naturally combined with the Generalized Method of Moments (GMM). Liquidity in the SDF framework has been considered by Martinez et al. (2005), Goyenko (2006) or Bekaert et al. (2007). With respect to Spain, Martinez et al. (2005) only theoretically addresses the SDF framework in the context of liquidity, while their empirical estimation is based on the traditional multifactor representation. Vaihekoski (2009) conducts an investigation of the pricing of liquidity risk in the Finnish stock market applying GMM, but he also only considers the standard multifactor beta representation. Hence, the research design considering the SDF as well as the GMM framework for investigating the pricing of liquidity in Europe contributes to the current, still scarce research evidence on this subject.

The one step asset pricing method presented by the stochastic discount factor and GMM frameworks possesses several advantages compared to traditional pricing tests. First, in the widely used two step method of asset pricing tests, as in Fama and MacBeth (1973), one first estimates the betas of each asset with respect to different risk factors. In a second step, based on these betas the factor risk premia are estimated, which is subject of an errors-in-variables problem, see Shanken (1992). The approach chosen here avoids this two step estimation procedure. Moreover, this stochastic discount factor model holds only under a few assumptions, e.g. the law of one price, and is not restricted to special equilibrium models. It is a flexible theoretical basis to test the multifactor representation of the stochastic discount factor. If one uses GMM, one does not need to specify assumptions about the distribution of the return data. In contrast, maximum likelihood estimation may be more efficient than GMM but imposes the restriction that one has to know the exact distribution of the data. For example, it is often assumed that returns and factors follow an independent and identical normal distribution, see an overview in Jagannathan and Wang (2002), but asset returns are usually not normally distributed as they e.g. have fatter tails. GMM does not impose such restrictions as it is only based on moment restrictions, see Hansen and Singleton (1982). Moreover, GMM allows for autocorrelated and heteroskedastic pricing errors which may be prevalent in asset pricing tests, especially when using daily data, as GMM is an appropriate estimation method as it is easily adapted in case of serial correlation and heteroskedasticity by choosing an adequate weighting matrix estimation method, whereas the distributional assumptions needed in two-pass regression or maximum likelihood based asset pricing tests may not be fulfilled.

In the context of linear asset pricing models, Jagannathan and Wang (2002) compare the SDF to the traditional beta method and find that, within the SDF framework, one is able to estimate risk premia asymptotically as precise as with the beta method. Even in finite samples, the two methods produce equally precise estimates. They find that under suitable assumptions GMM is also even as efficient as maximum likelihood. Hence, with respect to a data set of daily data, GMM is an appropriate estimation method.

Next, the theory of stochastic discount factors is briefly outlined.

4.3.3 Stochastic discount factors

I investigate the role of liquidity as a determinant of asset prices in the stochastic discount factor (SDF) framework, see among others Cochrane (1996), Ferson and Jagannathan (1996) and Singleton (2006) pp. 195. The respective theorems are e.g. laid out in Hansen and Richard (1987).

The stochastic discount factor framework is advantageous as a method of analysis as basically only a few assumptions are needed. These are mainly the law of one price and no arbitrage possibilities. The law of one price states that all assets with the same payoff must have the same price, implying the existence of a stochastic discount factor. The assumption of no arbitrage opportunities means that in the case of the stochastic discount factor m_{t+1} being a strictly positive random variable all portfolios of assets with payoffs that can never be negative, but that are positive with positive probability, must have a positive price. This guarantees existence of a positive discount factor. Thus, these two main assumptions provide for the existence of a strictly positive stochastic discount factor

m_{t+1}. However, unless in case of complete markets, there is no unique identification of m_{t+1} possible.[11] Furthermore, in the context of the SDF representation it is common to analyze so called gross returns (i.e. returns plus one). In line with this, it has to be assumed that the payoff space contains the unit payoff. Moreover, I impose that the payoff space contains the risk-free return in order to be able to analyze e.g. the market excess return. With respect to the empirical use of the stochastic discount factor framework it is in a first step not necessary to assume e.g. investor homogeneity, but such an assumption may be specified depending on the concrete model specification. A more detailed overview on the assumptions behind the SDF representation, like e.g. the conditions of HR-regularity, is given in Hansen and Richard (1987) (HR), Ferson and Jagannathan (1996) as well as Singleton (2006) pp. 196.

A stochastic discount factor m_{t+1} adapts itself to fulfill the following pricing condition with respect to future prices $\mathbf{P}_{t+1}$ and dividends $\mathbf{Div}_{t+1}$

$$\mathbf{P}_t = E_t(m_{t+1}(\mathbf{P}_{t+1} + \mathbf{Div}_{t+1}) \,|\, \Omega_t), \tag{4.2}$$

where Ω_t specifies an information set available at time t, and $E_t(. \,|\, \Omega_t)$ denotes a conditional expectation. All asset pricing models may then be viewed as specifying a particular SDF. For example, in the consumption CAPM of, among others, Breeden (1979) the stochastic discount factor contains the intertemporal marginal rate of substitution. In the SDF framework, asset-specific risk corrections are generated by correlations between random components of the common stochastic discount factor and asset-specific payoffs, see Cochrane (2001) p. 9. Later on, one may consider conditional as well as unconditional representations of the SDF framework.

Next, the model specification of the stochastic discount factor which is empirically estimated is presented.

4.3.4 Model specification of the stochastic discount factor

In the empirical part of this chapter, I consider multifactor models containing liquidity as a risk factor. A general model specification in line with such a factor representation includes $j = 1, ..., k$ factors $\tilde{\mathbf{f}}$, with $\mathbf{f} = [1, \tilde{\mathbf{f}}]'$ and parameters, i.e. $\mathbf{b} = [b_0, \tilde{\mathbf{b}}]'$. The stochastic discount factor then has the following linearly specified form (ignoring the time subscript)

$$m = \mathbf{b}'\mathbf{f} = b_0 + \tilde{\mathbf{b}}'\tilde{\mathbf{f}}, \tag{4.3}$$

[11] Markets are complete if there are as many linearly independent payoffs available in the securities markets as states of nature exist, see Ferson and Jagannathan (1996).

where one of the factors $\tilde{\mathbf{f}}$ equals the liquidity risk factor. Such a linearly specified form of the SDF is also in accordance with Dybvig and Ingersoll (1982) based on unconditional moments and Lettau and Ludvigson (2001) using a conditional framework.

Cochrane (1996) derivates that such a linearly specified stochastic discount factor as of Equation 4.3 is equal to the well-known multifactor representation of returns, see e.g. Hansen and Richard (1987), Ferson and Jagannathan (1996) or Singleton (2006) pp. 290, as shown now in more detail. The rationale behind the following demonstration is that in case of the above specified assumptions being fulfilled –i.e. e.g. without arbitrage possibilities– the stochastic discount factor makes the price of each gross return R equal to 1. Hence, the condition

$$1 = E(mR) = E(\mathbf{f}'\mathbf{b}R) = E(R\mathbf{f}')\mathbf{b} = E(R)E(\mathbf{f}')\mathbf{b} + cov(R,\mathbf{f}')\mathbf{b} \tag{4.4}$$

must hold.[12] After several conversions, one can show that this is equivalent to the well-known multifactor beta model

$$E(R) = R_f + \beta'\lambda, \tag{4.5}$$

where the expected return $E(R)$ is determined by the risk-free rate-of-return R_f, asset specific risk factor betas β and market-wide risk premia λ. This multifactor representation would then be in accordance with the arbitrage pricing theory of Ross (1976) or the equilibrium approaches of Merton (1973), Breeden (1979), and Cox et al. (1985) as given in Section 2.1.

In order to derive Equation 4.5, following Cochrane (1996), one converts Equation 4.4 the following way, see

$$E(R) = \frac{1 - cov(R,\mathbf{f}')\mathbf{b}}{E(\mathbf{f}')\mathbf{b}} = \frac{1 - cov(R,\tilde{\mathbf{f}}')\tilde{\mathbf{b}}}{E(\mathbf{f}')\mathbf{b}} = \frac{1 - cov(R,\tilde{\mathbf{f}}')cov(\tilde{\mathbf{f}},\tilde{\mathbf{f}}')^{-1}cov(\tilde{\mathbf{f}},\tilde{\mathbf{f}}')\tilde{\mathbf{b}}}{E(\mathbf{f}')\mathbf{b}}. \tag{4.6}$$

Then, one derives

$$E(R) = R_f - R_f\beta' cov(\tilde{\mathbf{f}},\mathbf{f}')\mathbf{b} = R_f - R_f\beta' E[(\tilde{\mathbf{f}} - E(\tilde{\mathbf{f}}))\mathbf{f}'\mathbf{b}] = R_f + \beta'\lambda \tag{4.7}$$

by using the following relationships

$$R_f = \frac{1}{E(\mathbf{f}')\mathbf{b}}, \tag{4.8}$$

[12]In the following derivation, for simplification only one asset is considered and the time subscript is ignored.

$$\beta = cov(R, \tilde{\mathbf{f}}')cov(\tilde{\mathbf{f}}, \tilde{\mathbf{f}}')^{-1} \tag{4.9}$$

and

$$\lambda = -R_f E[m(\tilde{\mathbf{f}} - E(\tilde{\mathbf{f}}))], \tag{4.10}$$

see Cochrane (1996). The last term in Equation 4.7 equals Equation 4.5, q.e.d. As

$$\lambda = -R_f E[(\tilde{\mathbf{f}} - E(\tilde{\mathbf{f}}))\mathbf{f}'\mathbf{b}] = -R_f cov(\tilde{\mathbf{f}}, \mathbf{f}')\mathbf{b} \tag{4.11}$$

holds, the hypotheses of $b_j = 0$ and $\lambda_j = 0$ for a factor j are equivalent only if the factors are orthogonal and hence $cov(\tilde{\mathbf{f}}, \mathbf{f}')$ is diagonal, as will be explained in more detail below.

The relevant empirical question is whether one can construct a stochastic discount factor m pricing the test assets to be examined –i.e. assets with gross returns– without the factor f_j of interest, see Cochrane (1996). According to Cochrane (2001) p. 260, if a factor significantly enters the SDF, it is marginally useful in pricing assets given the presence of the other factors in the SDF specification. However, if the estimated parameter on the factor is not significant, one can price other assets without this risk factor. The parameter b_j can be interpreted as a multiple regression coefficient of m on f_j given the other factors, whereas the λ_j gives the single regression coefficient of m on f_j. This results from

$$\lambda = -R_f cov(m, \tilde{\mathbf{f}}'), \tag{4.12}$$

whereas the SDF representation

$$m = \mathbf{b}'\mathbf{f} \tag{4.13}$$

can be interpreted as a multiple regression. While the parameter vector $\mathbf{b}$ can be interpreted as regression coefficients of m on $\tilde{\mathbf{f}}$, the β give the regression coefficients of R on $\tilde{\mathbf{f}}$, see also Cochrane (1996).

The pricing implications of the multifactor beta and the stochastic discount factor representations are equivalent only in case of uncorrelated factors, see also Singleton (2006) p. 292. Cochrane (2001) pp. 260 demonstrates that in the presence of correlated factors, as it may be an issue with e.g. the free-float weighted market excess return and liquidity factor in Section 3.3.2 which are characterized by a correlation of -0.30, the SDF method is more appropriate than the multifactor method. This aspect is ignored by many researchers when analyzing risk premia as they do not to take into account whether their factors are correlated. In the case of such correlated factors, for example, a spurious factor would possess a positive beta on other priced factors with which it is correlated and, hence, the spurious factor would receive a positive expected excess return in the traditional beta framework.

However, in the SDF framework, the spurious factor would not help to price other assets as the SDF automatically controls for the presence of other priced risk factors. Thus, it is more appropriate to test whether a factor j is a relevant part of the pricing kernel given the presence of these other factors by testing $b_j = 0$. Furthermore, the equation

$$\lambda = -R_f E(m(\widetilde{\mathbf{f}} - E(\tilde{\mathbf{f}}))) \tag{4.14}$$

can be rewritten with respect to factor j as

$$\lambda_j = -R_f(E(mf_j) - E(m)E(f_j)) = E(f_j) - R_f E(mf_j), \tag{4.15}$$

using the equivalence

$$R_f = \frac{1}{E(m)}. \tag{4.16}$$

If f_j is an excess return or the return on a zero investment portfolio or traded risk factor,

$$E(mf_j) = 0 \tag{4.17}$$

holds and, hence,

$$\lambda_j = E(f_j) \tag{4.18}$$

holds. Thus, the risk premium λ then equals the expected factor return, see also Cochrane (1996), Campbell et al. (1997) p. 231, Cochrane (2001) pp. 230 or Jagannathan and Wang (2002).

The role of liquidity is mainly analyzed by considering the two factor specification of the SDF as of Section 4.3.1. Thus, for this two-factor representation including the market excess return $R_M - R_f$ and the liquidity risk factor f_{ILLIQ}, the stochastic discount factor would equal

$$m = b_0 + b_1(R_M - R_f) + b_2 f_{ILLIQ}. \tag{4.19}$$

Hence, assuming traded risk factors, this would be equivalent to the return generating process specified in Section 4.3.1

$$E(R_i) = R_f + \beta_{M,i}(R_M - R_f) + \beta_{ILLIQ,i}\lambda_{ILLIQ} \tag{4.20}$$

for asset i. This specification results if the market excess return is orthogonal to the liquidity risk factor. Thus, if I find the liquidity factor to be significant in the linear SDF specification of Equation 4.19, this indicates that liquidity helps to price other assets.

Then, if liquidity is orthogonal to other factors in the SDF, this would be equivalent to liquidity being a priced risk factor.[13]

This model of the stochastic discount factor can be translated in pricing error conditions which can be empirically investigated as is shown next.

4.3.5 Empirical pricing error conditions

The adequate stochastic discount factor m leads to the following pricing error condition

$$E[m_{t+1}\mathbf{R}_{t+1} - \mathbf{1}] = \mathbf{0} \tag{4.21}$$

where $\mathbf{R}$ is a vector of simple gross returns, i.e. returns plus one, for $1,\dots,N$ assets. In an econometric asset pricing test, these expected pricing errors are minimized using GMM, see Hansen (1982), as outlined in the next section. Hence, one minimizes the following moment conditions

$$\mathbf{g}_T \equiv E_T[m_{t+1}\mathbf{R}_{t+1} - \mathbf{1}] = \frac{1}{T}\sum_{t=1}^{T}[m_{t+1}\mathbf{R}_{t+1} - \mathbf{1}] = \frac{1}{T}\sum_{t=1}^{T}[\mathbf{f}'_{t+1}\mathbf{b}\mathbf{R}_{t+1} - \mathbf{1}], \tag{4.22}$$

where E_T denotes the sample mean.

In the unconditional asset pricing tests applied in this chapter, the following moment restrictions as suggested by Cochrane (1996) as well as Ferson (2003) are taken into account. First, the pricing errors $\mathbf{u}_t$ shall have zero mean

$$\mathbf{g}_T = E_T[\mathbf{u}_t] = E_T[\mathbf{f}'_{t+1}\mathbf{b}\mathbf{R}_{t+1} - \mathbf{1}] = \mathbf{0}. \tag{4.23}$$

Second, the pricing errors shall be orthogonal to instruments $\tilde{\mathbf{z}}_t$

$$\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \tilde{\mathbf{z}}_t] = E_T[(\mathbf{f}'_{t+1}\mathbf{b}\mathbf{R}_{t+1} - \mathbf{1}) \otimes \tilde{\mathbf{z}}_t] = \mathbf{0}, \tag{4.24}$$

where $\tilde{\mathbf{z}}_t$ is a vector of $1,\dots,l$ lagged instruments. The symbol $\otimes$ denotes the Kronecker product with every element being multiplied by every other element. Even if one considers instruments $\tilde{\mathbf{z}}_t$ which are assumed to have predictionary power with respect to future returns, the correct stochastic discount factor would drive such a predictive ability out.

[13] This two factor specification of the SDF is similar to the one specified in Martinez et al. (2005) but they do not empirically analyze the pricing implications of liquidity in the stochastic discount factor framework. They rather consider a standard multifactor model. However, Martinez et al. (2005) implicitly assume that their factors are uncorrelated, otherwise the two representations would not be equivalent regarding their interpretation as has been shown above.

Thus, by imposing restriction 4.24, returns discounted by the SDF are unforecastable by linear regression. This representation using instruments as variables predicting returns results from the law of iterated expectations where one conditions down from the agents' information sets to coarser information sets observable with respect to selected instrument variables, see Cochrane (2001) pp. 134 or Farnsworth et al. (2002).[14] In Equation 4.24, if one includes the above specified factors $\tilde{\mathbf{f}}$ instead of instruments $\tilde{\mathbf{z}}$, this would be similar to a least squares condition with pricing errors being orthogonal to explanatory variables $\tilde{\mathbf{f}}$. This is an approach suggested by Hansen and Singleton (1982) and, for example, followed by MacKinlay and Richardson (1991) and Kan and Zhou (1999). Hence, in the following empirical research, I consider the orthogonality of pricing errors with factors

$$\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \tilde{\mathbf{f}}_t] = \mathbf{0}, \tag{4.25}$$

see also e.g. Campbell et al. (1997) p. 208 and MacKinlay and Richardson (1991). Applying the definition

$$\mathbf{f}_t = [1, \tilde{\mathbf{f}}_t], \tag{4.26}$$

one can summarize both conditions in Equations 4.23 and 4.25 into one condition of the form

$$\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t] = \mathbf{0}. \tag{4.27}$$

Further empirical conditions which have been proposed in the literature and which may later on be added to the research design impose that the stochastic discount factor should price the risk-less asset in order to increase estimation efficiency, see e.g. Farnsworth et al. (2002). Moreover, Farnsworth et al. (2002) also suggest an additional restriction that, in traded factor models, it is important that the model prices the traded factor. One could also impose the restriction that the factors only conditionally help to price assets. Thus, one analyzes scaled factor models where the factors in the stochastic discount factor itself are scaled by instruments, see Cochrane (1996) or Lettau and Ludvigson (2001). However, there are two disadvantages to this approach. First, the number of moment restrictions becomes quite quickly very large. Second, scaling of the factors in the SDF itself is much more subject to arbitrary choices in the instruments than only specifying orthogonality conditions with respect to instruments. Hence, I do not consider such a scaled factor model but only consider factors as instruments in orthogonality conditions.

According to Jagannathan and Wang (2002), the SDF method combined with the empir-

[14] A conditional explanation of the instrument variables is also given in Cochrane (1996) if one considers instruments that have empirical power to characterize the conditional distribution of returns.

ical method of GMM offers a convenient general framework for analyzing linear as well as nonlinear asset pricing models. So, GMM is explained in detail in the next section.

4.3.6 The Generalized Method of Moments

The Generalized Method of Moments (GMM) chooses parameters **b** to minimize the following weighted sum of squared pricing errors across individual assets

$$J_T = \mathbf{g}_T(\mathbf{b})'\mathbf{W}\mathbf{g}_T(\mathbf{b}), \tag{4.28}$$

with the parameter estimate being equal to

$$\hat{\mathbf{b}} = \arg\min_{\mathbf{b}} \mathbf{g}_T(\mathbf{b})'\mathbf{W}\mathbf{g}_T(\mathbf{b}). \tag{4.29}$$

GMM is based on Hansen (1982) and is for example described in detail in Cochrane (2001) pp. 189 or Singleton (2006) pp. 25. The main characteristic of the GMM estimate $\widehat{\mathbf{b}}$ is that it is a consistent, asymptotically normal and asymptotically efficient estimate of the parameter vector **b**. There are only a few assumptions needed when applying GMM. The variables in the pricing errors which are calculated in the stochastic discount factor framework must be stationary and ergodic random variables with finite fourth moments, see in detail Hansen (1982), Campbell et al. (1997) p. 208 and Singleton (2006) pp. 195.

In the Hansen (1982) and Hansen and Singleton (1982) two-step GMM estimation procedure, the first stage estimate is calculated considering

$$\mathbf{W} = \mathbf{I}. \tag{4.30}$$

This means that an identity matrix **I** is used as a weighting matrix **W** and that all moments $\mathbf{g}_T$ are equal-weighted in a first step. In the second stage, the estimate is calculated with

$$\mathbf{W} = \mathbf{S}^{-1}, \tag{4.31}$$

based on the covariance matrix

$$\mathbf{S} = \sum_{j=-\infty}^{\infty} E[\mathbf{u}_t(\mathbf{b})'\mathbf{u}_{t-j}(\mathbf{b})]. \tag{4.32}$$

With weighting matrix **S**, one pays less attention to moments from assets with high variation of the pricing errors.

This two-step GMM procedure is efficient and appropriate for empirical asset pricing studies, but it may be useful to check in later robustness tests whether these non-iterated two-step results are similar to those of an iterated GMM procedure. In such an iterated procedure, one iterates the above mentioned procedure by using the estimated weighting matrices $\hat{\mathbf{S}}_1^{-1}$, $\hat{\mathbf{S}}_2^{-1}, \ldots$ in each iteration step. This iterated, also efficient GMM estimator possesses the same asymptotic distribution as the two-step efficient estimator. According to Cochrane (1996) and Ferson and Foerster (1994), iterating does not change the asymptotic distribution theory, but small-sample properties are improved and results may be more stable across small variations in model setups. Overall, iterated GMM is asymptotically equivalent to two-step GMM, but it is computationally much more burdensome. For larger systems with more than a few test assets, this problem is prevalent and deficiencies, like failure to converge, are an issue, see Harvey and Kirby (1995). In systems characterized by smaller sample sizes and more complex models it may be that iterated GMM is preferable to the two-step GMM of Hansen and Singleton (1982) as, in such a case, the respective models may be rejected too often, see Ferson and Foerster (1994). This problem especially concerns large cross-sections with short time-series and complex models. However, as the data set considered in this chapter consists of a relatively small cross-section of assets and a quite long observation period based on daily data, applying the two-step estimation procedure is feasible. Moreover, linear models are considered which should not be too complex and hence should not deteriorate the two step results.

With respect to estimating the weighting matrix $\mathbf{S}$, the heteroskedasticity and autocorrelation consistent (HAC) covariance matrix is applied. The kernel used in the empirical analysis equals the quadratic kernel of Andrews (1991) with the Newey and West (1994) bandwidth method. This ensures a minimum asymptotic mean square error for the estimation of the covariance matrix $\mathbf{S}$. An appropriate choice of kernel shall ensure a weighting of the covariances considering consistency and positive semi-definiteness. The choice of bandwidth relates to the lags considered in the estimation of the kernel. For more information see in detail Hall (2005) pp. 79.

In the next section the respective tests are outlined.

4.3.7 GMM tests

One can test for the overall goodness-of-fit of asset pricing models which are empirically estimated by GMM by analyzing the minimized value of the target function of Equation 4.28, see e.g. Hansen (1982), Cochrane (2001) p. 196 as well as Singleton (2006) pp. 71.

This is the so called J-statistic where

$$TJ_T = T\mathbf{g}_T(\hat{\mathbf{b}}_T)'\hat{\mathbf{S}}_T^{-1}\mathbf{g}_T(\hat{\mathbf{b}}_T) \sim \chi^2(\#moments - \#param) \qquad (4.33)$$

holds. In the following empirical estimation procedure, *#moments* is calculated from the number of test assets times the number of instruments. The number of instruments equals the number of factors included in the SDF plus one for the constant. Then, the number of estimated parameters plus one (for the constant), i.e. *#param*, is subtracted. Thus, if one considers e.g. 50 test assets and two factors, one pricing error condition and 2 orthogonality conditions arise from the condition in Equation 4.25 in order to estimate two parameters and the constant. Then, the number of overidentifying restrictions equals $50*3-3 = 147$.

Furthermore, a test whether a parameter $\hat{b}_j$ is equal to zero has the following form

$$\frac{\hat{b}_j}{\sqrt{var(\hat{b})_{jj}}} \sim N(0,1), \qquad (4.34)$$

see Cochrane (2001), p. 192. If one finds an estimated parameter $\hat{b}_j$ to be significant regarding factor j, this means that factor j helps to price assets. Later on, Wald tests are also considered in order to test for the joint significance of the estimated parameters, see in detail Ferson and Jagannathan (1996).

In the next section, the data are going to be described.

4.4 Data

4.4.1 Time horizon

The relevance of liquidity pricing in the European capital market is investigated based on the daily data over the seven years period as derived from the risk factor data set of Chapter 3. The European capital market is proxied by the constituent stocks of a well-known European stock index as already described in detail in Section 3.2.1. Daily data in asset pricing tests are not as common as monthly data, but are used in e.g. Lewellen and Nagel (2006) with respect to the conditional CAPM or Mazouz et al. (2009) with respect to the investigation of liquidity on the LSE. GMM accounts for the statistical characteristics of daily data and microstructure issues of daily data will also be addressed in order to provide for robust daily estimates.

The time period of seven years which is given by the data set based on the European style indices presented in Chapter 3 is not extensive for an asset pricing test. However, as was the case with the LTCM break-down or the recent financial crisis, liquidity crises can evolve very quickly and, hence, the effects on asset prices should become obvious rather fast. Due to the fact that the regulatory differences in the European Union have only declined in the recent past, a pan-European asset pricing test which goes too far back into the past would not be reliable as well. This hence hampers a long-term pan-European asset pricing test. The high number of observations using daily data should provide for a feasible research design, even when only seven years of data are analyzed. Thus, the investigation of liquidity in a short-term context should be feasible to get a first insight on the pricing of liquidity risk in Europe. There are several studies which conduct asset pricing tests in the short term. For example, Rouwenhorst (1999), who take into account turnover as a measure of liquidity, examines returns in twenty emerging markets over often ten or less years. The analysis in Martinez et al. (2005) on the Spanish stock market analyzes a time period of seven years from 1993-2000. Jun et al. (2003) investigate the pricing of liquidity in emerging markets over the seven years period from 1992 to 1999.

Moreover, the data sample covers the recent financial market crisis. Especially the role of liquidity in this time period is of interest for a detailed empirical research as liquidity may be considerably interrelated with such crises. This was for example the case with the LTCM crisis of 1998 which was linked to flight-to-liquidity effects where investors searched for more liquid assets after the Russian government bond crisis, finally leading to the collapse of the Long-Term Capital Management (LTCM) hedge fund.

Next, the risk factors and test assets which are empirically examined are briefly outlined.

4.4.2 Risk factor portfolios and test assets

The risk factors which I examine in the following analysis refer to the risk factors in Chapter 3. These risk factors used to estimate the stochastic discount factor are calculated on the basis of simple total returns. The empirical analysis in this chapter is focused on the free-float weighted and quarterly rebalanced risk factors as these specifications are advantageous with respect to e.g. transaction costs, see the discussion in Chapter 3. Momentum refers to the factor based on the six month momentum index. The liquidity risk factor is constructed as a risk factor long in illiquid and short in liquid stocks as measured by the quarterly undetrended Amihud measure.

Now, the set of test assets which serve as independent variables in the SDF based asset pricing test are described. Whether to use individual stocks or portfolios as test assets possesses both advantages as well as disadvantages. Studies which investigate test portfolios are Vassalou (2003) as well as Petkova (2006) who both examine the 25 Fama and French portfolios as test assets. Pastor and Stambaugh (2003) investigate 10 portfolios sorted on liquidity factor loadings. Portfolios constructed based on specific criteria as test assets have more stable characteristics over time and smaller standard deviation than individual stocks, offering the possibility to conduct more precise asset pricing tests as idiosyncratic volatility and hence the standard errors in the estimated factor loadings are reduced, see also Malkiel and Xu (2004). Moreover, individual stock betas vary over time as e.g. the business they are in changes, whereas portfolios are more stable over time. However, Litzenberger and Ramaswamy (1979) argue that if one uses a larger number of individual stocks, the efficiency of the estimates is better as, otherwise, grouping leads to a loss of information. Moreover, the portfolio formation procedure may be arbitrarily chosen. As the academic discussion is still going on this issue, I use individual stocks as well as portfolios as test assets when estimating the SDF.

To proxy for the European market the set of test assets examined comprises the constituent stocks of the Stoxx Europe 50 index at the end of the observation period as indicated at www.stoxx.com. The Stoxx Europe 50 index is a blue-chip subindex of the Stoxx Europe 600, which also covers European countries which are not in the Eurozone, and it represents a quite stable data universe. All constituent stocks in the Stoxx Europe 600 are not used as test assets because of the very high estimation complexity of such a large system when using GMM. According to Cochrane (2001) pp. 213 and pp. 225, the number of test assets should not be large compared to the number of observations in order to avoid near singularity of the weighting matrix, as, then, the Hansen GMM two-step estimator can not be estimated. Such estimation problems arise because the system as well as the number of moments to be estimated become large very quickly.

The data on the individual Stoxx Europe 50 constituents comprise stock-split adjusted total returns which have been retrieved from Thomson Datastream. The simple returns, as usually considered in cross-sectional asset pricing tests, see Campbell et al. (1997) are calculated the following way as

$$R_{i,t} = \frac{P_{i,t} + Div_{i,t}}{P_{i,t-1}}. \tag{4.35}$$

As the risk-free rate of return R_f the three-month Euribor is considered. The $R_{i,t}$ in Equation 4.35 are aggregated into $\mathbf{R}$, referring to Equation 4.21, which is in this context a vector of the simple gross returns on the test assets.

An overview of the summary statistics for the individual Stoxx Europe 50 test assets is given in Table A.8 in Appendix A.3. This table gives geometric average returns and further summary statistics for these stocks. It is obvious that the performance of the stocks in the index differs a lot with respect to average per annum returns and minimum and maximum daily returns. The individual stock returns are characterized by significant risk as the relatively high per annum standard deviations suggest. Overall, there seems to be a considerable variation in the summary statistics across the individual stocks which should in the estimation later on be captured by the stochastic discount factor.

Moreover, as argued above, I also construct test portfolios based on different selection criteria which are applied to the Stoxx Europe 600 universe by using Wilshire Atlas. The subportfolios based on this data universe contain a large enough number of stocks and are well diversified. I proceed the following way to construct the test portfolios. First, I divide the universe of these 600 stocks into two groups by free-float market capitalization by applying the same rule like for the size indices specified in Section 3.2.2. Second, I divide the large cap and respectively small cap segment into thirds based on the criteria price-to-earnings ratio, price-to-book ratio as well as dividend yield.[15] Then, the portfolios are free-float weighted and quarterly rebalanced. Each kind of style portfolio set is only divided into six subgroups in order to guarantee that each subportfolio is well diversified and contains a large enough number of stocks. In Table 4.1, the summary statistics of the test portfolios are given. It is evident that due to a diversification effect the standard deviations of these portfolios are smaller than those of the individual test assets above. As suggested by the average per annum returns as well as the minimum and maximum daily returns, there is much less variation in the test portfolio returns than in individual asset returns. The average returns suggest that the small cap portfolios offer consistently higher returns than the large cap portfolios sorted on the same style, but this does not as clearly hold for the price-to-earnings, price-to-book, as well as dividend yield subclassifications. Hence, the classification criteria to form the test portfolio may influence the results, which emphasizes that it is important to analyze individual stocks as test assets as well.

In the next section, the empirical results on several aspects of pan-European liquidity are presented.

[15] The test portfolios are quite similar to the 2 x 3 size and book-to-market portfolios of Kenneth French.

Table 4.1: Summary statistics: Test portfolios

This table gives summary statistics on test portfolios which are sorted on market capitalization and either price-to-earnings (P/E), price-to-book (P/B) or dividend yield characteristics. Daily simple total returns are used to calculate geometric average per annum returns as well as annualized standard deviations. Moreover, daily minimum and maximum returns are given for each portfolio. Sample period: October 1, 2002 to September 30, 2009.

Test portfolio	Geometric average return p.a.	Min. ret. p.d.	Max. ret. p.d.	Std. dev. p.a.
Large cap and high P/E	7.77%	-8.00%	10.24%	20.30%
Large cap and med. P/E	9.52%	-9.17%	12.44%	21.73%
Large cap and low P/E	10.50%	-11.18%	14.91%	29.14%
Small cap and high P/E	12.43%	-8.58%	9.28%	20.63%
Small cap and med. P/E	13.23%	-9.13%	9.73%	21.52%
Small cap and low P/E	12.57%	-10.61%	11.66%	26.54%
Large cap and high P/B	3.50%	-6.16%	9.73%	17.90%
Large cap and med. P/B	6.34%	-8.01%	11.33%	21.69%
Large cap and low P/B	7.63%	-10.04%	13.54%	27.67%
Small cap and high P/B	7.72%	-7.25%	7.84%	19.22%
Small cap and med. P/B	10.47%	-7.44%	9.13%	20.12%
Small cap and low P/B	8.84%	-8.82%	9.69%	24.24%
Large cap and high div. yield	4.97%	-9.57%	12.03%	24.76%
Large cap and med. div. yield	6.12%	-8.00%	10.84%	20.48%
Large cap and low div. yield	4.59%	-7.02%	9.42%	20.78%
Small cap and high div. yield	6.59%	-7.93%	9.63%	22.04%
Small cap and med. div. yield	9.41%	-7.64%	8.92%	20.59%
Small cap and low div. yield	10.93%	-7.74%	7.84%	19.97%

4.5 Empirical analysis

4.5.1 Commonality in liquidity

As a first check on the pan-European role of liquidity in asset pricing I briefly check for the existence of commonality in liquidity as based on the procedure of Chordia et al. (2000), as this is a prerequisite as well as first indicator for liquidity being a priced risk factor, see e.g. the approach in Martinez et al. (2005). In this section, I examine whether commonality in liquidity with respect to the constituent stocks in the Stoxx Europe 600 index as of end of September 2002 exists, as retrieved from www.stoxx.com. As the empirical evidence on European commonality in liquidity is scarce, the findings in this section give additional insights on this issue.

For each index constituent I first calculate the individual Amihud illiquidity measure $ILLIQU_{i,t}$ in the same way as used to construct the liquidity style indices, see Section 3.2.3. The respective volume and price data for all stocks are retrieved from Thomson Datastream. Then, I calculate an aggregate illiquidity measure as a cross-sectionally equally weighted average $ILLIQU_{M,t}$ of these individual Amihud illiquidity measures which is then the explanatory variable in a regression of the following form

$$ILLIQU_{i,t} = a_i + b_i ILLIQU_{M,t} + e_{i,t}, \qquad (4.36)$$

similar to the specification in Chordia et al. (2000).[16] The so conducted ordinary least squares regression takes into account the covariance estimator of Newey and West (1987) for the calculation of the standard errors considering heteroskedasticity and autocorrelation in daily data. I also consider that the equally weighted Amihud measure may be distorted by a few outliers due to extreme daily illiquidity of only a few stocks.[17] To adjust for this I ignore 12 outliers in the overall time series of observations by applying the three sigma rule because some of the individual stocks are extremely illiquid on specific days.[18] As the number of observations for daily data over seven years is large, ignoring this small number of outliers from the overall number of observations should not significantly influence the results. Table 4.2 gives the summary statistics for this aggre-

[16] As the unscaled $ILLIQU_{i,t}$ numbers based on the original return and trading volume data are very small, they are scaled by 10^6, see Amihud (2002).

[17] For example, Arcelormittal is characterized by an extremely high Amihud measure on October 14th, 2002. Since that this may be the cause of data errors in the data source, I ignore the respective outlier observation.

[18] Even in case of not normally distributed data, this method provides for a first outlier check and a quick and objective outlier detection method, see e.g. Wells (1996) pp. 105. For a large number of observations, assuming a normal distribution may be feasible as suggested by the central limit theorem.

gate Amihud illiquidity measure. The aggregate Amihud measure is quite skewed to the right indicating that there are days of very high market illiquidity during the observation period.

Figure 4.1 shows the aggregate illiquidity measure $ILLIQU_{M,t}$, confirming this pattern of extreme illiquidity on some days. One can observe that aggregate illiquidity has been especially high during the bear market after the dotcom bubble and during the financial crisis starting end of 2007. These peaks are in line with the evidence in Pastor and Stambaugh (2003) that stress in market illiquidity is especially high during market downturns and Liu (2006) who find a highly negative correlation between liquidity and the market factor which reflects the state nature of systematic liquidity. Bank et al. (2010) report a similar behavior for the German stock market with an increased illiquidity during the 2002 / 2003 bear market and the global financial crisis at the end of their sample period, i.e. 2009. This confirms the importance of the analysis with respect to this European data set and emphasizes the assumption that liquidity may be an important state variable in the view of the Merton ICAPM.

Following Amihud (2002), I also consider a logarithmical version of the Amihud measure, smoothing the extreme peaks in Figure 4.1 which may not only be sign of extreme illiquidity on specific days, but also be caused by data outliers on specific days or holidays taking place only in specific European countries. Holiday trading is disputed because of the little number of stocks traded, leading to a different price formation process. Moreover, the logarithmic version considers that part of the illiquidity may be expected as well as unexpected by market participants. The logarithmic version of the equally weighted daily market illiquidity $\ln ILLIQU_{M,t}$ is determined by the following autoregressive process

$$\ln ILLIQU_{M,t} = a + b \ln ILLIQU_{M,t-1} + e_t, \tag{4.37}$$

where illiquidity of one day can be understood to be a predictor of next day's illiquidity. The fitted values from the left hand side of Equation 4.37 can then be interpreted as expected illiquidity, i.e. $\ln ILLIQU^{E}_{M,t}$, while the residual e_t displays a kind of unexpected illiquidity, i.e. $\ln ILLIQU^{U}_{M,t}$. In Table 4.2, the regression output is given for Equation 4.37. The results show that the previous period's illiquidity has a strong predictionary power with respect to the actual period's illiquidity. Actual aggregate illiquidity as well as expected and unexpected illiquidity are given in Figure 4.2. There, it becomes clear that unexpected illiquidity is relatively stable over time, while most of the dynamics in aggregate illiquidity comes from dynamics in expected illiquidity. More obviously than in Figure 4.1, where one is distracted by peaks of illiquidity on specific days, one ob-

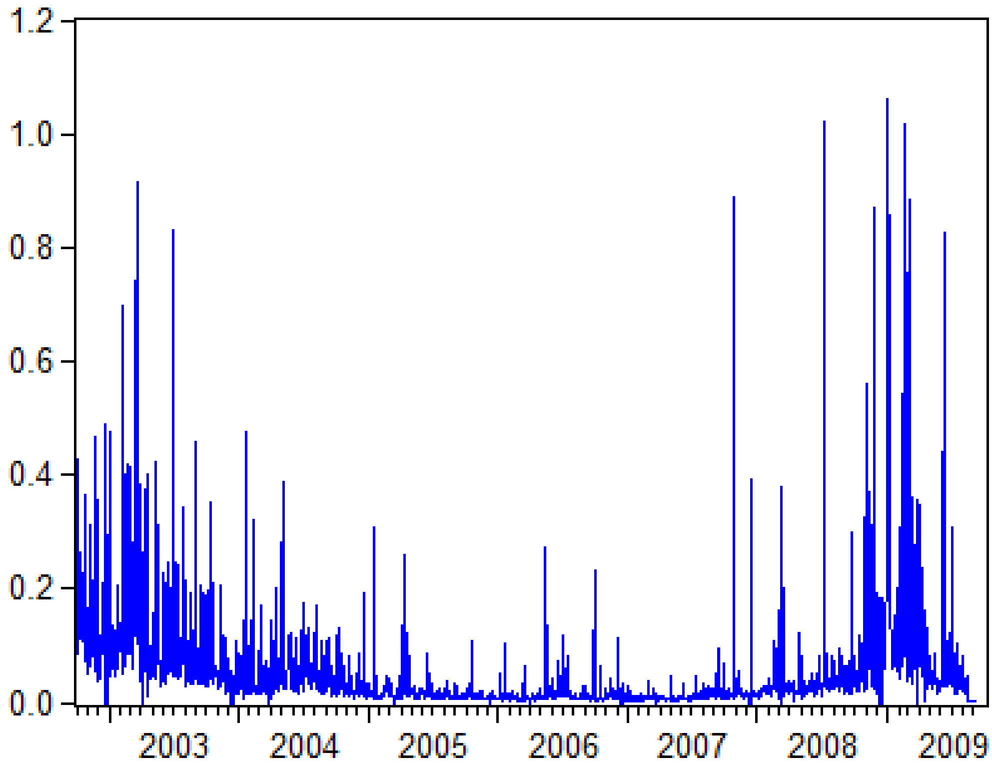

Figure 4.1: Daily market illiquidity

This graph shows equally weighted daily market illiquidity as proxied by the illiquidity measure of Amihud (2002) for the constituent stocks in the Stoxx Europe 600. Sample period: October 1, 2002 to September 30, 2009.

serves that around the start and the end of the observation period actual and expected market illiquidity have been highest, underlining the state variable view of liquidity risk as these have been the periods of market stress. Amihud (2002) emphasizes that expected illiquidity influences expected returns. Hence, expected returns should have risen in these periods of higher expected market illiquidity. This role of liquidity in asset pricing then needs to be verified.

Regarding commonality in liquidity, Table 4.2 gives the percentage of significantly positive coefficients b_i in the individual commonality in liquidity regressions across all Stoxx Europe 600 constituent stocks as of Equation 4.36. Here, almost all of the coefficients are significantly positive at the 5%-level, confirming that pan-European commonality in liquidity is an important issue as a high number of individual stocks is characterized by

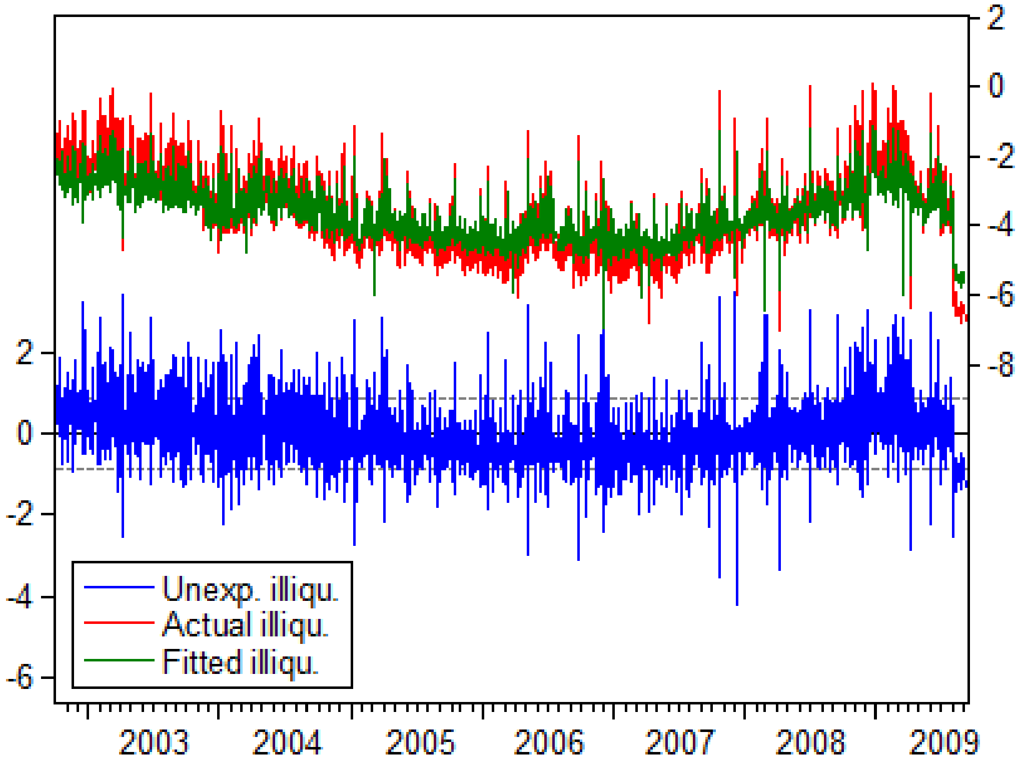

Figure 4.2: Expected and unexpected illiquidity

This graph shows actual logarithmic equally weighted daily market illiquidity as proxied by the illiquidity measure of Amihud (2002) for the constituent stocks in the Stoxx Europe 600. Moreover, expected illiquidity $\ln ILLIQU^E_{M,t}$ and unexpected illiquidity $\ln ILLIQU^U_{M,t}$ are given. Expected illiquidity is approximated by the fitted values from
$\ln ILLIQU_{M,t} = a + b \ln ILLIQU_{M,t-1} + e_t$,
while the residual e_t equals a measure of unexpected illiquidity. Sample period: October 1, 2002 to September 30, 2009.

a significantly positive correlation of their individual Amihud illiquidity with an average measure of illiquidity. The average coefficient on $ILLIQU_{M,t}$ is quite high and positive and the average t-statistic is also quite high. However, the R^2-statistics are not very high on average, but the result with respect to the R^2 is similar to the result in e.g. Brockman et al. (2009). However, there, less than one fourth of the firms possess a significant coefficient on commonality in liquidity, whereas, here, the results are more pronounced. Similar to the results presented here, De Jong and Mentink (2005) conclude that commonality in liquidity between Euro security markets exists. Moreover, Martinez et al. (2005) find for Spain that more than sixty percent of the firms exhibit a positive coefficient on commonality in liquidity, with also only an average R^2 of 0.140.

Overall, the results show the state variable nature of liquidity in Europe as well as commonality of liquidity. Hence, in the next sections, an in-depth investigation of the pan-European pricing of liquidity as a market wide risk factor is useful.

4.5.2 Analysis of the liquidity risk premium

Now, the liquidity risk premium is analyzed more deeply. If liquidity risk is priced in European stocks, one should find systematic differences in the risk-adjusted performance of liquidity sorted portfolios. Risk premia may be directly estimated from the simple sample means of the returns on zero investment portfolios, see Campbell et al. (1997) p. 231, Cochrane (2001) p. 231 and Section 4.3.4. In this way Eckbo and Norli (2007) create a zero investment liquidity portfolio and conclude that the unconditional mean portfolio return of this difference portfolio represents a good estimate of the risk premium in case of uncorrelated factors. In order to account for a possible bias in case of correlated risk factors, see Eckbo and Norli (2007) and Section 4.3.3, this will be complemented by a stochastic discount factor analysis.

In Section 3.3.2, the liquidity risk premium has been found to be significantly positive, i.e. 6.20% per annum for free-float weighted liquidity, whereas the other risk factors only show insignificant results. This is in accordance with the finding in Liu (2009) that liquidity has a significant and persistent premium in contrast to size, value and momentum. By additional risk-adjustments I also test whether the liquidity risk premium is still positive after adjusting for well-known risk factors. Thus, I estimate the abnormal return $\alpha_{i,CAPM}$ with respect to the CAPM and the CAPM beta β_i by a regression of the following form

$$R_{i,t} - R_{f,t} = \alpha_{i,CAPM} + \beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t} \tag{4.38}$$

with respect to simple returns $R_{i,t}$. I consider the covariance estimator of Newey and West

Table 4.2: Commonality in liquidity: Stoxx Europe 600 constituent stocks

This table gives the summary statistics for the aggregate, equally weighted Amihud measure $ILLIQU_{M,t}$ for the index constituent stocks of the Stoxx Europe 600 as of end of September 2009. Moreover, it gives the regression output of estimating $\ln ILLIQU_{M,t} = a + b \ln ILLIQU_{M,t-1} + e_t$ in order to receive a measure of expected (exp.) and unexpected (unexp.) illiquidity. The average coefficients and t-statistics of an ordinary least squares regression of the form $ILLIQU_{i,t} = a_i + b_i ILLIQU_{M,t} + e_{i,t}$ are given in the table as well. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). $ILLIQU_{i,t}$ equals the Amihud measure for each individual constituent stock of the Stoxx Europe 600. The table also displays the fraction of individual stocks with a significantly positive as well as negative coefficient b_i on the aggregate Amihud measure $ILLIQU_{M,t}$ in the regression of Equation 4.36. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

Aggregate Amihud measure	Mean	Median	Std. dev.	Skewness
$ILLIQU_{M,t}$	0.057	0.023	0.105	5.118
Estimation of exp. and unexp. liqu.		a	b	R^2
	$\ln ILLIQU_{M,t}$	-1.215***	0.666***	0.457
	T-stat.	-12.306	24.965	
Commonality in liqu.: Aggregate results		Average a_i	Average b_i	Average R^2
	Coeff.	0.001	0.981	0.059
	T-stat. (average)	11.806	4.224	
Commonality in liqu.: Individual stock results	Fraction of pos. coeff.	98.17%	Fraction of neg. coeff.	0.18%
	Fraction of signif. pos. coeff. (10%-level)	93.02%	Fraction of signif. neg. coeff. (10%-level)	0.50%
	Fraction of signif. pos. coeff. (5%-level)	91.03%	Fraction of signif. neg. coeff. (5%-level)	0.50%

(1987) for the calculation of the standard errors in order to take into account possible heteroskedasticity and autocorrelation in the daily data. The dependent variable $R_{i,t} - R_{f,t}$ includes the high and low liquidity portfolios minus the risk-free rate. Furthermore, it contains the liquidity risk factor of Chapter 3, but as the liquidity risk factor is already a difference portfolio, it is in this case not necessary to subtract the risk-free rate of return. All these variables are based on the free-float weighted, quarterly rebalanced top and bottom illiquidity European style indices or respectively risk factors, as calculated from the quarterly Amihud measure, see Chapter 3.

Moreover, I estimate the three-factor alpha $\alpha_{i,FF}$ and the respective factor sensitivities in the Fama and French (FF) three factor model in order to control for size and value vs. growth effects by including the $SIZE_t$ and VAL_t risk factors

$$R_{i,t} - R_{f,t} = \alpha_{i,FF} + \beta_{i,1}(R_{M,t} - R_{f,t}) + \beta_{i,2} SIZE_t + \beta_{i,3} VAL_t + \varepsilon_{i,t}. \tag{4.39}$$

The definition of the market excess return, size and valuation follows those on the free-float weighted, quarterly rebalanced risk factors from Chapter 3. The results on the risk-adjusted liquidity risk premium are given in Table 4.3.

The results in Table 4.3 suggest that neither inclusion of the CAPM nor the Fama and French factors can appropriately account for this liquidity premium. The difference portfolio between illiquid and liquid stocks possesses a significantly positive risk-adjusted per annum performance of 6.5% in the CAPM and 5.8% in the Fama and French model. In line with this, the risk-adjusted performance of the least liquid portfolio, i.e. the top illiquidity portfolio, is significantly positive and much higher than that of the most liquid portfolio. Hence, the liquidity premium is not captured by taking into account market excess return as well as size and valuation as further risk factors. The R^2- and adjusted R^2-statistics are improved if one moves from the one-factor to the multifactor model. Moreover, the R^2-statistics are much higher with respect to the individual top and bottom illiquidity portfolios than with respect to the difference portfolio representing the liquidity risk factor. This is probably due to the fact that these portfolios possess a large comovement with the market excess return, whereas this is not necessarily the case with the liquidity risk factor.

Next, I also explore the factor betas in order to more deeply examine the risk characteristics of the liquidity portfolios and factor. The liquidity risk factor possesses a small but significantly negative market beta in the CAPM. Hence, the liquidity risk premium is rather increasing during market downturns, see also the negative correlation between both risk factors in Section 3.3 and the state variable nature of liquidity presented above. More-

Table 4.3: Risk-adjusted performance of liquidity sorted portfolios: CAPM and Fama and French models

		LIQUIDITY RISK FACTOR	TOP ILLIQUIDITY PORTFOLIO	BOT. ILLIQUIDITY PORTFOLIO
CAPM				
	Alpha	0.000	0.000	0.000
	Alpha p.a.	0.065	0.055	-0.010
	T-stat.: Alpha	2.628***	2.718***	-1.236
	$\beta_{i,1}$ (market)	-0.117	0.923	1.040
	T-stat.: $\beta_{i,1}$ (market)	-6.613***	57.676***	188.159***
	R^2	0.087	0.898	0.988
	Adj. R^2	0.087	0.898	0.988
FAMA AND FRENCH				
	Alpha	0.000	0.000	0.000
	Alpha p.a.	0.058	0.052	-0.006
	T-stat.: Alpha	2.447**	2.592***	-0.833
	$\beta_{i,1}$ (market)	-0.028	0.992	1.021
	T-stat.: $\beta_{i,1}$ (market)	-0.665	28.514***	109.582***
	$\beta_{i,2}$ (size)	0.283	0.174	-0.110
	T-stat.: $\beta_{i,2}$ (size)	7.571***	5.441***	-10.037***
	$\beta_{i,3}$ (val.)	-0.149	-0.123	0.026
	T-stat.: $\beta_{i,3}$ (val.)	-1.491	-1.526	1.322
	R^2	0.201	0.908	0.989
	Adj. R^2	0.199	0.908	0.989
3 leads and lags				
	Alpha	0.000	0.000	0.000
	Alpha p.a.	0.058	0.049	-0.008
	T-stat.: Alpha	2.451	2.523	-1.072
	$\beta_{i,1}$ (market)	0.008	1.012	1.005
CAPM without Januaries				
	Alpha	0.000	0.000	0.000
	Alpha p.a.	0.066	0.053	-0.013
	T-stat.: Alpha	2.622***	2.560**	-1.600
	$\beta_{i,1}$ (market)	-0.121	0.919	1.041
	T-stat.: $\beta_{i,1}$ (market)	-6.557***	54.104***	180.362***
	R^2	0.092	0.896	0.988
	Adj. R^2	0.092	0.896	0.988

over, the liquidity risk factor is characterized by a significantly positive sensitivity towards the size factor, see the hypothesis in Amihud (2002) on size proxying for liquidity. This is also confirmed for the top and bottom illiquidity portfolios where top illiquidity possesses a positive size beta in contrast to the bottom illiquidity portfolio. The sensitivity of the liquidity risk factor towards the market and valuation factors is insignificant in the Fama and French model, which suggests that size dominates the explanatory power of the other variables. This is sensible with respect to the higher positive correlation of liquidity with size than with the other two factors. The high market betas of the top and bottom illiquidity portfolios are in line with the results in Section 3.3 on the style indices which are all very highly correlated with the overall market index, thus indicating a large comovement. The negative, but insignificant sensitivity of the top illiquidity portfolio towards the valuation factor confirms the results of Section 3.3, where the valuation and the liquidity factor have been negatively correlated. This provides for slight evidence that illiquid stocks are rather growth stocks in contrast to Liu (2006) who suspects illiquid stocks to be undervalued, distressed stocks. However, growth stocks may be illiquid as they are rather new to the investment community and, as suggested by the Merton (1987) model and the findings in Kadlec and McConnell (1994), investor recognition and liquidity still have to be improved.

I also take into account the microstructure aspect of asynchronous trading. When using daily data, infrequent and asynchronous trading, as e.g. discussed in Scholes and Williams (1977), may influence beta estimates as stale pricing may prevent changes in risk factors to be immediately reflected in returns. I follow the method of Asness et al. (2001), as applied in Bollen and Busse (2001) and being similar to the Dimson (1979) method, which McInish and Wood (1986) finds to be more successful in accounting for asynchronous trading than e.g. the Scholes and Williams (1977) method. With respect to the one factor model not only current but also lagged market returns are considered and the sum of these coefficients displays the adjusted beta estimator. Hence, I reestimate the CAPM by including three lags as well as leads with respect to each risk factor. The results with respect to the risk-adjusted liquidity risk premium are not changed, confirming the relevance of systematic liquidity. However, the market beta is now slightly positive with respect to the CAPM and the liquidity risk factor as well as the top and bottom illiquidity portfolios. Furthermore, it is useful to take into account that the liquidity risk premium may be concentrated on January months, see e.g. Eleswarapu and Reinganum (1993). If I ignore the Januaries in the data set, the results are basically not changed with respect to the CAPM. Overall, the results suggest that neither the CAPM nor the widely used Fama and French three factor model are able to explain the liquidity risk premium in Europe, as proxied by the constituents in the Stoxx Europe 600 index.

In the next section, I investigate whether liquidity helps to price other assets in context of the stochastic discount factor framework.

4.5.3 Stochastic discount factor based asset pricing test

As usually a possible correlation between factors is not specifically considered when analyzing liquidity risk premia, additionally applying the stochastic discount factor method provides for more robust results on the role of liquidity pricing in Europe. If the coefficient on the liquidity factor is significant in the estimation of the stochastic discount factor this provides for evidence on liquidity being a state variable which helps to price assets.

Table 4.4 gives the results for the two-factor SDF specification including the market excess return and the liquidity risk factor, considering the two-step estimation procedure of Hansen and Singleton (1982). The results are given for the individual test assets and the test portfolios. In all models empirically estimated, I do not restrict the constant in the systems to equal a special value, which is in line with e.g. Cochrane (1996). In the GMM results in Table 4.4 regarding the individual Stoxx Europe 50 stocks as test assets, the coefficient for the liquidity risk factor is significantly positive for the estimated stochastic discount factor. Moreover, the coefficient on the market excess return is statistically significant and negative. Negative coefficients in the estimation of the SDF are plausible in the context of the detailed explanation provided in Cochrane (1996). This explanation is related to the stochastic discount factor being proportional to the minimum-second moment return. Thus, it is on the lower portion of the minimum variance frontier whereas the returns on risk factors may be on the upper portion of the minimum variance frontier, thus leading to negative coefficients in the estimated SDF.[19]

The results for the Stoxx Europe 50 stocks suggest that both risk factors significantly help to price other assets. This is also confirmed by the results of the Wald test which indicate the joint significance of both risk factors in the estimation of the SDF. Moreover, the J-statistic of overidentifying restrictions does not reject the model. With 50 stocks and 3 instruments, i.e. two factors (market excess return and (il-)liquidity) and the constant, the number of overidentifying restrictions equals $50 \times 3 - 3 = 147$. Overall, the two-factor specification of the SDF is not rejected and the market excess return and liquidity seem to be important risk factors in helping to price other assets, which are here represented by the Stoxx Europe 50 constituent stocks.[20]

[19]For example, Brennan et al. (2004) also receive negative estimates of the coefficients in their GMM-based pricing kernel specification.

[20]The constant in the model is significantly positive but can not be economically interpreted. If additional

Table 4.4 gives the results which are estimated with respect to each group of test portfolios. The results for the constant b_0 are basically the same across the three different systems and are similar to the Stoxx Europe 50 results. In each system estimated, liquidity risk possesses again a significantly positive coefficient, whereas the coefficient on the market excess return is again significantly negative. Note that with respect to the price-to-earnings sorted portfolios the market excess return is only significant at the 10%-level. In line with the results above, the coefficients on the market excess return and the liquidity risk factor are jointly significant based on the Wald tests. However, the J-statistics are now able to reject the two factor SDF. Hence, with respect to the test portfolios the model seems to be misspecified. In the three test portfolio specifications given, it seems that the two factor SDF including liquidity is not able to capture the cross-sectional variation of portfolios sorted on other style characteristics, i.e. e.g. on market capitalization and price-to-book characteristics. The two-factor SDF does not seem to be able to price these test portfolios, while it is able to price the 50 individual stocks in the Stoxx Europe 50 index. It may be that the style based procedure used to form test portfolios provides for characteristics, like e.g. liquidity characteristics, in the test portfolios which are averaged too much and, hence, the two factor SDF is rejected in this context. Overall, it seems that the simultaneous test on individual assets as well as portfolios is useful in order to have a comparison with respect to different system specifications. It also has to be noted that, generally, low p-values for the J-statistics in asset pricing tests are not uncommon as it is e.g. the case in Brennan et al. (2004) where both the CAPM and the Fama and French three factor model are rejected with p-values being smaller than 1%.

assumptions regarding the payoffs like e.g. factors with a mean of zero, uncorrelated factors and factors with unit standard deviation were fulfilled, see e.g. Hansen and Jagannathan (1997), the constant in the SDF could be interpreted as the price assigned to the unit payoff and the elements in the parameter vector could be interpreted as factor prices.

Table 4.4: Two-step GMM estimation: Two-factor model

This table gives the results of a two-step GMM estimation of a linearly specified two factor SDF across systems of individual stocks and test portfolios which are sorted on market capitalization as well as either price-to-book (P/B), price-to-earnings (P/E) or dividend yield characteristics. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimation procedure takes into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance tests and the J-statistics to test for model mis-specifications are given. Sample period: October 1, 2002 to September 30, 2009.

Stoxx Europe 50 stocks	CONST.	MARKET EXC. RET.	ILLIQUIDITY
Coeff.	1.000	-0.978	0.507
P-value (t-stat.)	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	123.932	P-value of J-stat.	0.917
Number of overidentif. restrict.	147		
P/B sorted test portfolios	**CONST.**	**MARKET EXC. RET.**	**ILLIQUIDITY**
Coeff.	1.000	-0.747	1.306
P-value (t-stat.)	0.000	0.005	0.012
P-value of Wald test	0.000		
J-stat.	42.444	P-value of J-stat.	0.000
Number of overidentif. restrict.	15		
P/E sorted test portfolios	**CONST.**	**MARKET EXC. RET.**	**ILLIQUIDITY**
Coeff.	0.999	-0.556	1.791
P-value (t-stat.)	0.000	0.057	0.001
P-value of Wald test	0.000		
J-stat.	44.685	P-value of J-stat.	0.000
Number of overidentif. restrict.	15		
Div. yield sorted test portfolios	**CONST.**	**MARKET EXC. RET.**	**ILLIQUIDITY**
Coeff.	1.000	-0.515	1.250
P-value (t-stat.)	0.000	0.031	0.015
P-value of Wald test	0.000		
J-stats	56.427	P-value of J-stat.	0.000
Number of overidentif. restrict.	15		

4.5.4 Other risk factors and the SDF

In this section, the stochastic discount factor results on the Stoxx Europe 50 constituents are backtested taking into account further risk factors which may be linked to liquidity. The respective results are given in Table A.9 in Section A.4 in the appendix.

First, I additionally control for the size effect as Amihud (2002) suspects size to be a proxy for liquidity and as commonality in liquidity effects may be linked to the size effect, see Chordia et al. (2000), as well as the positive size beta of the liquidity risk factor in Table 4.3. Furthermore, Nagel (2005) finds that trading volume, which is in the denominator of the Amihud liquidity measure, is related to size. Multifactor models including the market factor, size and liquidity have been considered by Hearn and Piesse (2008) and Hearn et al. (2008). The results in Table A.9 suggest that the importance of liquidity is not decreased by additionally controlling for the size risk factor. The coefficient on the size risk factor is statistically significant and negative, similar to the coefficient on the market excess return, but it is much smaller in absolute value. Overall, the size risk factor does not cannibalize the importance of the other two risk factors in the estimation of the SDF. The results with respect to the Wald and J-statistics are similar to those above in Table 4.4. This result on size and liquidity is in line with James and Edmister (1983), who find no evidence that the liquidity premium associated with inactively traded shares directly explains the size effect, concluding that the size effect is not caused by trading activity.

Second, I control for idiosyncratic risk, see Section 2.3.3. To my knowledge, the analysis presented here is first to explicitly investigate this interrelation in the context of liquidity pricing and the stochastic discount factor framework. The results in Table A.9 suggest that the presence of the idiosyncratic risk factor in the SDF estimation does not change much the results on the liquidity risk factor as it still possesses a significantly positive coefficient. Idiosyncratic risk is statistically significant and positive in the estimated SDF. The coefficient on liquidity is a little bit smaller than without considering idiosyncratic risk but still highly significant. The Wald and J-statistic results are again in favor of this specification.[21] Hence, despite the close theoretical dependencies between liquidity and idiosyncratic risk, the additional consideration of idiosyncratic risk does not seem to cannibalize the importance of liquidity in the SDF and both risk factors capture different aspects in the cross-section if stock returns. This evidence is in line with e.g. UK evidence of Angelidis and Tessaromatis (2008) who conclude that idiosyncratic risk is not a proxy for liquidity risk. However, further evidence on this issue is still needed in order to provide for a clearer conclusion on the interrelation between both risk factors.

[21] A p-value of 1.000, resulting due to rounding, suggests that the model specification is not rejected.

Third, an additional momentum factor is considered, see Sadka (2003) and Pastor and Stambaugh (2003) who find that liquidity risk accounts for half of the profits of a winner-loser momentum portfolio. However, if I include the momentum factor additionally to the other risk factors into the SDF specification, the main results regarding the statistical significance and signs of the coefficients on the market and liquidity factors are not changed. The coefficient on momentum is statistically significant and positive, but only very small. The Wald and J-statistic results do not reject the joint significance of all risk factors and do not reject this model specification. Thus, in this model, the importance of liquidity does not seem to be diminished.

Fourth, I also include additional size and valuation factors as Liu (2006) finds that small stocks and high book-to-market stocks are less liquid and that the liquidity risk factor may capture the risks (e.g. distress risk) behind these factors more accurately, see also e.g. Brennan and Subrahmanyam (1996) or Hwang and Lu (2007) on the joint consideration of these risk factors. In Table A.9, considering the two Fama and French factors additionally to the other two risk factors does not change much the significance, sign and size of the coefficients on the market and liquidity risk factors. Size and valuation are not significant and the model specification seems to be weak as it is almost rejected at the 10%-level. When one only controlled for size alone, size was a significant risk factor in the stochastic discount factor but this is rendered insignificant by additionally controlling for valuation. Thus, size and valuation do not seem to be important in the SDF specification in contrast to market excess return and liquidity. This also suggests that even if liquidity and size are highly correlated, they capture different risks relevant in pricing other assets. Otherwise, size should be a stable and significant risk factor across all specifications of the stochastic discount factor and should not be influenced by including valuation with which it thus seems to be more closely related. Overall, I conclude that the importance of liquidity risk in addition to the market excess return in the SDF is stable with respect to the inclusion of the Fama and French factors.

In Tables A.10 to A.12 in the appendix, the robustness results on the GMM tests are also given for the test portfolios. The main results are confirmed that again all specifications are rejected by the J-statistics for the test portfolios and that the market excess return always possesses a significantly negative coefficient. Apart from one exception, size significantly negatively enters the SDF in all different SDF specifications and, moreover, in contrast to the Stoxx Europe 50 results, size renders liquidity partly insignificant. Most of the time, liquidity risk possesses a positive coefficient which is often significant. However, the results on the liquidity risk factor are not consistent across the different test portfolios with respect to the sign and statistical significance of the coefficient. The coefficient on liquidity becomes insignificant by including idiosyncratic risk, which is insignificant in the SDF as well, but the coefficient on liquidity is still positive. This is in contrast to the individual Stoxx Europe 50 results where both risk factors significantly influenced the stochastic discount factor. The inclusion of momentum, which is significant only for the dividend yield test portfolios, does not change much the importance and the signs of the coefficients on the market excess return and the liquidity risk factor for all test portfolios. Controlling for the Fama and French factors makes the liquidity factor insignificant with respect to all the different test portfolio results. Size and valuation are negative here but only significant with respect to the price-to-book and dividend yield sorted test portfolios. It seems that the test portfolios sorted on market capitalization and on value versus growth characteristics are more sensitive to including size and valuation related risk factors into the stochastic discount factor than individual stocks. As the sorting procedure used to form the test portfolios may be more biased and arbitrary than individual stock data, it is sensible that the results on the latter are probably more reliable. For these test assets, the liquidity risk factor has been significant and consistent across all the different model specifications examined and also when controlling for idiosyncratic risk.

Overall, the stochastic discount factor results confirm the first results in Section 4.5.2 that liquidity risk plays a role in asset pricing as liquidity is an important risk factors in the SDF, which also stays relevant in the presence of the market factor and other risk factors. Thus, market excess return and liquidity seem to be helpful to price the Stoxx Europe 50 stocks. In contrast to the studies of Martinez et al. (2005) and Mazouz et al. (2009) who do not find liquidity to be priced on the London Stock Exchange and in Spain, the results on the Stoxx Europe 50 index universe support the importance of liquidity in asset pricing. There are several possible explanations. First, the relevancy of liquidity as a determinant of asset prices has increased during the last years, including the financial crisis. Second, the results presented here are derived from a pan-European data set which makes direct comparisons with single countries difficult. Third, the results found above may only be a statistical artefact, but this is tested by conducting in depth robustness analyses in the next section. Overall, the results are in line with U.S. evidence, see Section 4.2.2, which emphasizes the impact of liquidity on asset prices.

4.5.5 Robustness Checks

Now, I also backtest the stochastic discount factor results based on an iterated GMM procedure. I only give the iterated results for the test portfolios as the iterated estimation of a system consisting of the 50 constituent stocks in the Stoxx Europe 50 and more than 1809 time series observations is computationally very burdensome.[22] Table A.13 in the appendix gives the iterated results on the price-to-earnings sorted test portfolios. The results with respect to the constant, i.e. b_0, are similar to those before and again the coefficient on the liquidity factor is significantly positive, with even higher magnitude and significance than for the two-step results. However, the market excess return is now no significant risk factor in the SDF estimation anymore but nevertheless still possesses a negative sign. The results with respect to the Wald test and the overidentifying restrictions test are unchanged. Hence, with respect to the iterated results the importance of liquidity in pricing the price-to-earnings sorted test portfolios is even more evident compared to the results for the market excess return. The GMM system specifications apart from the P/E and market capitalization sorted test portfolios do not converge after more than 2000 iterations, see the discussion in Section 4.3.6.[23] Hence, I focus the main estimations on the two-step procedure only, as this is asymptotically equivalent to iterated GMM, see Section 4.3.6. The Hansen (1982) and Hansen and Singleton (1982) two-step procedures are also feasible with respect to larger systems and are not characterized by the problems of e.g. no convergence or high computational burden.

Next, I also consider different system specifications with respect to the liquidity augmented CAPM and the Stoxx Europe 50 stocks as test assets, see Table A.14 of the appendix. First, I consider equally instead of free-float weighted risk factors. The results are basically unchanged as the coefficients on the market excess return and the liquidity risk factor are again significantly negative and positive, respectively, and the results on the Wald and J-statistics are similar. Second, I consider detrended liquidity instead of undetrended liquidity. The results on the market excess return are unchanged but the coefficient on the liquidity factor is smaller now but still significantly positive. Thus, this different specification leads to only slightly changed results, as also the Wald and J-statistics suggest. Third, I consider only the system condition based on simple pricing errors, thus ignoring further orthogonality conditions with respect to the factors. The results are different now as the coefficient on the liquidity risk factor is significantly negative. The Wald test is significant only at the 10%-level whereas the J-statistic is still in favor of the model. When ignoring the orthogonality conditions in this way, the number of overi-

[22] For example, Vassalou (2003) only uses the 25 Fama and French portfolios and argues that the number of observations must be large compared to the number of test assets in order to not compromise the behavior of the GMM estimator.

[23] An alternative is given by Guo (2006) who provides for a procedure in the case of non-iterated results. If GMM does not converge after 1000 iterations he uses the point estimates from another model as initial parameters and restricts the estimation procedure to only 5 iterations. However, this procedure is also rather arbitrary.

dentifying restrictions is much smaller than when imposing the additional orthogonality conditions. However, the simultaneous consideration of orthogonality as well as pricing error conditions is advantageous as this leads to a larger number of moment conditions and is interpretable in the sense of a linear least squares projection. Thus, the estimation procedure with additional orthogonality conditions using factors as instruments, see Kan and Zhou (1999), seems to be preferable.

Fourth, I also consider the risk factors for the 1 and 99%-cut-off-rates. This does basically not change the results regarding the statistical significance and sign of the coefficients as well as the joint significance of the coefficients and J-statistic results. Fifth, I estimate the system specification proposed in Farnsworth et al. (2002), where the SDF should not only price the test assets but also the riskless asset as well as the traded factors, which are here the market excess return and the liquidity risk factor. Again, the coefficient estimates and GMM test results regarding this specification are not changed much as suggested by the coefficient and test statistic results. Sixth, I estimate the two-factor SDF with respect to monthly instead of quarterly rebalanced risk factors. The results are also basically unchanged by this different rebalancing methodology regarding the sign and significance of the risk factor coefficients and the other GMM test results. Last, I simultaneously take into account outliers in the market as well as the liquidity factors. I neglect outliers which are more than three standard deviations away from the mean market excess return and the mean return on the liquidity risk factor. In this way, 38 of 1809 overall time series observations are ignored. Most of the outliers occurred in the autumn of 2008 which was around the very turbulent time period of the financial crisis. However, as the results in Table A.14 suggest, ignoring the outlier observations in both variables does not change the main results that a liquidity augmented CAPM specification of the SDF including the market excess return and systematic liquidity is helpful in pricing other assets in the Stoxx Europe 50 index.

Next, different subperiods are considered.

4.5.6 Different subperiods

The time-varying nature of illiquidity based on the tests on commonality in liquidity motivate to test the asset pricing role of liquidity across different subperiods for the SDF approach and the test portfolios. This is done by dividing the sample period into halves. The first subperiod comprises 906 observations from October 1, 2002 to March 31, 2006. The second subperiod contains 903 observations from April 3, 2006 to September 30,

2009. The second subperiod also covers the financial crisis starting in 2007 / 2008.[24]

The results for the first subperiod give a rather disperse picture on the ability of the two-factor SDF model in helping to price other assets, see Table A.15 in the appendix. The market excess return only significantly (negatively) enters the stochastic discount factor for the price-to-book and dividend yield sorted portfolios. In contrast to the results for the overall time period, liquidity risk is a significant part of the SDF for none of the different groups of test portfolios. It negatively enters the SDF for the price-to-book and dividend yield sorted portfolios. For these two groups of test portfolios, the Wald tests do not reject the joint significance of the coefficients. However, the results on the price-to-earnings sorted test portfolios are different as the coefficients on the market excess return and the liquidity risk factor have different signs than with respect to the other two test portfolio results. Furthermore, here, even the market factor does not significantly enter the SDF and the Wald statistic rejects the joint significance of the risk factor coefficients. With respect to the test portfolio specifications, the J-statistics do not reject the model specification for the P/E- and dividend yield sorted portfolios at very small p-values, but reject the model specification strongly at the 1%-significance level for the P/B-sorted test portfolios. Overall, the results are not so clear for the first subperiod, but are rather not so supportive of the two-factor model. For the first subperiod, the importance of liquidity risk in asset pricing is not confirmed. In this subperiod, it seems that liquidity risk is no important risk factor in helping to price other assets.

The results for the second subperiod suggest that the market excess return as well as liquidity risk are risk factors helping to price the test portfolios, see Table A.16. Both risk factors are highly significant in the estimation of the stochastic discount factor with the signs of the coefficients being consistent with the results of the overall sample period given in Table 4.4. Furthermore, the Wald tests are in favor of the joint significance of the models and the J-statistics do not reject the model specifications for all the test portfolios, even if for the P/E- and the dividend yield sorted test portfolios the p-values of the J-statistics are not larger than 10%. In contrast, during the overall sample period the model has been rejected for all test portfolios according to the J-statistic results. Thus, during the second subperiod, also the test portfolio results are in favor of the model specification including liquidity risk as suggested by the J-statistics, whereas during the overall period the J-statistics have rejected the model specification. Hence, during the second subpe-

[24] Analyzing here the Stoxx Europe 50 assets would not be useful as there would be an insufficient number of observations in each subperiod in comparison to the number of assets in the cross-section and, hence, the number of moment conditions to be estimated, which leads to near singularity of the weighting matrix, see also Cochrane (2001) pp. 213.

riod including the financial crisis, the two-factor specification for the SDF seems to be a convenient model and to be more adequate in pricing the test portfolios than during the overall sample period as well as the first subperiod for the test portfolios.

I conclude that, during the second subperiod, which contains the financial crisis and a considerable market turmoil, the role of liquidity risk in addition to market risk has considerably increased. This increased importance of liquidity risk in asset pricing during the financial crisis is in line with Pastor and Stambaugh (2003) or Fujimoto (2004) who find that aggregate liquidity is low when market volatility is high.

4.6 Conclusion

The evidence in this chapter confirms the relevance of liquidity in pricing European assets. First, a brief examination of aggregate liquidity for the Stoxx Europe 600 index constituent stocks suggests that commonality in liquidity exists with respect to this data set. For the broad set of these stocks, market liquidity is found to be an important explanatory factor of individual stock liquidity. Moreover, the evolution of systematic liquidity in European assets suggests that there have been periods of severe market illiquidity, especially during the phases of market downturn over the last seven years. This observation underlines the role of liquidity as a state variable linked to market crises in line with the state variable view of the Merton (1973) ICAPM and with the findings of Pastor and Stambaugh (2003).

Second, a brief examination of simple and risk-adjusted liquidity risk premia confirms U.S. findings that liquidity displays a priced risk factor with respect to the Stoxx Europe 600 constituent stocks. This result provides for important economic implications for European investors even if risk premium estimates per se may slightly be distorted in the presence of correlated factors. Hence, third, also a SDF and GMM based test is conducted. This test examines the role of liquidity in helping to price the Stoxx Europe 50 constituent stocks as well as diversified portfolios based on the Stoxx Europe 600 constituent stocks which are sorted on style. These data universes have been chosen as proxies for the European stock market due to their relevance for European investors, their representativeness and data availability and because they contain a relatively large fraction of the free-float market capitalization in Europe. Overall, the majority of the different SDF specification results shows that liquidity seems to be a risk factor which helps to price other assets in addition to the market excess return. This interpretation is also feasible in the case of correlated factors and when considering additional risk factors, like e.g. idiosyncratic risk. Finally, considering different methods of analysis and different robustness checks, I conclude that liquidity risk is an important aspect of asset pricing in Europe. Similar to the findings in e.g. Bank et al. (2010) who find for daily German data from 1999 to 2009 that investors in the German stock market consider illiquidity in their price setting behavior, I conclude that European investors care about liquidity risk as well.

In line with the model of Acharya and Pedersen (2005), the covariance between individual liquidity and market liquidity as well as market returns displays a risk which becomes especially relevant to investors when the overall market downturns. During the second subperiod of the data sample examined, which has been characterized by considerable market turmoil due to the financial crisis, the importance of liquidity risk in asset pricing in addition to market risk has considerably increased, being in line with Pastor and Stambaugh (2003). Thus, the results in this chapter confirm the state-dependent view of liquidity risk. As boom and dust phases like the dotcom bubble or the recent global crisis first starting from mortgage backed securities seem to be occurring at increasing frequency during the last years, this is an even more important issue. The results in this chapter should imply an increased awareness of investors to consider liquidity risk in their investment decisions as well as to actively manage this risk in portfolio management. As this result underpins the role of liquidity as a benchmark factor, liquidity risk in the context of mutual fund performance is investigated in the next chapter.

5 Mutual fund performance evaluation

5.1 Introduction

The evidence in Chapter 4 on the relevance of liquidity in asset pricing motivates to analyze in this chapter whether and how liquidity –as well as idiosyncratic risk– contribute to the set of risk factors typically used in mutual fund performance evaluation, as this has not yet been thoroughly evaluated. That is why, in this chapter, considering the results in Wagner and Winter (2013), alternative multifactor models of mutual fund performance considering liquidity as well as idiosyncratic risk are presented and tested on a large set of actively managed mutual funds which have a European stock market investment focus.

Thereby multifactor models of returns under various sets of risk factors are addressed. Investors as well as the fund management regularly evaluate whether a mutual fund is able to provide for a positive performance in excess of such risk factors. However, under the joint hypothesis of an efficient market and the specification of an adequate risk model, see Fama (1991), fund managers usually do not generate abnormal performance results. In this context, the Fama and French (1993) and Carhart (1997) three and four factor models have become two of the most prominent multifactor models. By introducing liquidity and idiosyncratic risk as additional factors the analysis presented here also tests for extensions of and alternatives to these standard risk models. As presented in Wagner and Winter (2013), it is unprecedented to examine whether liquidity as well as jointly idiosyncratic risk provide for useful extensions to standard multifactor models of performance evaluation. The examination of the time period covering the financial crisis and its impact on mutual fund performance is a further interesting issue of this empirical research.

The analysis presented contributes to the literature by providing new insights on fund performance evaluated under a comprehensive set of risk factors. In contrast to the vast literature on U.S. mutual fund performance, the performance of European mutual funds has not been studied as extensively. Examples for U.S. performance studies are e.g. Grinblatt and Titman (1989a), Malkiel (1995) or Gruber (1996). Studies on the less mature European mutual fund industry are relatively scarce. However, as private retirement provisions have become increasingly important due to the decreasing ability of the government retirement systems to encounter the demographic change, the assets under management of the European mutual fund industry are steadily increasing. The European financial services industry has historically been quite disperse, but institutional and regulatory differences have declined in the recent past, which improves the explanatory power and consistency of pan-European performance studies. Besides the body of studies analyzing the performance of mutual funds in individual European countries, only Grünbichler and Pleschiutschnig (1999), Otten and Schweitzer (2002) and Otten and Bams (2002) explicitly study the cross-country performance of European mutual funds, but not with respect to liquidity and idiosyncratic risk nor the financial crisis.[25] Overall, this chapter, based on the results in Wagner and Winter (2013), contribute to the mutual fund literature by providing new models and empirical findings on short-term risk-adjusted fund performance regarding a broad European data set.

The remainder of this chapter is organized as follows. Section 5.2 gives a literature overview which not only motivates the investigation of liquidity and idiosyncratic risk with respect of mutual fund performance, but also outlines the alternative performance models, including those with liquidity and idiosyncratic risk factors. Section 5.3 characterizes the data set including a description of the mutual fund data. Section 5.4 contains the results of the empirical investigation. Section 5.5 concludes.

5.2 Literature review and methodology

5.2.1 Liquidity, idiosyncratic risk and mutual funds

The analysis of mutual fund performance and liquidity in this chapter is motivated by the assumption that mutual fund managers may actively manage their exposure to common liquidity risk. Two situations may apply. First, mutual fund managers may actively focus on liquidity risk (in the sense of illiquidity) in order to take advantage of a positive liquidity risk premium. This is motivated by the literature review in Section 2.3, the empirical evidence for liquidity risk being a pan-European determinant of the cross-section of asset prices as well as the positive liquidity risk premium in Chapter 4. Thus, a risk factor important in asset pricing should also have an influence on mutual fund performance if one assumes rational mutual fund managers who take into account such risks in their portfolio decisions.

Second, one might examine the hypothesis that mutual fund managers may typically focus on the liquidity of their funds' assets, which in turn impacts their average expo-

[25] International cross-country performance is investigated by e.g. Ferreira et al. (2013).

sure to liquidity risk. Liquid fund holdings are less risky to fund managers when they face the risk of unexpected redemptions by fund holders as they usually can be sold with lesser market impact. In fact, large redemptions, which were triggered by the decline in asset prices, were critical for many actively managed mutual funds during the recent financial market crisis, especially as mutual fund investors can redeem invested money at any time. Mutual funds which have a higher exposure to liquidity risk do not provide investors a hedge against periods of crisis, when systematic illiquidity usually rises and when fund investors are rather poor, see the intuition in Pastor and Stambaugh (2003). This is underpinned by the findings of Huang (2008) who concludes that mutual fund managers rather invest in liquid stocks during more volatile market conditions and Cao et al. (2009b) who show that some fund managers successfully time market liquidity by decreasing market exposure in anticipation of less liquid markets and vice versa. Massa and Phalippou (2005) show that portfolio liquidity of mutual funds is actively managed. Moreover, Clarke et al. (2007) find that when mutual funds experience redemptions, mutual funds with relatively low portfolio liquidity have a distinct preference for selling their relatively most liquid stocks. Despite the above, little is known so far about the role of liquidity as a determinant of mutual fund performance and empirical evidence with respect to the financial crisis and the European capital market is still missing.

The role of idiosyncratic risk in mutual fund performance evaluation also deserves a closer analysis, see the literature review in Section 2.3.2, but related to the area of mutual fund performance as well as to Europe, there is only scarce evidence. In a holdings-based approach, Falkenstein (1996) finds with respect to a U.S. data set that mutual funds are rather averse to holding stocks with low idiosyncratic volatility. Hence, idiosyncratic risk in the context of mutual funds may be motivated by the behavior of institutional investors who may be willing to accept idiosyncratic risk in order to achieve higher returns in comparison to a benchmark, see Falkenstein (1996) and Malkiel and Xu (2004). Moreover, the market frictions mentioned in Section 2.3.2 may impact mutual fund managers and investors as well, as they may have incomplete information about the investment opportunity set as well as possess information different from other market participants. Furthermore, the overall fund strategy as well as specific requirements by the fund investors may impose additional restrictions with respect to the assets fund managers might invest in, which may hinder perfect diversification as well. Thus, it is useful to investigate how idiosyncratic risk affects fund portfolio returns.

Previous empirical results on jointly considering liquidity and idiosyncratic risk on mutual fund performance are also scarce, while the available evidence indicates that in the cross-section of returns, rather both liquidity and idiosyncratic risk play a role in determining asset prices, see the evidence on the constituents of the Stoxx Europe 50 in Chapter 4 as well as Malkiel and Xu (2004). Falkenstein (1996), by examining fund portfolio holdings, finds that liquidity and idiosyncratic volatility both are significant in explaining aggregate mutual fund holdings of individual securities. In his sample, managers prefer liquid stocks and show an aversion to stocks with low levels of idiosyncratic risk. However, the combined importance of idiosyncratic risk and liquidity has not explicitly been investigated in the context of mutual fund performance and it is unknown whether liquidity risk diminishes the importance of idiosyncratic risk as a risk factor or vice versa. Hence, the analysis in this chapter, as derived from the first findings on this issue in Wagner and Winter (2013), tries to fill this gap.

Next, the performance evaluation setting as well as methodology is outlined.

5.2.2 Performance evaluation

Multifactor models have become common in the context of performance evaluation of mutual funds and the performance measurement of mutual funds is often assumed to imply a specific asset pricing model, see Jensen (1968), Carhart (1997) or Elton et al. (1996a).[26] In the following, the analysis mainly focuses on liquidity and idiosyncratic risk in the context of the Fama and French (1993) and Carhart (1997) three and four factor models which, by now, have become two of the most prominent multifactor models in performance evaluation, motivated by the fact that managers should not be rewarded for exploiting such widely known anomalies like e.g. the value effect. Multifactor models including liquidity and idiosyncratic risk factors have been considered before but not in the context of mutual fund performance evaluation. For example, Pastor and Stambaugh (2003) and Avramov and Chordia (2006) introduce Fama and French and Carhart models with liquidity, whereas Hirt and Pandher (2005) analyze idiosyncratic risk while controlling for the Fama and French three factors. The inclusion of systematic liquidity and idiosyncratic risk in multifactor models can be motivated by the ICAPM if one interprets both risk factors as hedge portfolios, see Section 2.1. The relevance of choosing an adequate model is strengthened by Grinblatt and Titman (1994) who show that tests of performance are sensitive to the benchmark chosen and, hence, to the risk factors included in a model.

[26]See for example the studies by Jensen (1968), Malkiel (1995), Elton et al. (1996a), Ferson and Schadt (1996), Gruber (1996) and Carhart (1997), among many others.

The multifactor models tested basically assume a return generating process of the form

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,1}(R_{M,t} - R_{f,t}) + \sum_{k=2}^{m} \beta_{i,k} f_{k,t} + \varepsilon_{i,t}, \tag{5.1}$$

which include $m-1$ additional risk factors $f_{k,t}$ apart from the market excess return $R_{M,t} - R_{f,t}$. On the right hand side of Equation 5.1, the multifactor alpha α_i is a measure of risk-adjusted abnormal performance, i.e. of the managerial skills of the fund managers. The idiosyncratic component in the regression equation is $\varepsilon_{i,t}$. The coefficient $\beta_{i,k}$ denotes the regression coefficient of the risk factor k. The risk factors considered include the market risk factor as well as the other risk factors of Section 3.3.

In the following, as this chapter focuses on the significance of liquidity and idiosyncratic risk, the models include among others liquidity and idiosyncratic risk augmented Fama-French and Carhart models, following the models as presented in Wagner and Winter (2013):

- Carhart (a four factor model including market, size, valuation, momentum),
- Fama-French (FF) with liquidity (a four factor model including market, size, valuation, liquidity),
- Fama-French (FF) with idiosyncratic risk (a four factor model including market, size, valuation, idiosyncratic risk),
- Carhart with liquidity (a five factor model including market, size, valuation, momentum, liquidity),
- Carhart with idiosyncratic risk (a five factor model including market, size, valuation, momentum, idiosyncratic risk),
- Carhart with liquidity and idiosyncratic risk (a six factor model including market, size, valuation, momentum, liquidity, idiosyncratic risk).

Later on, also more parsimonious four factor models will be deferred from these models. The risk factor models given above represent extensions of as well as alternatives to standard models as proposed in the literature.[27]

As a short-term performance analysis covering the time period October 1, 2002 to September 30, 2009 is presented, these different multifactor models are estimated via

[27] As Otten and Bams (2002) find that European funds are only to a small and not significant extent exposed to bond returns a bond risk factor like in Elton et al. (1993) and Gruber (1996) is not included.

ordinary least square (OLS) regressions by using the covariance matrix of Newey and West (1987) for the calculation of the standard errors. This shall take into account heteroskedasticity and autocorrelation. This is especially important when using daily data.[28]

Next, the data set is outlined.

5.3 Data

5.3.1 Risk factors

The risk factors in this chapter refer to the free-float, quarterly rebalanced risk factors as of Section 3.3. The different risk factors used in the multifactor models include the market excess return, size, valuation, momentum, idiosyncratic risk and liquidity. The momentum risk factor is constructed on the basis of the past six month total return and the liquidity risk factor is based on the quarterly averages of the Amihud measure. Choosing the Stoxx 600 as the data universe for the risk factors may raise the concern whether these risk factors are useful in explaining the performance of European mutual funds as mutual funds may invest in smaller stocks as well. However, as the summary statistics of the risk factors show, there are enough return variation as well as differing liquidity and size characteristics for the subportfolios used to construct the risk factors. Furthermore, the universe of the Stoxx 600 has been chosen as a compromise between data availability, as specifically needed for the Amihud measure, and representativeness.

As discussed in Section 3.3, the rather novel liquidity and idiosyncratic risk factors are not characterized by high levels of positive or negative correlation with the remaining risk factors. This makes them appropriate candidates to be included in multifactor risk models. Regarding all these risk factors the absence of hidden multicollinearity which impairs the results of OLS regressions is also checked by calculating the variance inflation factor, see e.g. Greene (2003), p. 57. The variance inflation factor is defined as,

$$VIF = \frac{1}{(1-R_k^2)}, \tag{5.2}$$

where R_k^2 denotes the R^2-statistic and k denotes an explanatory variable. Each explanatory variable k is regressed against a constant and against all the other explanatory variables. The resulting R^2-statistics of each regression with respect to all k dependent variables are

[28] One disadvantage with respect to this procedure of performance evaluation, which has already been mentioned by Jensen (1968), is that the estimated parameters are supposed to stay constant over the estimation period and that only average performance characteristics are calculated. This assumption is relaxed in the dynamic analysis of Chapter 6.

then used to calculate the variance inflation factors. The VIF for each of the explanatory variables k measures the increase in the variance of the regression coefficient b_k due to the fact that this explanatory variable is not orthogonal to the other variables in the model. The results for the variance inflation factors of all main performance evaluation models of this chapter are given in Table 5.1. A variance inflation factor which is larger than 10 is usually interpreted as a sign of severe multicollinearity, see Neter et al. (1983), p. 392. However, the variance inflation factors in Table 5.1 are smaller than 2 and, hence, multicollinearity in the different model specifications does not seem to be problematic.

Next, the mutual fund data set is described.

5.3.2 Mutual fund data

In this section, the mutual fund data as first presented in Wagner and Winter (2013) are described. Data on 529 mutual funds, which are registered in Austria, Germany and Switzerland and which mainly invest in European equity, are analyzed.[29] The data are obtained from Lipper Analytical Services and comprehend mutual funds in existence as of October 1, 2009. Exchange traded funds and other index funds including "Index" or "Idx" in their name are excluded from the dataset in order to only take into account actively managed funds. Daily logarithmic total returns for the time period between October 1, 2002 and September 30, 2009 are used, yielding an overall number of observations of 1808.[30] The total returns are calculated based on fund net asset values with all dividends being reinvested and all data are denominated in Euro. The return data are net of operating expenses like for example the management fee and other transaction costs, but not net of any load fees.

The risk factor and mutual fund return observations are available at a daily frequency which allows for a timely short term mutual fund performance measurement in this chapter. Daily data in mutual fund performance evaluation are advantageous as they offer a prompt evaluation of performance, they are consistent with the frequency the fund management receives new information and they consider the typical decision frequency of mutual fund managers. Busse (1999), Busse (2001), Bollen and Busse (2001) and Bollen and Busse (2004) are among the first to use daily data in the context of mutual funds, timing and performance evaluation while many other mutual fund performance studies

[29] One mutual fund is dropped from the following regression analyses as its time series possesses less than 60 observations and, hence, no reliable estimation by regression would be possible. Moreover, single mutual funds are characterized by non-daily pricing processes, but as this only refers to around 2% of the data set, the overall results should not be influenced.

[30] The mutual fund data and the risk-free return are adapted to the holidays taken into account in the construction of the European style indices in Chapter 3 in order to provide for a consistent data set.

are based on monthly data. Bollen and Busse (2004) investigate daily data in mutual fund performance and performance persistence evaluation.

Table 5.2 gives the annualized summary statistics on the individual mutual funds in the data set. Overall, the average per annum return has been small with a value of 0.20% and an average standard deviation of 21.64%. The small average return is probably caused by the market turmoil during the global financial crisis when successful fund management has been especially difficult. However, the minimum and maximum numbers suggest that there have been individual funds with very good as well as bad performance results. The respective summary statistics confirming this as well as number of observations for each individual mutual fund in the data sample are given in Table A.17 in Appendix A.5.

Survivorship bias is an important aspect in studies analyzing mutual fund performance, see Elton et al. (1996b). If unsuccessful or very risky funds disappear from the data set the measured performance will be overstated, see the U.S. evidence in Malkiel (1995) based on Lipper fund data, where over the time period from 1971-1991 the performance of all funds is 150 b.p. smaller than the performance of the surviving funds. Otten and Bams (2002) specify the overestimation by survivorship bias for four European countries: Average returns are overestimated by 0.11% (Netherlands), 0.12% (Germany), 0.15% (UK) and 0.45% (Italy). Compared to the estimate of Malkiel (1995) for U.S. data this seems to be not as severe for European data sets. This finding is also confirmed by lower average reported mortality rates for Europe, which may be linked to differences in the regulatory and legal framework or to different risk taking behavior. As the data set considered here does not take into account funds that terminated operation during the time period examined, it is not possible to analyze risk as well as performance characteristics for those funds which have left the fund sample. This and the sample choice of funds listed as of October 1, 2002, imply that the average age of the funds investigated increases every year, see also Wagner and Winter (2013). However, in order to gain first insights on short term performance and risk characteristics of mutual funds in Europe as well as on model specification, this data set should be feasible and the analysis of surviving vs. non-surviving funds is left for further research.

For model comparisons it may not only be adequate to analyze individual fund data, but also funds in the aggregate. Two ways of aggregation are applied, following Wagner and Winter (2013). First, an equally weighted mutual fund portfolio is considered, see e.g. Chan et al. (2002). Each fund enters this equally weighted fund portfolio upon its initiation and the portfolio is updated daily whenever a new fund, which is not contained in the sample during the overall sample period, enters the data set.[31] The summary statis-

[31]The mutual fund with the shortest history is in the sample for 63 trading days. However, as only a few

tics on the equally weighted fund portfolio are given in Table 5.2. It offers a mean per annum return of 5.17% at a relatively moderate standard deviation of 14.84% per annum. This result differs from the cross-sectional mean results for the individual mutual funds as the mutual funds enter the fund portfolio at different points in time as the fund sample is not survivorship bias free. Hence, in the beginning of the data sample there have been less funds included in the fund portfolio, which are probably more successful as they have been existing over the whole sample period. Thus, the equal-weighted fund portfolio may have characteristics different from those of the individual mutual funds as it overemphasizes the role of these funds.

An equally weighted fund portfolio may miss information about individual properties and style characteristics of mutual funds. Therefore, second, the whole set of mutual funds is classified into different equally weighted fund subgroups based on beta deciles whose members are characterized by relatively similar characteristics.[32] For each mutual fund, a univariate model only containing the market excess return is estimated by a heteroskedasticity and autocorrelation consistent Newey and West (1987) regression over the whole observation period in order to estimate the fund's beta coefficient. Then, the funds are grouped into beta decile groups which contain a large enough number of funds in order to be well diversified and which should be representative for their respective levels of market risk, with classification criteria being consistent within each group. Then, the fund portfolios are equally weighted with weights that are updated daily whenever a new fund enters the data set.

Table 5.2 shows the descriptive statistics of these mutual fund style portfolios, see also the overview on fund portfolio summary statistics in Wagner and Winter (2013).[33] With respect to the beta decile fund portfolios, one observes that the mean per annum return does not rise when taking more risks, while the standard deviation and the excess kurtosis almost monotonically increase from the lowest (decile 1) to the highest beta decile (decile 10). This pattern shows that beta alone is no satisfying criterion to explain return differences between beta deciles. The skewness of the fund portfolio returns tends to be negative for low betas and close to zero for the three highest beta deciles, which indicates that low beta deciles incur negative skewness. The beta derived from Equation 3.5 is small

mutual funds in the data sample possess time series of data which are as short, a potential bias should be negligible.

[32]For example, Carhart (1997) groups his fund data into different deciles based on past returns and then equally weights the so constructed portfolios. Ferson and Schadt (1996) also equally weight their mutual fund groups.

[33]This aggregation procedure in order to construct different mutual fund subgroups implicitly assumes that a mutual fund follows the same style over time. The assumption of constant subgroups over the observation period should be viable at this moment, but could be relaxed in further research.

Table 5.1: Multicollinearity tests

The table displays the results on multicollinearity tests for the variance inflation factor with respect to various four, five and six factor models. The variance inflation factor is defined as $VIF = \frac{1}{(1-R_k^2)}$. R_k^2 denotes the R^2-statistic of an ordinary least squares regression which regresses the kth explanatory variables against all other variables and a constant. Sample period: October 1, 2002 to September 30, 2009.

	MARKET EXC. RET.	SIZE	VALUAT.	MOM.	ILLIQU.	IDIOS. RISK
CARHART	1.152	1.007	1.460	1.429		
FF WITH LIQU.	1.123	1.017	1.156		1.040	
FF WITH IDIOS. RISK	1.353	1.021	1.160			1.089
CARHART WITH LIQU.	1.158	1.020	1.559	1.442	1.044	
CARHART WITH IDIOS. RISK	1.355	1.022	1.674	1.531		1.141
CARHART WITH LIQU. AND IDIOS. RISK	1.425	1.029	1.701	1.531	1.101	1.229
FOUR FACTOR MODEL WITH MOM. AND IDIOS. RISK	1.190	1.015		1.094		1.052
FOUR FACTOR MODEL WITH MOM. AND LIQU.	1.120	1.015		1.096	1.018	
FOUR FACTOR MODEL WITH IDIOS. RISK AND LIQU.	1.161	1.008			1.084	1.145

for the equal-weighted mutual fund portfolio which suggests that it does not possess substantial exposure to market risk. This may be because smaller funds, which seem to avoid exposure to market risk, are overweighted in the equal-weighted mutual fund portfolio. As expected, the beta regarding the beta decile fund portfolios rises monotonically from low beta to high beta funds. The average beta of the beta decile 1 is even slightly negative. This means that some of the mutual funds in this decile also hold short positions like it is the case with 130-30 funds.

Next, the empirical evidence is given.

Table 5.2: Summary statistics of mutual funds and fund decile portfolios

This table gives the summary statistics of the per annum cross-sectional averages of returns and standard deviations of individual mutual funds with European investment focus as well as of an equally weighted fund portfolio and of beta decile fund portfolios. All statistics are calculated using daily logarithmic returns. The returns are total returns which are calculated on the basis of net asset values with all dividends being reinvested. The return data are net of operating expenses, but not net of any load fees. Means, medians and standard deviations are annualized assuming 250 trading days per year. The excess kurtosis is the kurtosis minus the kurtosis of a normally-distributed variable. Beta is derived from Equation 3.5. The equally weighted mutual fund portfolio (EQUAL) contains all the individual funds in the mutual fund data set. The fund decile portfolios are constructed based on a beta ranking derived from the univariate market model based on OLS regressions considering the heteroskedasticity and autocorrelation consistent Newey and West (1987) covariance estimator. Then, the funds are grouped into beta decile groups according to their univariate regression coefficient rankings. Beta decile 1 contains funds with the lowest beta ranking. All fund portfolios are equally weighted with weights that are updated daily whenever a new fund enters the data set. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

Individual mutual funds	Mean p.a. avg. ret.	Median p.a. avg. ret.	Min. p.a. avg. ret.	Max. p.a. avg. ret.	Min. p.a. std. dev.	Max. p.a. std. dev.	Avg. p.a. std. dev.	Median p.a. std. dev.
Overall	0.20%	2.83%	-37.00%	65.18%	2.21%	39.02%	21.64%	20.92%
25%-percentile	-13.27%	-12.65%	-37.00%	-3.85%	2.99%	38.56%	26.31%	26.73%
Median	0.43%	0.94%	-3.78%	2.83%	5.29%	39.02%	21.02%	20.97%
75%-percentile	3.76%	3.76%	2.83%	4.80%	2.21%	27.47%	19.70%	20.53%
Maximum	9.88%	6.33%	4.85%	65.18%	5.10%	30.93%	19.56%	19.45%
Fund portfolios	Mean p.a.	Median p.a.	Std. dev. p.a.	Skewness	Excess kurtosis	Beta		
EQUAL	5.17%	22.45%	14.84%	-0.352	6.896	0.108		
BETA DEC. 1	4.00%	20.15%	15.55%	-0.408	6.926	-0.034		
BETA DEC. 2	5.73%	17.20%	11.28%	-0.114	7.155	0.195		
BETA DEC. 3	4.68%	21.63%	15.36%	-0.389	7.844	0.470		
BETA DEC. 4	5.13%	19.80%	17.17%	-0.323	7.080	0.573		
BETA DEC. 5	5.58%	21.30%	16.82%	-0.374	7.336	0.631		
BETA DEC. 6	5.45%	19.03%	17.31%	-0.278	7.730	0.706		
BETA DEC. 7	5.00%	21.08%	17.64%	-0.175	7.869	0.803		
BETA DEC. 8	4.53%	19.00%	19.09%	-0.044	8.364	0.900		
BETA DEC. 9	3.98%	19.73%	20.35%	0.016	8.243	0.965		
BETA DEC. 10	4.05%	22.43%	22.00%	0.019	8.344	1.042		

5.4 Empirical evidence

5.4.1 Liquidity and idiosyncratic risk exposures of mutual funds

First, liquidity and idiosyncratic risk exposures of individual mutual funds are examined based on the methodology presented in Section 5.2. Table 5.3 gives the number of funds which have a significant exposure to the different risk factors in each multifactor specification with respect to the 10%- and 5%-significance levels, see also the results presented in Wagner and Winter (2013). More than 75 percent of the funds possess a significantly positive exposure to the market excess return and towards size, i.e. small minus big. This result is quite stable across the different multifactor specifications. Only a very small amount of funds has a negative exposure to the market excess return (and to size) which probably means that those funds are not typical actively managed funds but e.g. follow a different investment strategy like e.g. the already mentioned 130-30 funds. The results with regard to valuation are not as pronounced as the number of funds with a significant exposure is much smaller than with respect to the market excess return and size. More than 200 funds –in the Carhart model with liquidity and idiosyncratic risk– possess a significant exposure to valuation, but the number of positive or negative exposures depends on the model. For example, in models including momentum, it seems that mutual funds rather have a positive valuation exposure, i.e. they prefer value over growth. In contrast to the inclusion of momentum, in models which include idiosyncratic risk or liquidity, significantly positive and negative valuation exposure is much more balanced. Overall, fund managers try to find past winners as a considerably large amount of mutual funds –up to 210 within the Carhart model with idiosyncratic risk, for example– possesses a significantly positive exposure towards momentum.

Across the different model specifications, around one third of the mutual funds is characterized by a significant exposure to the liquidity risk factor. Here, more funds exhibit a negative exposure to illiquidity, i.e. they focus more on liquid stocks, than those that are characterized by a positive exposure to liquidity risk. However, some funds actively carry liquidity risk as documented by their significant and positive coefficients. Thus, over the overall observation period, a considerably large amount of funds have a negative exposure towards liquidity risk. The number of funds with a significant exposure to idiosyncratic risk is quite comparable to that regarding liquidity risk. More funds possess a negative exposure to idiosyncratic risk and, thus, the funds rather avoid this risk factor, while a minority of funds exhibit a significantly positive risk factor exposure. It is notable that the results regarding liquidity and idiosyncratic risk are quite stable across the different models and are not changed by inclusion or exclusion of the momentum factor in contrast to the results on the valuation factor. Also, I find that the significance of idiosyncratic risk is not diminished by controlling for liquidity and vice versa in the most comprehensive six factor model. This is also basically consistent with Malkiel and Xu (2004) who find that the explanatory power of idiosyncratic risk is not taken away by controlling for the liquidity risk factor. In sum, market excess return and size are the most important risk factors, followed by momentum, which is again followed by valuation, liquidity and idiosyncratic risk. Interestingly, the evidence regarding liquidity and idiosyncratic risk, which are rather new in performance evaluation, is not less pronounced than regarding valuation which is already part of most standard performance models.

The above findings are also underpinned by the results of Wagner and Winter (2013), as presented in Table 5.4, which gives the cross-sectional mean, median, maximum and minimum numbers of the risk factor exposures of the individual mutual funds. In the aggregate, the mutual funds possess a substantially positive exposure to market excess return and size. In the different augmented multifactor models, on average, the additional variables also play a role. It has to be noted that, in the different models, the average exposure to valuation does not seem to be higher than that to momentum, liquidity and idiosyncratic risk. In the Carhart model, valuation and momentum have median exposures of 0.038 and 0.052, respectively. In the augmented multifactor models, the additional risk factors show comparable median exposures. In the Fama-French model with liquidity, the median exposure to liquidity risk is -0.053 which underlines the funds' rather negative illiquidity exposure. The Fama and French model with idiosyncratic risk yields a slightly negative idiosyncratic risk exposure with -0.025. The average exposure to valuation seem to be dominated by illiquidity or idiosyncratic risk in the two augmented Fama-French models, as the inclusion of these risk factors visibly reduces the average exposure to valuation. In the six factor model, the average magnitudes and the signs of all risk factors are in line with the former results and the average exposure to the liquidity risk factor is slightly more pronounced than the exposure to idiosyncratic risk. Apart from having pronounced market and small cap exposure, the fund managers in the data sample on average seem to slightly focus more on value stocks, past winners and liquidity, while their exposure towards idiosyncratic risk is rather neutral with respect to the six factor model.[34] Despite these observations on aggregate risk factor behavior, the results for

[34]This resembles the findings of Otten and Bams (2002) on five European countries which suggest that European funds prefer value stocks with a high book-to-market ratio. However, the only slight focus on valuation is in line with Davis (2001) who concludes that most funds do not have a large exposure to a value factor.

individual funds may strongly deviate. The minimum and maximum coefficients in Table 5.4 suggest that there are individual funds which have an extremely positive or negative exposure to specific risk factors and seem to be managed with extreme factor exposures.[35] This can also be noticed with respect to the more novel liquidity and idiosyncratic risk factors.

The average adjusted R^2-statistic of the different models is around 58%, see Table 5.5, as also given in Wagner and Winter (2013). This means that on average a quite good part of the performance of the mutual funds can be explained by the multifactor models. Moreover, on average, the adjusted R^2-statistic can be slightly increased by including liquidity and idiosyncratic risk in the multifactor models. The six factor Carhart model with liquidity and idiosyncratic risk achieves the highest mean and median R^2-statistic of all models. However, the minimum numbers also show that there are some individual funds following a totally different investment strategy, where the adjusted R^2-statistic can even become negative. Their performance and, thus, their investment strategies can not at all be described by these models, whereas the highest adjusted R^2-statistics show that regarding some funds the goodness-of-fit is almost perfect. Here, the mutual fund return is almost perfectly explained by the risk factors. Moreover, on average, the F-statistics provide evidence in favor of the joint significance of the multiple risk factors, but there are also some funds that show no joint significance at all.[36] Figure 5.1 displays the histogram of the adjusted R^2-statistics in the liquidity and idiosyncratic risk augmented six factor Carhart model which illustrates the considerable variation in goodness-of-fit across funds.

Overall, the results suggest that two of the risk factors, namely market excess return and size, can usually not be actively managed by individual mutual funds. In contrast to hedge funds, mutual funds can not hedge market risk. Thus, it is rather impossible for mutual fund managers to avoid exposure to the market excess return. Investing in a large number of assets, which themselves are also often quite linked to the evolution of the market, the mutual funds display a considerable exposure to market risk. This is especially evident during periods of financial crises when the correlation between assets increases. Considering size, it appears that mutual fund managers look for small, possibly undervalued stocks which are overseen by the investment community. This is part of the active selection component of active investing. As it is known that over certain periods of time smaller stocks provide for abnormal returns, the focus on such a strategy is reason-

[35] The negative exposures with regard to the market excess return again suggest that the respective mutual funds also partly hold short positions, like e.g. in so called 130-30 funds.

[36] Only 5 out of 528 mutual funds show no significant F-statistic at the 5%-significance level for the six factor model, which compares to 6 mutual funds for e.g. the Carhart model. Hence, focusing on joint significance based on F-statistics does not give here additional insights on the model comparisons.

Table 5.3: Individual fund risk exposures

This table gives the number of significant individual fund risk exposures for various four, five and six factor models. Regressions are estimated using the HAC-consistent covariance estimator of Newey and West (1987). See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

Overall period		MARKET		SIZE		VALUATION		MOMENTUM		ILLIQU.		IDIOS. RISK	
	Number of funds with exp.	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level
Carhart	Sig. neg.	14	6	39	30	39	23	16	11				
	Sig. pos.	455	455	402	389	174	129	210	157				
FF with Liqu.	Sig. neg.	23	17	37	29	131	109			127	94		
	Sig. pos.	455	455	402	389	126	95			36	25		
FF with Idios. Risk	Sig. neg.	2	0	31	26	130	116					131	108
	Sig. pos.	457	455	408	397	122	92					39	28
Carhart with Liqu.	Sig. neg.	15	8	30	25	52	44	21	16	110	86		
	Sig. pos.	455	455	412	399	153	123	198	164	45	32		
Carhart with Idios. Risk	Sig. neg.	2	0	29	26	50	42	26	22			112	101
	Sig. pos.	457	455	413	403	159	114	211	169			62	47
Carhart with Liqu. & Idios. Risk	Sig. neg.	2	0	28	26	61	52	26	22	118	91	112	102
	Sig. pos.	456	454	416	400	146	105	210	171	64	49	80	63

Table 5.4: Summary statistics of fund risk exposures

This table gives summary statistics for the coefficients on fund regressions for all individual mutual funds and various four, five and six factor models as presented in Section 5.2. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

		MARKET EXC. RET.	SIZE	VAL.	MOM.	ILLIQU.	IDIOS. RISK
CARHART	Mean	0.650	0.412	0.042	0.057		
	Median	0.719	0.462	0.038	0.052		
	Maximum	1.174	1.717	0.388	0.717		
	Minimum	-0.196	-0.402	-0.491	-0.315		
FF WITH LIQU.	Mean	0.638	0.396	0.001		-0.042	
	Median	0.709	0.432	-0.002		-0.053	
	Maximum	1.187	1.854	0.379		0.417	
	Minimum	-0.209	-0.466	-0.558		-0.464	
FF WITH IDIOS. RISK	Mean	0.651	0.406	-0.002			-0.026
	Median	0.718	0.451	-0.002			-0.025
	Maximum	1.130	1.944	0.375			0.236
	Minimum	-0.222	-0.478	-0.568			-0.638
CARHART WITH LIQU.	Mean	0.648	0.419	0.037	0.055	-0.027	
	Median	0.718	0.460	0.036	0.050	-0.035	
	Maximum	1.171	1.696	0.410	0.772	0.525	
	Minimum	-0.210	-0.474	-0.452	-0.297	-0.447	
CARHART WITH IDIOS. RISK	Mean	0.653	0.418	0.037	0.055		-0.010
	Median	0.720	0.464	0.034	0.050		-0.011
	Maximum	1.128	2.129	0.346	0.793		0.219
	Minimum	-0.220	-0.479	-0.512	-0.307		-0.717
CARHART WITH LIQU. AND IDIOS. RISK	Mean	0.650	0.422	0.035	0.054	-0.023	-0.006
	Median	0.717	0.471	0.033	0.050	-0.032	-0.001
	Maximum	1.127	2.137	0.355	0.859	0.585	0.276
	Minimum	-0.272	-0.512	-0.471	-0.280	-0.512	-0.698

Table 5.5: Summary statistics of adjusted R^2- and F-statistics

This table gives summary statistics of adjusted R^2- and F-statistics on individual performance evaluations for various four, five and six factor models. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

		Mean	Median	Maximum	Minimum
CARHART					
	adj. R^2	0.583	0.623	0.983	-0.017
	F-stat.	1716.861	527.279	16076.380	0.742
FF WITH LIQU.					
	adj. R^2	0.581	0.624	0.983	-0.021
	F-stat.	1707.828	533.123	15242.140	0.675
FF WITH IDIOS. RISK					
	adj. R^2	0.582	0.623	0.983	-0.009
	F-stat.	1716.043	531.943	15053.250	0.682
CARHART WITH LIQU.					
	adj. R^2	0.585	0.625	0.983	-0.020
	F-stat.	1395.033	429.113	12937.510	0.748
CARHART WITH IDIOS. RISK					
	adj. R^2	0.585	0.625	0.983	-0.006
	F-stat.	1395.670	433.080	12889.900	0.877
CARHART WITH LIQU. AND IDIOS. RISK					
	adj. R^2	0.587	0.626	0.983	-0.016
	F-stat.	1177.704	365.194	10782.770	0.752

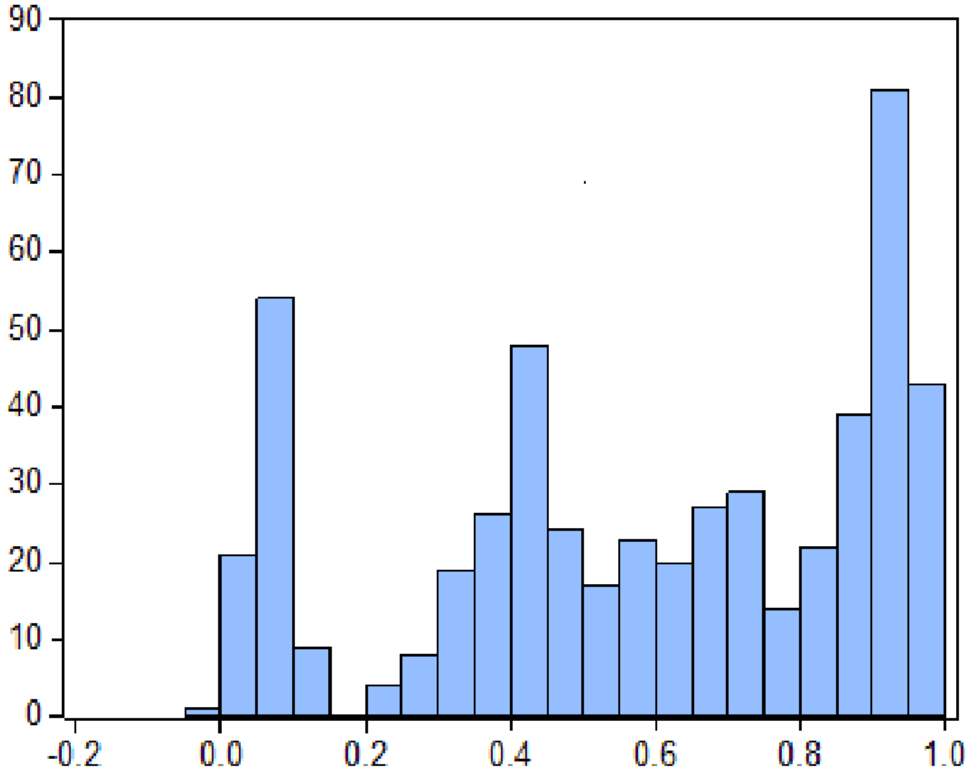

Figure 5.1: Frequency distribution of adjusted R^2-statistics

This figure displays the frequency distribution of the adjusted R^2-statistics in the Carhart model augmented by liquidity and idiosyncratic risk for the sample of 528 mutual funds. Sample period: October 1, 2002 to September 30, 2009.

able. All other risk exposures are managed or not specifically managed by individual fund managers and, therefore, only matter for certain funds. The evidence on liquidity risk is in line with this. Some portfolio managers focus on assets which are liquid and have a negative exposure towards liquidity risk as this may be favorable during market downturns when the risk of redemptions by fund investors is high. However, other managers may focus on illiquidity in order to earn the liquidity risk premium as a reward. Many other managers simply achieve a neutral liquidity risk exposure as they are not so much concerned by liquidity risk. Furthermore, the results are not more in favor of the importance of the valuation factor of Fama and French (1992, 1993) than of the novel liquidity or idiosyncratic risk factors. In the next section, more thorough model comparisons are conducted in order to find adequate models of performance evaluation.

5.4.2 Model comparisons

Given the models outlined above, the relative performance of alternative multifactor models is now investigated in order to test which of the above models may be preferable. Model comparisons regarding nested tests can be conducted by comparing the adjusted R^2-statistics of different models. A first comparison of the adjusted R^2-statistics of the different models in Section 5.4.1 allows for the conclusion that the six factor Carhart model with liquidity and idiosyncratic risk - which nests all other models - on average achieves the highest adjusted R^2-statistics and is hence a good choice.[37]

In order to be able to compare also non-nested models, a non-nested test on the equal-weighted fund portfolio and the beta decile fund portfolios is conducted, following the approach in Wagner and Winter (2013). Therefore, the J-test of Davidson and MacKinnon (1981) is used in order to compare various four and five factor models. In this test, the fitted values of one model A (e.g. Carhart) are added to the explanatory variables of an alternative model B (e.g. liquidity augmented Fama and French). Under the null hypothesis that model B is superior, the fitted values of model A should not possess any explanatory power once added in the estimation of model B. In case the coefficient on the fitted values is significant, as indicated by its p-value, model A (e.g. Carhart) is preferred over the alternative model B (e.g. liquidity augmented Fama and French). Apart from the situations where no clear conclusion is possible which model to favor, the J-test provides a good approach for model selection. The p-value results are given in Table 5.6, see also the results in Wagner and Winter (2013). Focusing on the equal-weighted fund portfolio results, the null hypothesis of a model being superior as compared to another is rejected at the at least 5%-significance level in the following cases: Carhart is rejected with respect to Fama-French with idiosyncratic risk, and bilateral rejections imply a stand-off between Fama-French with idiosyncratic risk and Fama-French with liquidity as well as between Carhart with idiosyncratic risk and Carhart with liquidity. Thus, here the J-test gives no clear hint which model to prefer.

Based on the beta deciles, the Carhart model seems to be preferable to the idiosyncratic risk augmented Fama-French model, as fitted values from the Carhart model enter the Fama-French model with idiosyncratic risk significantly for seven out of ten decile subgroups. The same applies to the liquidity augmented Fama-French model, although to a lesser extent. The fitted values from the liquidity augmented as well as from the id-

[37]Cross-sectional correlation in mutual fund returns may lead to bias in the Newey and West standard errors, which are used in the comparison of the nested models. However, the bias with respect to the Newey and West results is much smaller than compared to those of standard OLS results, see e.g. Driscoll and Kraay (1998).

Table 5.6: Alternative model tests: Four and five factors

This table reports Davidson and MacKinnon (1981) J-test results in a comparison of alternative four and five factor models. The null hypothesis is that the fitted values of model A should not be significant explanatory variables when added to model B, when model B is superior to model A. The table shows the p-values of the fitted values when entering the alternative models. Comparisons are given with respect to an equal-weighted fund portfolio (EQUAL) and beta decile fund portfolios. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

FITTED VALUES	FROM CARHART:		FROM FF WITH LIQU.:		FROM FF WITH IDIOS. RISK:		FROM CARHART WITH IDIOS. RISK:	FROM CARHART WITH LIQU.:
	FITTED VALUES ENTER:							
	IN FF WITH IDIOS. RISK	IN FF WITH LIQU.	IN CARHART	IN FF WITH IDIOS. RISK	IN CARHART	IN FF WITH LIQU.	IN CARHART WITH LIQU.	IN CARHART WITH IDIOS. RISK
EQUAL	0.991	0.390	0.177	0.029**	0.030**	0.004***	0.001***	0.028**
BETA DEC. 1	0.624	0.652	0.499	0.532	0.682	0.591	0.102	0.549
BETA DEC. 2	0.078*	0.170	0.318	0.242	0.009***	0.003***	0.975	0.252
BETA DEC. 3	0.096*	0.176	0.879	0.790	0.347	0.595	0.962	0.869
BETA DEC. 4	0.039**	0.109	0.895	0.692	0.739	0.833	0.346	0.346
BETA DEC. 5	0.144	0.234	0.525	0.471	0.739	0.833	0.346	0.346
BETA DEC. 6	0.037**	0.077*	0.450	0.461	0.805	0.968	0.306	0.483
BETA DEC. 7	0.000***	0.000***	0.653	0.952	0.225	0.066*	0.303	0.970
BETA DEC. 8	0.000***	0.000***	0.388	0.492	0.291	0.122	0.319	0.480
BETA DEC. 9	0.011**	0.036**	0.138	0.094*	0.529	0.568	0.832	0.086*
BETA DEC. 10	0.692	0.561	0.150	0.062*	0.777	0.647	0.546	0.063*

iosyncratic risk augmented Fama and French models do barely enter the Carhart model. Hence, regarding the beta decile portfolios, it seems that the Carhart model is the most useful four factor model. Moreover, based on the beta decile fund portfolios, the J-test statistics indicate that the comparison between the liquidity or idiosyncratic risk augmented Fama-French models is in favor of the liquidity augmented model with respect to the two highest beta deciles. As the adjusted R^2-statistic with respect to the Carhart model may slightly be increased by including liquidity or idiosyncratic risk, it is useful to also compare the liquidity and idiosyncratic risk augmented Carhart models. In the class of five factor models, it appears that the liquidity augmented Carhart model is to be preferred with respect to the other model alternatives. Overall, the beta decile comparisons are probably more adequate as they offer a more detailed analysis in comparison to the very aggregate equally weighted fund portfolio, which may also be characterized by a small fund bias.

Next, more parsimonious models as well as further research questions are addressed.

5.4.3 Four factor models and further research implications

In Section 5.4.1, it has been shown that liquidity and idiosyncratic risk are useful and important risk factors in model specifications of up to six risk factors. However, six factor models are not parsimonious, may be subject to some kind of overfitting and four factor models like especially the Carhart model are now among the most widely used models of performance evaluation. Hence, more parsimonious four factor models whose benchmark is the widely used Carhart model are addressed, following Wagner and Winter (2013). Before, in bilateral comparisons, the Carhart model as well as the liquidity and idiosyncratic risk augmented Fama and French models have already been tested against each other. As the J-tests have shown, the comparisons are rather in favor of the Carhart four factor model based on the decile fund group results. This has been quite clear with respect to the idiosyncratic risk augmented Fama and French model, but less obvious with respect to the liquidity augmented model. Hence, this horse race indicates that the Carhart model seems to be more useful than the other augmented Fama and French models. The question arises which other more parsimonious model is also a good four factor model apart from the widely established Carhart model.

The results above indicate that only market and size are indispensable risk factors which are relevant for almost all funds, whereas the remaining factors are not always relevant and allow for variation. Hence, four factor model specifications which differ from the widely used Fama and French based models may be useful in performance evaluation.

For example, if a mutual fund manager is aware that she is especially not focusing on undervalued or growth stocks, but rather on liquid past winner stocks, a benchmark model without valuation, but which consists of liquidity and momentum additionally to market and size, may be adequate. So, four factor models are investigated which comprise the market and size factors, but which also contain two of the following risk factors: Valuation, momentum, liquidity and / or idiosyncratic risk. Hence, in addition to the Carhart and the liquidity or idiosyncratic risk augmented Fama-French four factor models, where the Carhart model is found to be preferable in Table 5.6, three additional models are worth to be examined: (i) a four factor model with momentum and liquidity risk (FFML), (ii) a four factor model with momentum and idiosyncratic risk (FFMI), and (iii) a four factor model with liquidity and idiosyncratic risk (FFLI). The last model is of specific interest as it does neither contain the well-known momentum nor valuation factors. In a further step, the Carhart model is compared to the models (i) to (iii).

An interpretation of the results of the J-test in Table 5.7, as based on the results in Wagner and Winter (2013), indicate that, first, the four factor model with liquidity and idiosyncratic risk is strongly dominated by all the other models when the beta decile results are considered. The fitted values from this model only significantly enter the four factor model with momentum and idiosyncratic risk with respect to two beta deciles. Thus, the model with liquidity and idiosyncratic risk is rather unfavorable compared to the other models. Second, the results with respect to the four factor model with momentum and idiosyncratic risk appear to be weak: The fitted values from both the Carhart as well as the four factor model with momentum and liquidity enter this model with respect to two beta deciles, whereas, vice versa, the fitted values from the four factor model with momentum and idiosyncratic risk have additional explanatory power in the Carhart and the four factor model with momentum and liquidity only with respect to one beta decile. Third, the comparison between the Carhart model and the four factor model with momentum and liquidity is only in favor of the Carhart model regarding the highest beta decile subgroup, whereas vice versa there is no significant beta decile. Hence, there is only a slight preference for the Carhart model. Except for one significant term in the tenth beta decile, one may attest that the Carhart model and the four factor model with momentum and liquidity do not dominate each other. Hence, these two models, with a slight advantage for the Carhart model, arise as undominated four factor model alternatives in the comparison.

The equal-weighted fund portfolio results do not provide new insights as many models are dominated by each other, which does not allow for straightforward conclusions. The Carhart model is preferable compared to the four factor model with momentum and idiosyncratic risk as the fitted values from the Carhart model significantly enter this model. The four factor model with momentum and liquidity is preferable to the four factor model with momentum and idiosyncratic risk as well. However, in the comparison based on the fitted values from the four factor model with momentum and idiosyncratic risk, the Carhart model as well as the four factor model with momentum and liquidity are both dominated by the four factor model with momentum and idiosyncratic risk. This indicates a stand-off and is in contrast to the comparisons based on the fitted values from the Carhart model and the four factor model with momentum and liquidity. The fitted values from the liquidity and idiosyncratic risk augmented model enter all the alternative four factor model specifications which stands in contrast to the beta decile results. Thus, there is no clear conclusion possible based on the equal-weighted fund portfolio results, which might be interpreted in light of a possible small fund bias of the equal-weighted fund portfolio.

Last, I would like to address the relationship between the liquidity and idiosyncratic risk factors. The J-test results with respect to the four factor models and the beta deciles are rather in favor of models that include liquidity additionally to other Fama and French or momentum factors compared to those containing idiosyncratic risk. Thus, liquidity based models seem to be slightly preferable to idiosyncratic risk based models for the mutual funds examined. Unfortunately, the four factor results indicate that models only with liquidity and idiosyncratic risk are not so useful. However, as the different model specifications (with up to six factors) in Section 5.4.1 showed, liquidity and idiosyncratic risk, even considered at the same time, may be important risk factors for large subgroups of mutual funds. Hence, the importance of these two risk factors is not cannibalized by considering them at the same time in addition to momentum and valuation as well as market and size risk factors. This overall result is also intuitive if one considers again the correlations between these two risk factors which are quite moderate. Hence, these risk factors seem to capture different aspects in the cross-section of mutual funds returns, even if they may be theoretically and empirically linked to some extent as the above mentioned literature suggests. This is in line with the empirical result in Malkiel and Xu (2004) and also conforms to the asset pricing results in Chapter 4. Nevertheless, two main conclusions can be drawn. First, in more parsimonious models and with respect to the beta deciles, liquidity seems to be more important to be included as a risk factor than idiosyncratic risk. Second, even if liquidity is a slightly more important risk factor in more parsimonious four factor models, it may be useful for mutual funds to also additionally take into account idiosyncratic risk in performance evaluation.

Overall, the results illustrate that the valuation and the liquidity risk factor are about equally important in four factor models which cover market, size, and momentum. Given the four factor models, the results are in favor of models that include illiquidity additionally to other Fama and French or momentum factors rather than idiosyncratic risk. In the sample investigated, the Fama and French based models including valuation are not necessarily the best ones. The Carhart model is preferable to the augmented Fama and French models but not much better than the four factor model including momentum as well as liquidity. Hence, in this sample, momentum and liquidity may be even more important than the widely used valuation factor to be included in four factor models which leads to the conclusion that Fama and French based models including a valuation factor are not necessarily the best choices. Thus, the Carhart as well as the four factor model including momentum and liquidity seem to be the most feasible and preferable four factor models. However, on the other hand, the results in general and the performance of the six factor Carhart in particular indicate that liquidity and idiosyncratic risk may jointly improve model fit. Hence, while illiquidity somewhat dominates idiosyncratic risk, the relevance of one of those factors is not diminished by considering them jointly.

Next, the performance of the mutual funds is evaluated.

5.4.4 Mutual fund performance

In Table 5.8, the main results of individual time series regressions on the whole set of individual mutual funds are given for the various Carhart and the Fama and French models augmented by liquidity and / idiosyncratic risk as well as the four factor models, as described in the previous section and as presented in Wagner and Winter (2013). On average, the per annum alphas are quite negative with respect to all models. The average risk adjusted performance is smaller than -3% per annum, reflecting an aggregate underperformance based on net returns after fund expenses and after consideration of risk. However, the maximum numbers also suggest that there are funds which provide for a very good performance. Moreover, the number of funds with significantly negative and positive as well as insignificant multifactor alphas are displayed for each model with respect to the 10%-significance level. Most funds possess a risk-adjusted performance which is statistically indistinguishable from zero. Only a negligibly small number of mutual funds –with a maximum of 5 mutual funds concerning the Carhart model and the four factor model with momentum and liquidity– possesses a significantly positive abnormal performance. Much more funds, i.e. more than 100 funds regarding the idiosyncratic risk augmented Carhart model– are characterized by a significantly negative risk-adjusted performance. In the aggregate, most of the mutual funds do not possess a positive risk-adjusted perfor-

Table 5.7: Alternative model tests: Four factors

This table reports Davidson and MacKinnon (1981) J-test results in a comparison of alternative four factor models. The null hypothesis is that the fitted values of model A should not be a significant explanatory variable when added to model B, when model B is superior. The table shows the p-values of the fitted values when entering the alternative models. Comparisons are given with respect to an equal-weighted fund portfolio (EQUAL) and beta decile (D.) fund portfolios. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

FITTED VALUES	FROM CARHART:			FROM FFML			FROM FFMI			FROM FFLI		
	FITTED VALUES ENTER:											
	IN FFML	IN FFMI	IN FFLI	IN CARHART	FFMI	IN FFLI	IN CARHART	IN FFML	IN FFLI	IN CARHART	IN FFML	IN FFMI
EQUAL	0.532	0.095*	0.165	0.170	0.013**	0.867	0.033**	0.029**	0.910	0.001***	0.024**	0.010**
BETA D. 1	0.132	0.079*	0.099*	0.447	0.310	0.926	0.981	0.789	0.922	0.463	0.943	0.324
BETA D. 2	0.474	0.219	0.095*	0.307	0.145	0.288	0.042**	0.028**	0.313	0.240	0.743	0.141
BETA D. 3	0.925	0.916	0.032**	0.915	0.777	0.027**	0.572	0.658	0.027**	0.841	0.828	0.813
BETA D. 4	0.796	0.466	0.002***	0.976	0.820	0.002***	0.520	0.484	0.002***	0.407	0.480	0.729
BETA D. 5	0.757	0.927	0.004***	0.551	0.540	0.006***	0.642	0.986	0.006***	0.513	0.863	0.547
BETA D. 6	0.619	0.413	0.020**	0.453	0.369	0.015**	0.688	0.696	0.015**	0.496	0.400	0.396
BETA D. 7	0.864	0.526	0.000***	0.721	0.963	0.000***	0.260	0.345	0.000***	0.294	0.326	0.675
BETA D. 8	0.166	0.193	0.000***	0.386	0.432	0.000***	0.295	0.241	0.000***	0.265	0.244	0.479
BETA D. 9	0.326	0.227	0.025**	0.137	0.092*	0.028**	0.527	0.650	0.036**	0.168	0.707	0.096*
BETA D. 10	0.005***	0.001***	0.000***	0.142	0.062*	0.000***	0.945	0.750	0.000***	0.162	0.904	0.061*

mance, but do at least cover their expenses, as the fund data are net of expenses. Hence, an investor investing in mutual funds must especially be aware of not buying one of those funds with significantly negative performance.

Only one of the mutual funds with a significantly positive exposure to liquidity risk and only one with respect to idiosyncratic risk possesses a positive performance, as given by the Carhart model augmented by liquidity and idiosyncratic risk and the 10%-significance level. However, 15 of these mutual funds regarding idiosyncratic risk and 16 regarding liquidity are characterized by a negative alpha. This indicates that mutual fund managers can not take advantage of focusing on liquidity risk, which is in contrast to the hypothesis that one can profit from a higher liquidity risk exposure because of higher expected returns. Hence, it seems to be more sensible to fund managers to focus on more liquid holdings or respectively holdings which are less sensitive to liquidity risk. A similar conclusion can be drawn from the results on idiosyncratic risk. Hence, both risk factors may affect the cross-section of mutual fund returns but not necessarily in the direction expected, as fund managers are not able to realize higher abnormal returns by investing on these risk factors. However, this also holds for the other well established risk factors which have been examined, like e.g. the market excess return, as only up to 5 mutual funds of the whole sample are able to achieve a positive alpha, while almost all mutual funds have a positive exposure to the market factor.

A Bonferroni correction is taken into account to control for the fact that if one tests a lot of hypotheses on a set of data, one probably sees quite often significant events simply due to chance, see e.g. Ferson and Schadt (1996). In the Bonferroni test, the p-values of the highest (most positive) and smallest (most negative) t-statistics in the overall distribution of the t-statistics on the alpha estimates are compared with the Bonferroni-adjusted significance level. This adjustment changes the significance level which is divided by the number of funds, i.e. 528. Hence, for a stricter significance level of 5% the relevant significance level is then $\frac{0.05}{528} = 0.0000947$.[38] The results of the Bonferroni tests indicate that with regard to the different models in Table 5.8, also based on a joint perspective, some mutual funds possess a significantly negative abnormal performance, whereas the results are able to reject the hypothesis that the alphas are jointly significantly positive. Thus, there is no joint evidence of significantly positive risk-adjusted performance but evidence of a significantly negative abnormal return, as the p-value for the mutual fund with the most negative alpha t-statistic is smaller than the Bonferroni-corrected significance level.

Figure 5.2 displays the distribution of the per annum alphas in the liquidity and id-

[38] With respect to a significance level of 10% the results would be similar. The corrected significance level is then $\frac{0.10}{528} = 0.000189$.

iosyncratic risk augmented Carhart model. The figure confirms that only a few funds possess a positive alpha whereas most funds possess a neutral or negative alpha. One has to take into account the potentially present survivorship bias in this study, implying that the empirical results presented here are rather too optimistic. This would indicate that the risk-adjusted performance found in this empirical analysis would even be worse.

These pan-European results which show that the multifactor alphas after costs (and after Bonferroni corrections) are rather indifferent from zero or negative are quite comparable to the results of well-known U.S. performance studies, see e.g. Jensen (1968), Grinblatt and Titman (1989a) or Gruber (1996).[39] The overall result, which suggests that most mutual funds cover their costs on a risk-adjusted basis, is consistent with the Grossman and Stiglitz (1980) definition of market efficiency. Here, managers on average just earn the abnormal performance that is necessary to cover the costs of their respective information acquisition activities.

Next, in order to complement the analysis on individual funds, the results are given for fund portfolios as well.

5.4.5 Fund portfolio results

In order to backtest the individual mutual fund results above, Table 5.9, as derived from Wagner and Winter (2013), gives the exemplary results of the exposures of the equal-weighted fund portfolio and the beta decile fund portfolios, which have been used in the J-test on model comparison. The results are displayed for the liquidity and idiosyncratic risk augmented Carhart model. Regarding the equal-weighted fund portfolio the size, liquidity and idiosyncratic risk factors are statistically significant, whereas the market excess return, valuation and momentum strikingly are not. The F-statistic is in favor of the joint significance of the coefficients at the 1%-level. However, the adjusted R^2-statistic of 6.1% is quite small. In line with these results the beta of the equal-weighted mutual fund portfolio has been small. Thus, the portfolio seems to account too much for small funds, which appear to choose small firms with low betas and high idiosyncratic risk. However, the equal-weighted fund portfolio has a negative exposure to systematic illiquidity which is not very intuitive as its small fund and size focus should lead to a focus on more illiquid holdings.[40] However, as the annualized alpha is positive, this

[39]These results are in contrast to Otten and Bams (2002) and Otten and Schweitzer (2002) who conclude that European mutual funds deliver positive risk-adjusted performance to investors even after costs. However, Grünbichler and Pleschiutschnig (1999) do also find a negative risk-adjusted performance with respect to the Carhart four factor model.

[40]In contrast Falkenstein (1996) finds that small-cap funds prefer small cap stocks which also rather seem to be those with relatively low liquidity.

investment strategy seems to pay off positively. It seems that because of the financial crisis less exposure towards the market positively paid back. As the results on the equal-weighted fund portfolio differ strongly from the results of the individual fund regressions, the analysis of the equal-weighted fund portfolio is maybe too aggregate and biased by its focus on small funds. This may also be an explanation why the results on the J-test have somehow been contradictory in Tables 5.6 and 5.7, where there arise different implications for the equal-weighted compared to the beta decile fund portfolios.

Regarding the beta deciles, the market excess return and size are usually highly statistically significant and positive which is in line with the individual mutual fund results, but in contrast to the results on the equal-weighted fund portfolio. Due to the beta ranking the coefficient with respect to the market excess return rises from the low beta group (beta decile 1) to the high beta group (beta decile 10). Only the 10th beta decile fund portfolio with a market beta close to 1 does not exhibit a significant exposure with respect to size, which is intuitive as these funds typically are large cap funds. The coefficients with respect to the valuation factor are only significant with respect to single beta subgroups, i.e. the first and 10th beta decile, indicating that value seems to be a significant characteristic for these funds only. Momentum is significant for seven out of ten subgroups. However, idiosyncratic risk is not statistically significant for the beta deciles. Hence, the beta portfolios do not reveal an aggregate manager preference to idiosyncratic risk, which appears to be only relevant to small funds, which are overweighted in the equal-weighted fund portfolio which is highly sensitive with respect to this risk factor. The illiquidity factor is significantly negative for the 9th and 10th beta decile, which shows that the high beta (large cap) fund managers prefer liquid stocks on average. Here, overall, the focus on less liquidity risk is slightly more pronounced than the focus on the idiosyncratic risk.

The adjusted R^2-statistics range from less than 10% for the beta decile 1 to more than 98% for the highest beta fund group. This result suggests that portfolios of fund managers taking a lot of market risk are characterized by a high comovement with the overall market and can hence be well explained by models including the market factor. The F-statistics regarding the joint significance of the coefficients are all statistically significant at the 1%-level. Furthermore, the risk-adjusted abnormal returns, i.e. annualized alphas, are always negative with the exception of the 2nd beta decile. This result is statistically significant for the four highest beta fund subgroups and is basically consistent with the individual performance evaluation results. This is again intuitive, as many mutual fund managers follow quite large exposures to the market, with, during the crisis, the whole Stoxx Europe 600 index having been characterized by a considerable downturn.

Next, I test for the robustness of the model selection and evaluation results.

Table 5.8: Mutual fund performance

This table displays summary statistics of abnormal performance in individual performance evaluations for various four, five and six factor models. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). The number of significantly positive and negative alphas is given for the 10%-significance level tested against the null hypothesis of a zero abnormal performance. The p-values of the smallest and largest t-statistics for the alphas refer to the Bonferroni tests. The Bonferroni tests are based on stricter significance levels which are adjusted by the overall number of funds. The relevant significance levels are then $\frac{0.05}{528} = 0.0000947$ and $\frac{0.10}{528} = 0.000189$ with a significance level of 5% and 10%, respectively. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

	Mean α_i p.d.	Mean α_i p.a.	Maximum	Minimum	Signif. neg. Alphas	Indifferent Alphas	Signif. pos. Alphas	Total number of funds	P-value (smallest t-stat)	P-value (largest t-stat)
CARHART	-0.0001	-0.033	0.0024	-0.0012	103	420	5	528	0.0000	0.0223
FF WITH LIQU.	-0.0001	-0.029	0.0025	-0.0012	78	446	4	528	0.0000	0.0224
FF WITH IDIOS. RISK	-0.0001	-0.032	0.0022	-0.0012	95	429	4	528	0.0000	0.0483
FFML	-0.0001	-0.030	0.0025	-0.0012	76	447	5	528	0.0000	0.0190
FFMI	-0.0001	-0.034	0.0022	-0.0012	99	425	4	528	0.0000	0.0386
FFLI	-0.0001	-0.031	0.0022	-0.0012	81	444	3	528	0.0000	0.0496
CARHART WITH LIQU.	-0.0001	-0.032	0.0024	-0.0012	85	440	3	528	0.0000	0.0220
CARHART WITH IDIOS. RISK	-0.0001	-0.035	0.0023	-0.0011	106	419	3	528	0.0000	0.0416
CARHART WITH LIQU. & IDIOS. RISK	-0.0001	-0.033	0.0022	-0.0011	92	433	3	528	0.0000	0.0429

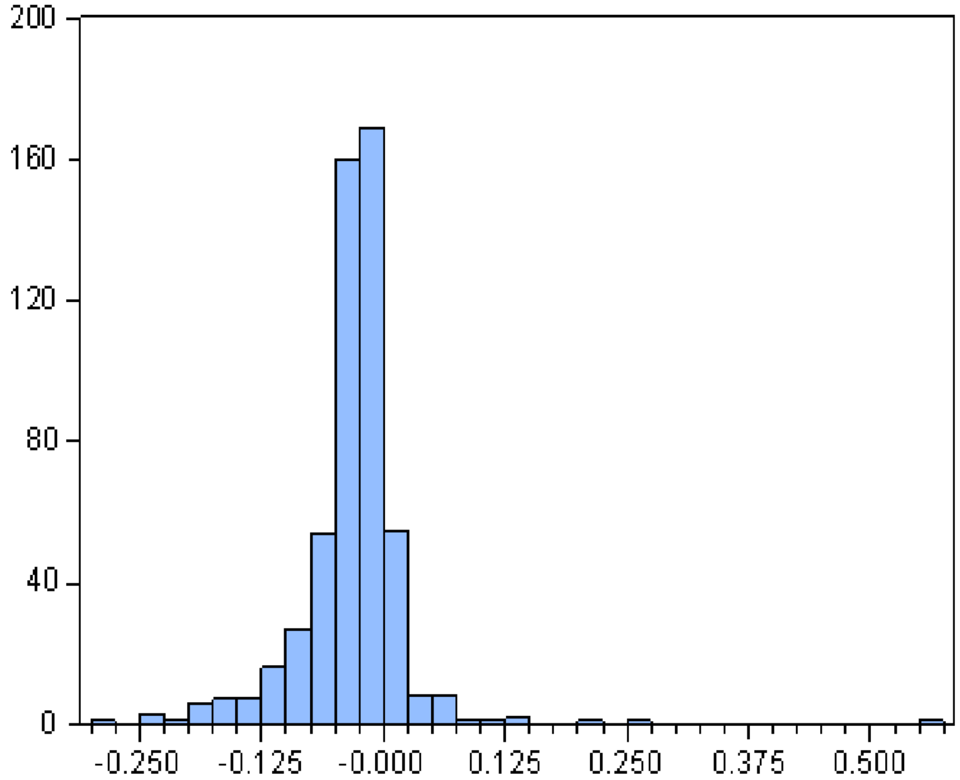

Figure 5.2: Frequency distribution of per annum alphas

This figure displays the frequency distribution of the annualized alphas in the liquidity and idiosyncratic risk augmented Carhart model. Sample period: October 2002 to September 2009.

Table 5.9: Fund portfolio performance results

This table gives the estimated regression coefficients, i.e. the risk exposures, for the equal-weighted fund portfolio (EQUAL) and the beta decile (D.) fund portfolios in the Carhart model with liquidity and idiosyncratic risk. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. T-statistics are given in parentheses. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

	α_i p.a.	MARKET EXC. RET.	SIZE	VAL.	MOM.	ILLIQU.	IDIOS. RISK	Adj. R^2-stat.	F-stat.
EQUAL	0.020	0.023	0.236	0.099	0.044	-0.220	0.145	0.061	20.732***
	(0.339)	(0.506)	(2.141**)	(1.629)	(1.004)	(-2.429**)	(3.667***)		
BETA D. 1	-0.007	-0.040	0.544	0.093	0.034	-0.079	0.005	0.073	24.619***
	(-0.121)	(-1.153)	(6.134***)	(1.683*)	(0.810)	(-0.921)	(0.125)		
BETA D. 2	0.007	0.206	0.451	0.049	0.057	-0.092	0.030	0.213	82.718***
	(0.172)	(9.069***)	(7.444***)	(1.236)	(1.936*)	(-1.494)	(1.174)		
BETA D. 3	-0.025	0.520	0.667	0.014	0.054	-0.032	0.016	0.502	304.345***
	(-0.821)	(11.531***)	(11.137***)	(0.389)	(1.720*)	(-0.470)	(0.475)		
BETA D. 4	-0.025	0.630	0.720	0.002	0.065	-0.041	0.031	0.573	405.530***
	(-0.881)	(14.687***)	(11.795***)	(0.061)	(2.104**)	(-0.568)	(0.972)		
BETA D. 5	-0.018	0.689	0.663	-0.016	0.041	-0.050	0.010	0.691	673.625***
	(-0.753)	(19.102***)	(12.790***)	(-0.503)	(1.515)	(-0.820)	(0.364)		
BETA D. 6	-0.021	0.748	0.600	0.022	0.050	-0.040	0.008	0.786	1103.971***
	(-0.991)	(24.185***)	(12.099***)	(0.799)	(2.112**)	(-0.908)	(0.320)		
BETA D. 7	-0.024	0.869	0.426	-0.004	0.068	-0.005	-0.019	0.934	4295.065***
	(-1.838*)	(50.524***)	(13.029***)	(-0.285)	(5.783***)	(-0.179)	(-1.168)		
BETA D. 8	-0.020	0.923	0.169	0.015	0.036	-0.022	-0.014	0.975	11801.060***
	(-2.470**)	(80.304***)	(7.538***)	(1.392)	(4.776***)	(-0.781)	(-1.080)		
BETA D. 9	-0.021	0.966	0.055	0.015	0.019	-0.052	-0.005	0.984	17968.510***
	(-3.261***)	(117.966***)	(2.607***)	(1.376)	(2.899***)	(-1.824*)	(-0.346)		
BETA D. 10	-0.022	1.009	0.028	0.051	-0.005	-0.051	0.008	0.982	16506.730***
	(-2.987***)	(143.044***)	(1.131)	(3.776***)	(-0.766)	(-1.952*)	(0.578)		

5.4.6 Robustness analysis

This section gives the results of several robustness tests with respect to the more general and comprehensive Carhart model with liquidity and idiosyncratic risk, see also Wagner and Winter (2013).

First, I control for the microstructure aspect of asynchronous trading by using the Dimson (1979) method, see also the backtests of Chapter 4. Table A.18 in Section A.6 in the appendix displays the results of the average summed coefficients with respect to the individual mutual funds by taking into account one or three lags on the risk factors. The importance of the size effect seems to be diminished, whereas the average mutual fund possesses a coefficient with respect to the market excess return which is now closer to one. The coefficients with regard to valuation, momentum and idiosyncratic risk are still not very high. Most interestingly, the sign of the valuation and idiosyncratic risk coefficients are dependent on the number of lags included, whereas momentum is quite stable. The liquidity coefficients seem to be larger now than those regarding valuation and momentum and the average summed exposures to idiosyncratic risk are smaller than those to liquidity. In contrast to the results above the average mutual fund is now positively exposed to liquidity risk. Overall, the results regarding the potential contribution of liquidity and idiosyncratic risk are confirmed, but individual risk factor results are not so robust to applying this method in order to take account of asynchronous trading.

Second, I also backtest for different model specifications. As some of the free-float weighted risk factors, like e.g. liquidity and idiosyncratic risk, are characterized by a high kurtosis and by outliers which mainly happened during the financial crisis, now the results are also given for the equally weighted risk factors which are more representative of the performance of small companies. The results in Table A.18 on the number of funds with statistically significant risk factor exposures suggest that mainly the results on size and liquidity are changed. Much more funds now exhibit a significant exposure to liquidity, whereas the results with respect to size have become much less pronounced. Moreover, with respect to size, the small minus big exposure of the majority of the funds has disappeared. Thus, some evidence of the size focus of the mutual funds found for the free-float weighted factors has now passed over to evidence in favor of the liquidity risk factor. This is intuitive as these two risk factors are influenced most by equal-weighting which is assumed to put more emphasis on less liquid stocks and on stocks with smaller market capitalization, see Section 3.3. The results with respect to the other risk factors do not indicate substantial differences. Table A.19 also gives backtests regarding the J-tests for the equal-weighted fund portfolio and the equal-weighted risk factors. Overall, the results basically reproduce those of the free-float weighted risk factors. As an exception, the statistical significance of liquidity as opposed to idiosyncratic risk weakens.

Third, if one includes detrended liquidity, i.e. a liquidity risk factor based on the Amihud measure where volume is detrended by its 100 trading days average instead of undetrended liquidity, the results with respect to the other risk factors remain quite stable. However, the importance of liquidity rather is increased compared to the evidence in Table 5.3. The results now suggest a slight, but not too pronounced preference for higher liquidity risk.

Fourth, I also check for the stability of the results regarding potential outliers, which mostly occurred during the financial market crisis, i.e. especially during the autumn of 2008. First, I conduct the robustness test for the risk factors based on the European style indices with the 1%- and 99%-cut-off-rates. Second, I control for outliers in the liquidity and idiosyncratic risk factors, which may influence the estimation results above by applying the three sigma rule regarding outliers in the liquidity and idiosyncratic risk variable. In this way, 13 outliers regarding liquidity and 26 outliers regarding idiosyncratic risk are detected. The results of the reestimation of the liquidity and idiosyncratic risk augmented Carhart model are also given in Table A.18. One observes that the number of funds with a significant exposure to the idiosyncratic risk and liquidity risk factors remains principally unchanged. Hence, overall, these different specifications do not significantly change the main implication of the usefulness of liquidity and idiosyncratic risk as determinants of fund performance.

Fifth, I consider the Bonferroni adjusted 5%- and 10%-significance levels (adjusted by the number of funds investigated, i.e. by 528) when analyzing the number of funds with a significant exposure to the risk factors in the liquidity and idiosyncratic risk augmented Carhart model. Even when applying these stricter significance levels, the joint hypotheses of zero factor exposures can be rejected with respect to all risk factors and their positive and negative t-statistics. The only hypothesis that can not be rejected is that there is no fund with a significantly negative exposure to the market excess return. This confirms that no conventional mutual fund is able to possess a negative exposure towards the market factor and that the slightly negative beta for the group of funds with the lowest beta is not statistically significant.

Sixth, I analyze the impact of mutual fund fees on the performance results, see Sharpe (1966). To check for this I obtain current, disclosed annual percentage charges for each mutual fund in the data set. For around 17% of the mutual funds, no annual percentage charges are available, so I have to use information on maximum past annual percentage charges.[41] Unfortunately, no data at all can be obtained for around 5% of the funds in the data set. The average annual fees of the individual mutual funds investigated are 1.4%, with a minimum of zero annual fees and a maximum of 5%. First, I analyze the relationship between per annum alpha and the annual percentage charges. The correlation between these two is only -0.05 which is quite small. Thus, one can not conclude that mutual fund managers are able to provide for a better performance if they charge higher fees. The evidence is even slightly in favor of the opposite. Then, I analyze gross risk-adjusted performance with respect to the liquidity and idiosyncratic risk augmented Carhart model. I find that, before consideration of fees, the average risk-adjusted performance is -1.77% per annum which is better than the -3.25% per annum after fees. However, the results indicate that, still, even before costs, the average mutual fund is not able to provide for a positive risk-adjusted performance. It has to be noted that all results do not take fund load fees into account, which are typically charged when shares in a fund are bought.

Seventh, I consider monthly and weekly data, see Table A.20 in the Appendix A.6.[42] The number of observations of 84 months is not so large. Especially, if one considers that many funds started to exist after the beginning of the observation period. Only around one half of the funds, i.e. 273, is characterized by data which cover the overall observation period. With respect to monthly data, the results indicate that almost all funds possess a significant exposure to the market and more than half of the funds on size which are still the most important risk factors for the mutual funds examined. The importance of the other risk factors (valuation, momentum, idiosyncratic risk and liquidity) seems to be diminished. The other risk factors, even the standard ones like valuation or momentum, are only relevant for subsets of the mutual funds. Moreover, the adjusted R^2-statistics are improved, whereas the F-statistics are now much smaller. In an additional backtest on weekly data, 505 mutual funds with a return history of at least 60 observations are analyzed. The results in Table A.20 reveal that the relevance of the market and the momentum factors is relatively unchanged, whereas the number of mutual funds with significant size and valuation exposures has slightly decreased. Most importantly, illiquidity and idiosyncratic risk are still relevant risk factors for a large fraction of mutual funds. However, almost an equal subgroup of the funds now possesses a positive versus negative illiquidity exposure as the number of funds with significantly negative illiquidity exposure has decreased. Regarding the weekly results, the fraction of funds with significantly

[41] Hence, the charges are rather overestimated and, consequently, the estimate of the performance before fees may be biased as well.

[42] I construct the monthly and weekly mutual fund data set by aggregation from the daily logarithmic mutual fund data.

positive idiosyncratic risk exposure has almost disappeared, whereas the number of funds with significantly negative idiosyncratic risk exposure has remained stable. This confirms the rather neutral or negative idiosyncratic risk exposure of most mutual funds. Overall, the results for the weekly backtests combined with the relatively high mean adjusted R^2-statistic of almost 80 percent and the high average F-statistic for the cross-section of mutual funds mainly confirm the results for the daily tests.

Eighth, in order to provide for an alternative fund subgroup ranking method used in the J-tests, see Table 5.6, I also construct equally weighted fund quintile portfolios based on the market beta, the size coefficient and the liquidity coefficient in univariate models only containing either the market, size or the liquidity factor. Comparing the results of the backtest in Table A.21 with those of Table 5.6, it becomes clear that the style classification when constructing the mutual funds subgroups may influence the result.[43] The backtests show that the Carhart model is again the preferred model based on the beta and size quintile fund portfolios. Based on the illiquidity quintile portfolios, no straightforward conclusion applies, but the results are rather in favor of the idiosyncratic risk augmented Fama and French model. Thus, the J-test results are somehow dependent on the ranking method of the fund subgroups which confirms the advantage of the individual fund analysis above.

Last, I consider different subperiods by dividing the observation period into halves. The first half from October 1, 2002 to March 31, 2002 mainly covers the market upturn after the burst of the technology bubble, whereas the second half from April 3, 2006 to September 30, 2009 is characterized by a short upturn, then the crash during the financial crisis and the current market upturn since spring 2009. In the first subperiod, due to the fund sample derived from the Lipper database which does not contain dead funds, only 380 of the 528 funds possess enough data to be used in regressions.[44] Again, see Table A.22 in the appendix, almost all funds –of those funds with enough data– have a significantly positive exposure to market excess return and size. The evidence regarding valuation shows that up to one third of the funds is exposed towards valuation with more funds having a negative exposure to valuation. This means that the funds rather preferred a growth over value exposure during that subperiod. Slightly more funds, about one third, have an exposure towards momentum, but during the first subperiod, the evidence in favor of winners over losers is almost as large as the evidence regarding a negative exposure to

[43]See e.g.Ferson and Harvey (1999) who argue that the Fama and French factors are designed to explain the returns on size and book-to-market portfolios and, hence, they expect them to explain worse portfolios formed based on different criteria.

[44]The series of 385 funds contain data during the first half of the sample. However, for 5 of these mutual funds, the series comprises less than 60 observations and, hence, these funds are ignored in the backtest.

momentum. During the first subperiod, liquidity is a more important risk factor than valuation and momentum. Around 200 of the 385 funds possess a significant exposure to illiquidity. Here, around 150 of the funds prefer liquidity whereas the remaining ones prefers illiquidity. The number of funds with a significant exposure towards idiosyncratic risk is slightly smaller, with more funds possessing a positive exposure to idiosyncratic risk. Thus, during the first subperiod, after market excess return and size, liquidity has been a more important risk factor in determining individual mutual fund performance than standard valuation and momentum. But also the innovative idiosyncratic risk factor has not been less important as a risk factor than valuation and momentum.

During the second half (see Table A.23 in the appendix) data an all 528 mutual funds are included. The results with regard to the market excess return and size are basically unchanged. Now, it seems that the number of funds with an exposure to valuation rather has increased. But, similar to the results for the overall observation period, the number of funds with a positive exposure to valuation dominates in models which include momentum. In contrast, in models without momentum, there is rather an equal amount of funds with positive and negative exposure towards valuation. In the second subperiod, the evidence regarding momentum is still quite high as around 200 funds in the different models focus on winners over losers. The evidence regarding illiquidity is smaller than in the first subperiod, but again more funds focus on liquidity than on illiquidity as the number of funds with a negative exposure to illiquidity is larger. However, interestingly, the evidence regarding idiosyncratic risk is now stronger than during the first subperiod. The majority of the exposures towards idiosyncratic risk possess a negative sign. Thus, mutual fund managers restrained from idiosyncratic risk. During the financial crisis with more asymmetric information and uncertainty being in place among investors, idiosyncratic risk became even more risky and, hence, was avoided by the fund managers, whereas, during the first subperiod, some fund managers may have tried to gain some additional return by focusing on this anomaly. A similar motivation may hold for liquidity. With respect to the abnormal return during the first subperiod, at the 10%-significance level, 44 funds possess a significantly negative and 50 funds a significantly positive abnormal return, whereas during the second subperiod 104 funds are characterized by a significantly negative and only one fund by a positive alpha. This is sensible as a successful fund management is much more difficult during a crisis period. During periods of crisis redemptions by fund investors are much more likely which may hinder the fund managers to implement strategies which might offer a better performance. Thus, overall, these backtests seem to indicate that mutual fund managers have changed their exposures towards the different risk factors over time. However, dividing the sample periods into halves only provides for an inaccurate approach to test for dynamics in risk exposures and a more sophisticated approach on this issue is needed.

5.5 Conclusion

In this chapter, liquidity and idiosyncratic risk, which are not yet established as standard risk factors in models of mutual fund performance, have been analyzed with respect to their role as risk factors determining mutual fund performance in addition to well-known Fama / French and Carhart factor models. Adding to the evidence of anomalies in asset pricing in Chapter 2, the analysis confirms that liquidity and idiosyncratic risk both provide relevant extensions to the Fama / French and Carhart models and are relevant for mutual fund performance. The vast number of funds which possess a significant exposure towards the liquidity and idiosyncratic risk factors demonstrates that the new family of equity style indices from which the risk factors are derived represents a valid basis for the derivation of risk factors. While market excess return and size are dominant risk factors, liquidity and idiosyncratic risk are statistically significant for subsets of funds, with evidence being almost as pronounced as that with respect to the established valuation and momentum factors.

The results on the funds' liquidity exposure support the hypothesis that mutual fund managers on average prefer liquid stocks, being in line with theoretical models on this issue. There is no evidence for the behavioral hypothesis that fund managers on average prefer positive exposure to idiosyncratic risk, while this may indeed be the case for some smaller funds. Overall, the number of funds with significant exposure to idiosyncratic risk is comparable to that with respect to liquidity. The importance of these two risk factors is neither diminished by considering them jointly nor by considering them in addition to the other risk factors. These risk factors seem to capture different aspects in the cross-section of mutual funds returns, even if they may be theoretically and empirically linked as the above mentioned literature in Chapter 2 suggests. While both liquidity and idiosyncratic risk are relevant risk factors, there seems to be no specific dominance of the two risk factors with respect to any factor in the Carhart model, which leads to a Fama-French-Carhart model with liquidity and idiosyncratic risk. Furthermore, when considering more parsimonious models of performance evaluation with only four factors, the Carhart model as well as a four factor model containing the market, size, momentum and liquidity risk factors, where hence the valuation factor is replaced by liquidity, may seem to be appropriate. Hence, substituting the valuation by the liquidity factor may offer a valid alternative to the established factor models. Robustness tests, which address the aspects of asynchronous trading, different risk factor weights, trends in volumes (as used for the Amihud measure of illiquidity) and outliers in factor returns, confirm these findings.

An analysis of the funds' individual net performance with respect to the different models reveals that for most funds the performance is statistically indistinguishable from zero. This would suggest a Grossman and Stiglitz (1980) equilibrium where managers earn the abnormal performance that is necessary to cover the costs of their respective information acquisition activities. Joint Bonferroni tests of risk-adjusted performance in the sample show that a substantial number of individual funds have significantly negative risk-adjusted performance, whereas none of the funds possesses significantly positive performance. Moreover, the results indicate that, still, even before costs, the average mutual fund is not able to provide for a positive risk-adjusted performance and the average risk-adjusted performance is even negative. One explanation could be that the growing size of the active management industry makes it more difficult to outperform the benchmark as investment opportunities due to mispricing have already been exploited by competing asset managers, see Pastor and Stambaugh (2012). The findings are also important for investors who decide to either invest in actively or passively managed funds as the findings presented here show that selecting an outperformer fund in advance is rather infeasible. It may be that fund investors suffer from behavioral biases, which lead them to be too optimistic about fund manager ability. Furthermore, mutual fund performance results must always be interpreted with caution as they may be biased due to drawbacks in risk factor construction and the design of multifactor models, see Cremers et al. (2008), Huij and Verbeek (2009), and Chan et al. (2009). This includes among others that transaction costs are usually ignored in factor construction or that nonzero alphas are assigned to even passive benchmarks.

In addition to the evidence on liquidity and idiosyncratic risk, the results indicate that the risk factor exposures of the funds may depend on the time period analyzed. As the fund managers seem to have changed the risk exposures of their portfolios across different subperiods, I next explicitly take into account the dynamics in these risk exposures and analyze whether the risk exposures are actively timed by fund managers.

6 Dynamic abilities of mutual fund managers

6.1 Introduction

Mutual fund managers are assumed to not only offer superior stock picking but also market timing abilities to their clients. If the market (or another risk factor) goes up, the exposure towards this risk factor should increase and if the market is expected to go down the mutual fund manager should diminish market exposure. Considering such dynamics in risk exposures is motivated by the evidence on unconditional performance of mutual funds in the preceding chapter which showed that the mutual fund managers have changed the risk exposures of their portfolios over the two different subperiods examined. The analysis in this chapter aims to enlarge the scarce European evidence on risk factor timing not only based on unconditional timing tests like those of Treynor and Mazuy (1966) and Henriksson and Merton (1981), but also based on an innovative, dynamic timing test specifically taking into account time-variation in risk exposures.

Evidence that risk exposures of mutual funds are not constant goes back to e.g. Kon and Jen (1978). A conditional evaluation of performance assumes that fund managers change their portfolios' compositions according to publicly available information and contingent on the fund managers' information sets, see among others Ferson and Schadt (1996) and Bessler et al. (2009). The findings in Ferson and Schadt (1996) suggest that the use of conditional models has even more impact than moving from a one factor to multifactor models, which has been investigated in detail in Chapter 5. However, available instrument variables only provide for a narrow approximation of investment opportunity and information sets or are unavailable at a daily frequency as they are often macroeconomic in nature. That is why, in this chapter, the time-varying risk exposures are estimated based on a statistical technique, i.e. the Kalman filter, which has been transferred from its use in engineering to an econometric tool and which allows for smooth as well as swift portfolio shifts as well as for changes in risk factor exposures due to factors unobservable by the econometrician. This approach then directly exploits dynamic mutual fund strategies taking into account time-variation in risk factor exposures.

Then, it is investigated whether the time-variation in risk exposures can be linked to timing abilities of fund managers. Here, the analysis in this chapter contributes to the empirical risk factor timing literature by examining the timing abilities of fund managers as based on a comprehensive dynamic timing approach. Moreover, it represents a short-term approach which is adequate with respect to shorter time series of data as well as daily data, as given by the Kalman filter which is used to model the time variation in the risk exposures. In contrast to Daniel et al. (1997) which apply a holdings based timing measure, the Kalman based approach also needs no holdings of the mutual funds.

Furthermore, this chapter gives evidence on liquidity timing as motivated by the evidence and literature in Chapters 4 and 5. Liquidity timing is especially important during periods of crises as fire sales may be caused by market-wide liquidity shocks which are often correlated with market shocks. Hence, mutual fund managers should be interested in actively timing liquidity as it is an important risk factor which is dynamic in nature, see Watanabe and Watanabe (2008). However, there is no study yet which analyzes liquidity timing itself (and not liquidity related market timing like in Cao et al. (2009b)) for mutual funds. As will be shown in more detail in the literature review in this chapter, there seems to be no study with respect to Europe as well. Hence, the analysis in this chapter tries to fill this gap in the empirical literature.

This chapter is structured the following way. First, a broad review on timing literature as well as the Kalman filter methodology is given in Sections 6.2 and 6.3. Then, the dynamic timing model is described in Section 6.4. Moreover, in Section 6.5, the empirical research design as well as the data set are outlined. The empirical findings are given in Section 6.6 and Section 6.7 concludes.

6.2 Literature review on timing

6.2.1 Unconditional timing tests

This section gives a brief overview on the literature and empirical evidence on market and risk factor timing. I first give an overview on unconditional timing methods by outlining the Treynor-Mazuy and Henriksson-Merton approaches which are among the most widely used methods of timing analysis, see e.g. Lehmann and Modest (1987), and which offer a first insight on the existence of timing abilities.

According to Treynor and Mazuy (1966), timing is analyzed for each mutual fund i based on the following return generating process

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{m} \beta_{i,k} f_{k,t} + \sum_{k=1}^{m} \delta_{i,k} f_{k,t}^2 + \varepsilon_{i,t}. \tag{6.1}$$

This nonlinear, quadratic relationship between mutual fund excess returns $R_{i,t} - R_{f,t}$ and risk factor returns $f_{k,t}$ results from the specification of each risk factor beta as

$$\beta_{i,k,t} = \beta_{i,k} + \delta_{i,k} f_{k,t}, \tag{6.2}$$

where the $\beta_{i,k,t}$ with respect to each risk factor k are dynamic as a reaction to a movement in $f_{k,t}$, with the coefficients $\delta_{i,k}$ serving as timing measures. As mentioned in e.g. Benos et al. (2010), managers trying to time a risk factor will purchase stocks with a significant exposure towards this risk factor if they anticipate an upward movement on that risk factor and vice versa, causing the fund's realized return to be a convex function of the risk factor.

Based on Henriksson and Merton (1981), timing is evaluated in the following framework

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{m} \beta_{i,k} f_{k,t} + \sum_{k=1}^{m} \gamma_{i,k} max(0, f_{k,t}) + \varepsilon_{i,t}. \tag{6.3}$$

This relationship between mutual fund excess returns and the risk factor returns results from the specification of the risk factor beta as

$$\beta_{i,k,t} = \beta_{i,k} + \gamma_{i,k} I_{f_{k,t}>0} \tag{6.4}$$

with $I_{f_{k,t}>0}$ being an indicator function which is equal to one if $f_{k,t} > 0$ and zero otherwise. If the performance of the risk factor is positive at time t, the timing coefficient $\gamma_{i,k}$ is also positive and, in Equation 6.3, the second term is added to the unconditional risk factor exposure $\beta_{i,k}$. Otherwise, the timing coefficient $\gamma_{i,k}$ is zero.

However, Jagannathan and Korajczyk (1986) show that the Henriksson-Merton approach is not able to adequately detect timing as evidence of artificial timing may arise by investing in option-like securities. This bias may be a possible explanation of previous empirical findings that indicate that mutual funds possess, on average, a negative timing ability and that selectivity and timing performance are negatively correlated, see among others Bollen and Busse (2001). Goetzmann et al. (2000) show that the Henriksson-Merton test for daily timers using monthly data is weak because a market timer makes decisions at a more frequent interval than the one over which the value of the implicit put option on the market is calculated. However, with daily data this problem should be negligible. Lockwood and Kadiyala (1988) argue that the Henriksson and Merton (1981) model assumes that macroforecasters alter their portfolio only with drastic adjustments. Here, managers only adjust their portfolios when reversals in the sign of the factor returns occur, which imposes strict assumptions on the market timing activity of investors. A further issue is that the assumption of constant or only drastically changed factor exposures may be violated for managed portfolios. Hence, a dynamic timing approach which avoids these problems would be advantageous. Such an approach should model time-variation in parameters and adequately consider drastic as well as smoothed changes in risk exposures.

In the next section, an outline of the market and risk factor timing literature is given.

6.2.2 Market and risk factor timing

The main block of the mutual fund timing literature focuses on the relationship between fund returns and the market return. Empirical studies on market timing such as e.g. Treynor and Mazuy (1966), Chang and Lewellen (1984) or Daniel et al. (1997) show that fund managers rather do not possess such a market timing ability. However, Bollen and Busse (2001) provide for evidence of a significant daily timing ability of mutual funds. Chance and Hemler (2001) –with respect to daily data– as well as Ferson and Schadt (1996) using a conditional approach also find some evidence of market timing.[45]

Recent studies investigate the ability of fund managers to time risk factors in multifactor specifications of mutual fund performance as relevant risk factors should be actively timed by rational mutual fund managers. With respect to risk factor timing, Chan et al. (2002) investigate timing of the Fama and French risk factors using the Henriksson and Merton (1981) methodology, but find no evidence of timing abilities regarding the market nor the other Fama and French factors for an equally weighted fund portfolio. Other evidence on negligible risk factor timing abilities with respect to the Fama and French factors has been found by Sehgal and Jhanwar (2008) and Benos et al. (2010). Timing abilities with respect to single risk factors or single mutual funds has been found by Swinkels and Tjong-a-Tjoe (2007) and Budiono and Martens (2009) with respect to the Fama and French factors and momentum. With respect to timing of macrofactors inconclusive evidence on respective abilities is given by Kryzanowski et al. (1997). Overall, evidence on risk factor timing seems to be rather inconclusive.

With respect to the timing of risk factors European evidence is generally scarce. Annaert and van Campenhout (2007) investigate daily return data on European equity funds over a ten year period and find that these funds exhibit style breaks. They suspect these style changes to be caused by economic motives such as herding, timing or anticipation of changes in economic conditions, but concrete evidence on risk factor timing is missing in their study.

[45]There are also studies on the timing of market volatility, see Busse (1999). Busse (1999) finds that fund managers rather reduce exposure to market risk during high volatility periods and vice versa.

Overall, pan-European evidence and the consideration of novel risk factors like e.g. liquidity seem to be missing, as is outlined next.

6.2.3 Timing of liquidity and idiosyncratic risk

The unconditional evidence in Chapter 5 has shown that the mutual fund managers examined vary the exposures towards the liquidity risk factor across the two halves of the 2002 to 2009 sample period which motivates to investigate liquidity timing by asset managers. In a holdings-based analysis, Massa and Phalippou (2005) find that mutual fund managers actively choose the liquidity level of their portfolio. They find that liquid funds overperform during illiquid periods and underperform during liquid periods, suggesting that fund liquidity and performance vary over time due to market-wide liquidity shocks. According to Edelen (1999), the appearance of poor market-timing performance and the underperformance of mutual funds are related to liquidity. This results from the liquidity service that fund managers provide in order to avoid large and random fluctuations in the cash position of the fund, which is linked to an asymmetrically informed market where liquidity motivated traders lose in comparison to informed traders. Hence, their results underline the dynamic nature of liquidity risk, which emphasizes that it is relevant for mutual fund managers to actively time these dynamics.

With respect to the recent financial crisis it is of special interest to analyze liquidity timing. This is motivated by Pastor and Stambaugh (2003) who find that aggregate liquidity is low when market volatility is high which should be anticipated by sophisticated fund managers. In the dynamic equilibrium model of Vayanos (2004) it is assumed that fund managers are subject to withdrawals when fund performance falls below a threshold which is more likely the case during more volatile periods of time. This causes time-varying preferences for liquidity which a prudent fund manager should try to time. Their model shows that during more volatile time periods liquidity premia are rising and the preferences with respect to illiquid assets are decreasing, as liquid assets are much more easily converted into cash in order to meet withdrawal enquiries by the investors of the mutual fund. Huang (2008) examines the relationship between expected market volatility and the demand for liquidity in mutual funds. He finds that fund managers tilt their holdings more heavily toward liquid stocks when the market is expected to be more volatile which then provides for higher abnormal returns. Hence, in periods of market stress one expects rational fund managers to try to decrease the exposures towards the liquidity risk factor. As there is until now no knowledge on the issue of liquidity timing in the context of the 2007 / 2008 crisis, this chapter aims at filling this gap.

Regarding timing of liquidity in the sense of a risk factor for mutual funds there seems to be no study yet which explicitly examines liquidity timing and not liquidity related market timing. Starting from the Acharya and Pedersen (2005) model, Cao et al. (2009b) show liquidity risk to be an important factor in mutual fund managers' timing decisions. They find that fund managers reduce the market exposure in illiquid markets and increase it in liquid markets. A similar study is published by Cao et al. (2009a) with respect to hedge funds. Another related study is conducted by Ferson and Qian (2004) who study the fund managers' ability to time market returns conditional on e.g. a market liquidity state variable. To my knowledge, this study is first to directly investigate liquidity timing.

The evidence in Chapter 5 has shown that the mutual fund managers examined also vary their exposures towards idiosyncratic risk across different subperiods. As it is important to control for idiosyncratic risk when investigating liquidity, see Section 2.3.3, and as idiosyncratic volatility has time-varying characteristics, see Fu (2009), backtesting for idiosyncratic risk when investigating liquidity timing is useful. Hence, this chapter contributes to the timing literature as there is no study analyzing the timing of idiosyncratic risk by mutual fund managers, neither during the financial crisis nor together with liquidity risk. Moreover, none of the above mentioned studies considers a more sophisticated dynamic method like e.g. the Kalman filter to take into account time-variation in risk exposures, which is outlined in the next section.

6.3 The Kalman filter

6.3.1 The Kalman filter in financial applications

This section gives an overview on the methodological background of the Kalman filter as well as related empirical studies where the Kalman filter is applied in finance and econometrics.

As e.g. Roncalli and Teiletche (2008) criticize, most of the empirical studies on time-varying risk exposures are based on OLS regressions estimated over rolling windows, see e.g. evidence in Ferson and Harvey (1999), Swinkels et al. (2003), Chen and Liang (2007) or Rummer and Schwindler (2008). However, the rolling windows are usually determined in an ad-hoc way, the exposures are restrictively assumed to be constant within the arbitrarily chosen rolling window periods and overlapping regression windows are a further issue of concern.

Fortunately, more efficient econometric techniques are available, such as the Kalman filter. Applying the Kalman filter is advantageous compared to alternative methods as betas estimated using the Kalman Filter are consistently more efficient when compared to other alternative methods like GARCH-type models or an extended, time-varying heteroskedastic market model, see Faff et al. (2000). Swinkels and van der Sluis (2006) conclude that the Kalman filter and Kalman smoother methodologies are much closer to the true underlying investment style than the rolling window alternative. Choudhry and Wu (2008) find that based on in-sample and out-of-sample stock return forecasts using beta estimates, the Kalman filter is superior to other GARCH-based estimation techniques when estimating time-varying betas. Moreover, compared to other methods, like e.g. GARCH-based models, the Kalman filter beta exhibits the most evident sensitivity to changes in beta, see Faff et al. (2000). In contrast to the changepoint regression or switching regime models in Bollen and Whaley (2009), Patton and Ramadorai (2009) or Billio et al. (2009), the Kalman filter method is not only able to easily model abrupt but also smooth changes in risk factor sensitivities over time. Mamaysky et al. (2008) find the Kalman filter estimates to be smoother than rolling window OLS estimates.

The Kalman filter enables to estimate time-varying risk exposures conditional on present and past information without knowing the information sets of mutual fund managers or having to use arbitrary instruments proxying for these information sets, like e.g. the dividend yield in the conditional approach of Ferson and Schadt (1996). The Kalman filter also represents an adequate technique for estimating daily data where macroeconomic instrument variables are often unavailable, as it offers to introduce time variation only with the help of unobservable state variables. Moreover, the information used by the fund managers is usually unobservable by the econometrician as the fund managers' timing decisions are possibly based on private or more detailed information. Hence, it seems to be useful to consider conditioning information in the form of unobservable state variables, making the Kalman filter a suitable model to investigate dynamic risk exposures as well as style variations of mutual funds. The Kalman filter technique is also adequate for daily data as it reacts swiftly to changes in the factor exposures. Moreover, it is adequate for estimating shorter sample periods in contrast to rolling regressions which would need a sufficient number of observations before the start of the estimation period. Also, with respect to outliers (as e.g. during periods of crises) rolling regressions in contrast to the Kalman filter technique are disadvantageous as the outliers cause distortions if they are occurring inside the rolling regression period or not.

The Kalman filter as an instrument to estimate time-varying betas with respect to risk factors is for example applied by Fisher and Kamin (1985), Black et al. (1992), Wells (1994) or McKenzie et al. (2000).[46] Swinkels and van der Sluis (2006) as well as Corielli

[46]A broad overview on empirical studies which consider nonstationarity in beta and on the use of the

and Meucci (2004) use the Kalman filter approach with respect to the return-based style analysis of mutual funds of Sharpe (1992). Bollen and Whaley (2009), Racicot and Théoret (2009) and Bodson et al. (2010) examine hedge funds using a Kalman filter analysis. Here, Racicot and Théoret (2009) apply the Kalman filter to analyze time-varying market betas with respect to hedge fund returns while controlling for the Fama and French three factor model. Bodson et al. (2010) consider the Kalman filter in the context of a return-based style analysis of hedge funds in the presence of time-varying style or risk exposures.

The separate analysis of timing abilities is necessary in addition to the simple analysis of the time-varying risk exposures of the Kalman state variables as Alexander et al. (1982) claim that beta nonstationarity is not a sufficient condition for identifying funds that actively engage in timing decisions. There are only a few studies which consider risk factor timing in the context of the Kalman filter approach. Swinkels et al. (2003) combine the Kalman filter with a conditional timing test dependent on observable information and model a mean reversion tendency in betas in the respective transition equation. Swinkels and van der Sluis (2006) address that the timing ability of a fund manager can be analyzed by the correlation between risk / style exposures towards the returns on these indices, for which the Kalman filter would be the appropriate statistical technique. They do not conduct an in depth timing analysis but first results on a comparison between rolling regressions and Kalman smoother based approaches indicate that the method used to estimate the timing ability has an impact on the timing result. Matallin-Saez (2008) applies a Kalman filter approach to investigate market timing across Spanish mutual funds by analyzing changes in dynamic betas. He argues that the Kalman filter is able to more properly estimate the dynamics of the beta as well as the dynamic relations between mutual fund returns and the market return. Matallin-Saez (2008) emphasizes that these estimates can then be used to measure timing with greater robustness than models without considering endogenous changes in beta risk. Risk factors like the Fama and French and momentum factors are considered as well, but no concrete analysis of timing with respect to these risk factors is conducted.

Mamaysky et al. (2008) conceive a dynamic timing model which allows for time-varying factor loadings due to the mutual fund manager's active trading activity. Here, the manager's trading signal is a state variable generated by a first-order autoregressive process and represents the unobservable factor in the transition equation of the Kalman state space model. They estimate the beta time series in the CAPM as well as the Carhart

Kalman filter methodology in finance is given by Wells (1996) in Chapters one and four.

model using the Kalman filter approach and analyze the correlation between this estimated beta time series and the market return across deciles of 10 size sorted portfolios. However, they do not take into account factor timing with respect to other risk factors than the market factor, although they calculate the respective time-varying factor exposures. This assortment of studies on risk factor timing and Kalman filter based timing studies shows that a detailed analysis of risk factor timing using the Kalman filter is still scarce. This also relates to European data as well as to the dynamic analysis of liquidity and idiosyncratic risk. That is why the empirical analysis in this chapter aims at bringing more insights into these issues.

Now, the theoretical background and the state space representation behind the Kalman filter approach are briefly outlined.

6.3.2 The Kalman filter and the state space representation

The Kalman filter is usually set up in the form of a state space model where unobserved variables are taken into account along with an observable model. Such a state space model comprises an observation or measurement equation together with a transition or state equation. The general representation of a state space model gives, first, a measurement equation of the form

$$\mathbf{y}_t = \mathbf{Z}_t \alpha_t + \mathbf{d}_t + \varepsilon_t \tag{6.5}$$

for $t = 1, ..., T$, where the signal $\mathbf{y}_t$ includes N elements and the state vector α_t as well as $\mathbf{Z}_t$ and $\mathbf{d}_t$ are of dimension m x 1, N x m, as well as N x 1, respectively. The transition equation in its general form equals

$$\alpha_t = \mathbf{T}_t \alpha_{t-1} + \mathbf{c}_t + \mathbf{R}_t \eta_t, \tag{6.6}$$

where $\mathbf{T}_t$, $\mathbf{c}_t$, $\mathbf{R}_t$ and η_t are of dimension m x m, m x 1, m x g and g x 1, respectively. For more information on the Kalman filter algorithm as given in this section as well as on the Kalman filter applied in econometrics, see Harvey (1989) pp. 100, and in finance, see Wells (1996) Chapter four.

The disturbances ε_t, being a N x 1 vector, and η_t, being a g x 1 vector, in the above specified equations are assumed to be serially uncorrelated with mean zero and covariance matrices $\mathbf{H}_t$ and $\mathbf{Q}_t$, respectively. It is useful to assume that the initial state vector α_0 possesses a mean of $\mathbf{a}_0$ and a covariance matrix of $\mathbf{P}_0$. Usually it is also assumed that the disturbances of both Equations 6.5 and 6.6 are at all points of time uncorrelated with each other as well as with the initial state. For the algorithm of the Kalman filter the system matrices $\mathbf{Z}_t$, $\mathbf{d}_t$, $\mathbf{H}_t$, $\mathbf{T}_t$, $\mathbf{c}_t$, $\mathbf{R}_t$ and $\mathbf{Q}_t$ are usually assumed to be non-stochastic as well as $\mathbf{a}_0$ and $\mathbf{P}_0$ are assumed to be known at all points of time, see Harvey (1989) pp. 104.

I now briefly outline a general representation of the Kalman filter algorithm based on the above specified state space model, see Harvey (1989) pp. 100. The specification in Equations 6.5 and 6.6 lead to the following m x m covariance matrix of the estimation error

$$\mathbf{P}_{t-1} = E\left[(\alpha_{t-1} - \mathbf{a}_{t-1})(\alpha_{t-1} - \mathbf{a}_{t-1})'\right], \tag{6.7}$$

with $\mathbf{a}_{t-1}$ being the optimal estimator of the state vector α_{t-1} based on the observable signal up to and including $\mathbf{y}_{t-1}$. This results in prediction equations where (i) the optimal estimator of α_t based on $\mathbf{a}_{t-1}$ is equal to

$$\mathbf{a}_{t|t-1} = \mathbf{T}_t\mathbf{a}_{t-1} + \mathbf{c}_t, \tag{6.8}$$

and where (ii) the optimal estimator based on the covariance matrix of the estimation error $\mathbf{P}_{t-1}$ depends on some of the system matrices as well as on the covariance matrix of the disturbances of the transition equation, i.e. $\mathbf{Q}_t$, see

$$\mathbf{P}_{t|t-1} = \mathbf{T}_t\mathbf{P}_{t-1}\mathbf{T}_t' + \mathbf{R}_t\mathbf{Q}_t\mathbf{R}_t'. \tag{6.9}$$

As specified in the following updating equation, $\mathbf{a}_{t|t-1}$ is updated when a new observation on $\mathbf{y}_t$ is given via

$$\mathbf{a}_t = \mathbf{a}_{t|t-1} + \mathbf{P}_{t|t-1}\mathbf{Z}_t'\mathbf{F}_t^{-1}(\mathbf{y}_t - \mathbf{Z}_t\mathbf{a}_{t|t-1} - \mathbf{d}_t), \tag{6.10}$$

which represents an estimator of the state vector α_t. In the second part of Equation 6.10 the difference between the observed and the estimated signal is weighted by the uncertainty of the current estimation step. This is done by considering the estimated covariance matrix of the estimation error as well as the inverse of an innovation covariance matrix $\mathbf{F}_t$ which will be described in more detail below. The second updating equation equals

$$\mathbf{P}_t = \mathbf{P}_{t|t-1} - \mathbf{P}_{t|t-1}\mathbf{Z}_t'\mathbf{F}_t^{-1}\mathbf{P}_{t|t-1}, \tag{6.11}$$

where

$$\mathbf{F}_t = \mathbf{Z}_t\mathbf{P}_{t|t-1}\mathbf{Z}_t' + \mathbf{H}_t, \tag{6.12}$$

which represents the innovation covariance matrix, holds, see Harvey (1989) pp. 100. $\mathbf{F}_t$ contains not only the estimator of the covariance matrix of the estimation error but also the covariance matrix of the disturbances of the signal equation. Thus, in Equation 6.10 those observations with a higher uncertainty –as given by these covariance matrices– have a smaller impact in updating the left hand side of Equation 6.10. Equations 6.7 to 6.12 basically represent the Kalman filter which provides for an optimal estimator of α_t whenever a new observation is processed, starting from $\mathbf{a_0}$ and $\mathbf{P_0}$ as initial conditions. Then, the estimator of the state vector is based on the full information set after all T observations have been considered.

In state space form, Equation 6.5 is defined as the measurement equation and Equation 6.6 as the transition equation. The measurement equation gives the relationship between the observable vector and a state vector, which is described in detail by the transition equation. The transition equation then details the generating process of the unobservable state variables α_t. These state variables are of special interest as they reflect the time-varying risk exposures of the mutual funds examined.

Then, the recursive algorithm of the Kalman filter is used to estimate this system, see Hamilton (1994) pp. 372 and Harvey (1989) pp. 100. In this way, the Kalman filter approach is conditional on information up to time t and provides for time-variation as well as an efficient use of available information. The Kalman filter estimates the states of a dynamic system from a series of noisy measurements and is also well suited for linear specifications. Moreover, one may interpret the Kalman filter as an algorithm for calculating linear least squares forecasts of state vectors on the basis of data observations through time t, see Hamilton (1994) p. 377. Thus, the Kalman filter approach is similar to a dynamic least squares estimation where the coefficients of the model are updated when new information arrives.

As laid out in e.g. Harvey (1989) p. 111, the Kalman filter procedure assumes the disturbances –as well as the initial state vector– to be normally distributed and, hence, the respective distributions are completely specified by their means and their covariance matrices. Under normality, the Kalman filter represents a minimum mean square estimator, see Harvey (1989) p. 111. However, without the assumption of normally distributed disturbances, the Kalman filter is still an optimal estimator as it minimizes the mean square error within the class of all linear estimators and still gives an unconditionally unbiased estimate of the state vector whose expected value equals the true state, see Harvey (1989) p. 111, Black et al. (1992), Hamilton (1994) p. 385, or Wells (1996) p. 79. As in Hamilton (1994) pp. 377, one can also use the idea of linear projections to derive the Kalman filter without specifically using the properties of multivariate normal distributions. Hence, even in case of violation of the assumption of normal distribution, which is a relevant issue to consider when analyzing return data, the Kalman filter can be used to calculate linear projections on past observations and a quasi maximum likelihood method can be applied to calculate consistent and asymptotically normal estimates of the parameters, see Hamilton (1994) p. 389. Thus, non-normality of the disturbances with respect to linear specifications is no issue of concern.

Next, a comprehensive dynamic approach to test for timing abilities as based on the Kalman filter is outlined.

6.4 A dynamic timing test

6.4.1 Conditional timing model

The deficiencies of the standard timing measures, i.e. the Treynor-Mazuy and Henriksson-Merton approaches, as well as consideration of dynamics in risk exposures motivate the presentation of an improved timing model in this section. This dynamic approach contributes to the timing literature as it displays a comprehensive and innovative approach based on the Kalman filter which is not subject of the disadvantages of the above mentioned unconditional approaches and which is also adequate for daily as well as shorter time series of data.

If one assumes the return generating process for a mutual fund i to be determined by

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,t}' \mathbf{f}_t + \varepsilon_{i,t}, \tag{6.13}$$

where $\mathbf{f}_t$ is a return vector of $1, \ldots, m$ risk factors and $\beta_{i,t}'$ is a vector of risk factor exposures, this leads to the following conditional expectation about the mutual fund's excess return

$$E_{t-1}(R_{i,t} - R_{f,t}) = \alpha_i + E_{t-1}(\beta_{i,t}' \mathbf{f}_t), \tag{6.14}$$

leading by the variance covariance decomposition to

$$E_{t-1}(R_{i,t} - R_{f,t}) = \alpha_i + E_{t-1}(\beta_{i,t}') E_{t-1}(\mathbf{f}_t) + Cov_{t-1}(\beta_{i,t}', \mathbf{f}_t). \tag{6.15}$$

The first term in Equation 6.15 represents the selectivity component of the mutual fund performance which is first assumed to be time-invariant in the following analysis.[47] The second term is the simple product of the conditional means of the (time-varying) factor

[47] This assumption is quite realistic if one assumes that changes in fund management, which might lead to a drastic change in the selectivity ability, do not happen very often, whereas, otherwise, management quality and hence selectivity is rather expected to be stable over time. However, in backtests going to be presented later on, I include time-variation in selectivity in the estimation as well.

exposures and the factor returns. Moreover, the third term is a straightforward measure of the timing ability of the manager of mutual fund i as it captures the conditional covariance between the vector of (time-varying) factor exposures $\beta_{i,t}'$ and the vector of (time-varying) factor returns $\mathbf{f}_t$. Conditional on the given information and its time-varying nature, the fund manager should increase the factor exposure when he expects increasing factor returns and vice versa. Equation 6.15 is quite similar to a conditional version in Swinkels et al. (2003) and an unconditional but time-varying version in Lo (2008) Chapter six.[48]

However, a conditional analysis as of Equation 6.15 demands knowledge of the information set of the respective mutual fund manager or the use of some instrument variables proxying for these information sets, which is subject to several deficiencies, as has been explained above. This calls for an adequate econometric approach which takes this into account, as it is going to be presented next.

6.4.2 Timing and time-varying risk exposures

The empirical problems with respect to a conditional analysis above may partly be solved by combining the above specified timing model with the Kalman filter approach which is an adequate technique to model time-variation in risk exposures. It is not subject to the disadvantages of alternative approaches like rolling regressions and it models risk exposures in a flexible way in contrast to e.g. switching regime beta models which model rather abrupt changes in regimes, see Billio et al. (2009). The main advantage of applying the Kalman filter is its characteristic to model unobservable state vectors without having to model and proxy for complete information sets. In line with Mamaysky et al. (2008), it should capture portfolio shifts or shifts in factor exposures due to factors unobservable by the econometrician. This makes the Kalman filter also an appropriate tool for the analysis of risk factor timing in Equation 6.15.

Considering the relations in Equations 6.13 to 6.15, the Kalman filter based timing analysis proceeds as follows. First, the time-varying risk exposures with respect to a multifactor model are estimated in the context of a state space representation and via the Kalman filter algorithm. Second, once the time series of the time-varying risk exposures $\widehat{\beta}_{i,k,t}$ with respect to each risk factor have been estimated via the Kalman filter approach, one can use this information in order to analyze whether mutual fund managers anticipate risk factor performance and accordingly change the factor exposures of their managed portfolios. The timing ability, as well as conditioning and forecasting as presented below,

[48] The assumptions basically needed to test for this relation are that returns follow stationary and ergodic stochastic processes with finite fourth moments. This ensures that means and covariances are well defined and can be estimated in a useful way.

is now estimated by the following regression with the $\widehat{\beta}_{i,k,t}$, i.e. the output for the filtered states in the transition equation of the Kalman filter, being the dependent variables with respect to each risk factor k

$$\widehat{\beta}_{i,k,t} = a + \sum_{j=0}^{r} b_{i,k,t-j} f_{k,t-j} + \upsilon_{i,t}, \tag{6.16}$$

In this specification, the $b_{i,k,t-j}$ are the regression coefficients of risk factor returns on the $\widehat{\beta}_{i,k,t}$ which have been estimated by the Kalman filter. Equation 6.16 combined with the time-varying estimates of the $\widehat{\beta}_{i,k,t}$, which are based on unobservable information as modeled by the Kalman filter, provides for an econometrically applicable proxy for the conditional covariance $Cov_{t-1}(\beta'_{i,t}, \mathbf{f}_t)$ in Equation 6.15.

Different leads and lags on the risk factor returns are considered in Equation 6.16 as the time-varying $\widehat{\beta}_{i,k,t}$-series offers to analyze the temporal order of the data as well as timing, conditioning and forecasting. This is useful in order to appropriately capture dynamic effects when determining timing abilities and refers to dynamic manager abilities in a more comprehensive way than standard covariance. By considering different leads and lags timing is also taken into account in a more comprehensive way than in Matallin-Saez (2008) or Mamaysky et al. (2008).

First, in the case of no time lag ($j = 0$), the correlation between the time-varying betas estimated by the Kalman filter and the current factor returns is calculated. This can be understood in the sense of a standard timing measure, see e.g. Grinblatt and Titman (1989b), where market timing is measured as the covariance between the beta and the market excess return, providing for a direct link between timing abilities and higher performance, or a time-varying version in Mamaysky et al. (2008). In contrast to the standard timing models like e.g. Treynor-Mazuy where a quadratic relation or Henriksson-Merton where drastic portfolio changes are assumed, this timing approach is also more flexible as it is not necessarily restricted to a specific relationship between mutual fund returns and the market return. A related approach is conducted by Matallin-Saez (2008). However, he relates change in beta modeled by the Kalman filter to the current market excess return in order to evaluate timing. This approach excludes beta dynamics which are not linked to market timing and does not simultaneously analyze performance while evaluating timing. In addition, it ignores that if the market excess return is up, the beta should have already been increased. In this setting, Matallin-Saez (2008) assumes that beta is only increased in the moment the signal arrives.

Second, with respect to for example one lag ($j = 1$) of the risk factor return one analyzes whether the mutual fund manager has adequately reacted to the development of the risk factor performance in the past. In such a case, this is not necessarily related to a higher current risk factor return and hence must not result in a higher fund performance. However, if the fund manager perceives information on past factor returns to be helpful indicators of future factor returns, nevertheless, this may be a sensible strategy. Furthermore, the analysis also helps to identify how fast the fund manager reacts to already observed positive or negative factor performance. Moreover, with respect to daily data, it is sensible that changes in the portfolio composition as a cause of timing activities which are aimed at increasing or decreasing exposure to a specific risk factor may need a few days to be implemented, and hence to become measurable. This may be the case if the fund manager tries to restrict market impact by his trading activities.

In the context of a conditional model, Equation 6.16 may be understood as the time-varying $\widehat{\beta}_{i,k,t}$ being related to an information signal about the risk factor development. With respect to past factor returns, Equation 6.16 corresponds to the factor exposure on the left hand side of the equation being conditioned on past information on risk factors. Thus, the risk factors $\mathbf{f}$ may be interpreted to serve as lagged instruments $\mathbf{z}$ similar to the relation

$$\beta(\mathbf{z}_{t-1}) = b_o + \beta'\mathbf{z}_{t-1} \tag{6.17}$$

specified in Ferson and Schadt (1996). These instruments $\mathbf{z}$ often include macroeconomic information helping to predict changes in the investment opportunity set, where the linear relation in Equation 6.17 results from a Taylor series approximation. Considering factor returns as the relevant information instruments implies a kind of timing measure where fund managers use information on past risk factor returns to derive future optimal risk factor exposures. The Ferson and Schadt (1996) specification refers to the semi-strong form of market efficiency by conditioning on observable public information, whereas the Kalman filter approach models unobservable state variables as well. If the instrument variables which proxy for public information were available at a daily frequency, one could combine both methods and model the timing ability dependent on observable macroeconomic information as well, see Mamaysky et al. (2008). In this way one measures timing over and above reaction on macroeconomic information, see the approach in Swinkels et al. (2003).

Third, one may also consider leading factor returns (with $j < 0$) in order to investigate whether the fund manager has an ability to predict future factor returns and to build up an adequate factor exposure in advance based on his expectation about future factor returns. In this way, the dynamic timing approach outlined in this section considers not only the time order of the data as well as the time-variability of the factor exposures, but also takes into account whether fund managers appropriately react to perceptions about future factor returns. Overall, Equation 6.16 simultaneously does not only take into account current, but also lagged and leading factor returns in order to determine factor timing abilities as well as conditioning and forecasting activities in a comprehensive way. Thus, this represents a more comprehensive version of the market timing approach as given in e.g. Grinblatt and Titman (1989b) who measure market timing ability as the covariance between the beta and the market factor.

One has to note that the risk exposures $\widehat{\beta}_{i,k,t}$ estimated by the Kalman filter are the dependent variables in Equation 6.16 and, hence, may contain some measurement error. However, an estimation error in a dependent variable is not as severe as when compared to an estimation error in an explanatory variable, see Wooldridge (2002) pp. 71. It is laid out in detail in Wooldridge (2002) pp. 71 that it is viable to estimate such models by ordinary least square methods and to ignore the fact that the dependent variables are imperfectly measured. However, if the measurement error were systematically related to one or more of the explanatory variables, then there may be biases in OLS. Otherwise, Wooldridge (2002) pp. 71 claims that OLS is perfectly appropriate.[49] As it is a sensible assumption that the measurement error in the $\widehat{\beta}_{i,k,t}$ based on the Kalman filter estimations is not systematically related to the $f_{k,t-j}$, this OLS-based timing analysis seems to be viable. Hence, the application of this procedure of timing analysis should be appropriate. Next, the empirical research design is laid out in more detail.

6.5 Empirical research design

6.5.1 The Kalman filter specification

Now, the state space system which is estimated in the following empirical analysis is specified. This considers a Kalman filter specification of the following form in order to identify the time-varying parameters $\beta_{i,k,t}$

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{m} \beta_{i,k,t} f_{k,t} + \varepsilon_{i,t}, \tag{6.18}$$

$$\beta_{i,k,t} = \beta_{i,k,t-1} + \xi_{i,k,t}. \tag{6.19}$$

In the case of $t = 1, \ldots, n$ observations, $k = 1, \ldots, m$ risk factors as well as for each mutual

[49] He argues that the larger error variance and the larger asymptotic variances for the OLS estimators do not violate the assumptions needed for OLS estimation to have its desirable large-sample properties.

fund i examined (hence considering stacked equations), $f_{k,t}$ is a 1 x n known risk factor vector for each risk factor k and $\varepsilon_{i,t}$ is a 1 x n vector of error terms for each mutual fund i examined. $\beta_{i,k,t}$ represents a 1 x n vector of the time-varying risk exposures with respect to each risk factor k (and each mutual fund i). $\xi_{i,k,t}$ is a 1 x n vector of error terms with respect to each transition equation and, hence, with respect to each risk factor k (as well as mutual fund i for the stacked equations). The transition equation details the generating process of the unobservable state variables, i.e. the $\beta_{i,k,t}$. These state variables are of special interest as they reflect the time-varying exposures of the mutual fund with respect to each risk factor k. The disturbances are assumed to have the following distributions with $\varepsilon_{i,t} \sim NID(0, \sigma_{\varepsilon}^2)$ as well as $\xi_{i,k,t} \sim NID(0, \sigma_{k,\xi}^2)$, where NID is an independent sequence of normally distributed random numbers.

The above specified model is then estimated by maximum likelihood estimation with the variances of the measurement and transition disturbances, i.e. σ_{ε}^2 and $\sigma_{k,\xi}^2$ respectively, being hyper-parameters which are estimated in order to get the model structure and the stochastic properties of the model, see e.g. Harvey (1989) p. 103. In line with the frequency of the data, the Kalman filter recursively estimates the above specified state space model in order to obtain the time-varying $\beta_{i,k,t}$. Thus, the use of the Kalman filter enables to estimate unobservable model parameters in a dynamic way.

In the transition equation of the Kalman filter model, the estimates for the state vector are conditioned on the information before and including time t which is then used to estimate the time-varying risk factor exposures of interest. I specify the transition equation in the following way with respect to each risk factor k

$$\beta_{i,k,t} = \beta_{i,k,t-1} + \xi_{i,k,t}, \tag{6.20}$$

considering a random walk model. Faff et al. (2000) propose such a random walk specification for the time-varying exposures as they find that this appears to give the best characterization of the time-varying betas, see also e.g. Swinkels and van der Sluis (2006), Roncalli and Teiletche (2008) or Monarcha (2009). The random walk specification assumes that changes in risk exposures are due to one-off changes in the active investment strategy, where, in the absence of new information, risk exposures remain unchanged, see Monarcha (2009). The fund manager alters the exposures only in case of new information arrival, see Faff et al. (2000), and any shock to an asset's systematic risk will persist indefinitely into the future until the next shock, which seems to be a sensible assumption with respect to active mutual fund management. Swinkels et al. (2003) and Mamaysky et al. (2008) conceive the Kalman filter model in a way which includes a mean reversion tendency in fund betas. However, this is also a strong assumption during a time period covering the financial crisis, when probably more drastic changes in risk factor exposures have become necessary.

The Kalman filter (see e.g. Mamaysky et al. (2008) or Matallin-Saez (2008)) and not the Kalman smoother (see e.g. Swinkels and van der Sluis (2006)), which uses the complete data sample in order to model rather smooth changes over time, is considered. Swinkels and van der Sluis (2006) conclude that the use of the Kalman smoother is superior to that of the Kalman filter when exposures are varying slowly over time, but that the Kalman smoother has trouble capturing sudden changes in exposures. As the Kalman filter better helps to detect swift changes in daily risk exposures and as timing is also rather an issue related to frequent information arrival, especially when analyzing a crisis period, the Kalman smoother is left for backtests. As initial conditions for the $\beta_{i,k,t}$ diffuse priors are used, see Harvey (1989) pp. 12, as there is no prior information on the model parameters. So, the initial positions of the state vector are assumed to be Gaussian variables. Then, the Kalman filter is used to recursively estimate time-varying betas from this initial set of priors to generate a series of conditional risk exposures. Furthermore, the manager ability α_i is first modeled to be constant. Heaney et al. (2007) find that the selectivity ability of mutual fund managers varies over time. Hence, an alternative would be to model the α_i to be time-varying as well. However, as, in this chapter, the main interest relates to the time-variation in risk exposures and not the selectivity ability of the mutual funds, the alpha is hold to be constant, but separate backtests will come back to this issue.

One also has to be aware of possible convergence problems of the Kalman filter which may be a sign of misspecification in the transition equation, see Faff et al. (2000). For example, Faff et al. (2000) use 250 iterations to convergence with respect to daily data. However, they find that the convergence rates are best with respect to the random walk specification as this seems to be most appropriate to characterize the time-varying betas, which emphasizes the specification in Equation 6.20. Furthermore, as McKenzie et al. (2000) argue, the Kalman filter approach often has so called start-up value problems where very large positive and negative parameter values may be generated in the initial stages of estimation. They avoid this problem by excluding the first 2 years from the time period of their analysis. Hence, it may be useful to exclude such a training period from the observation period in the empirical analysis as will be outlined in more detail later on. Moreover, the OLS regressions applied to estimate Equation 6.16 take into account the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987) as a viable estimator for daily data.

Next, the different multifactor models which will be estimated are represented.

6.5.2 Multifactor models

In addition to the liquidity augmented CAPM presented in detail in Chapter 4, the multifactor models considered in the empirical part of the section comprise the following models:

- Liquidity augmented CAPM (market, liquidity),
- CAPM (market),
- Fama-French (FF) (market, size, valuation),
- Carhart (market, size, valuation, momentum),
- Liquidity augmented CAPM with idiosyncratic risk (market, liquidity, idiosyncratic risk),
- Liquidity augmented CAPM with Fama and French factors (market, liquidity, size, valuation),
- Liquidity augmented CAPM with Carhart factors (market, liquidity, size, valuation, momentum).

Thus, the set of models considered comprises not only the standard CAPM, Fama and French and Carhart models, but also four liquidity augmented models derived from the parsimonious liquidity augmented CAPM of Chapter 4. The main model analyzed refers to the liquidity augmented CAPM as it is a parsimonious model which may be estimated with higher estimation quality by the Kalman filter for a large number of individual mutual funds. As liquidity timing is still an unexplored issue, this model also helps to answer whether dynamic liquidity management and timing exist, while taking into account market risk as suggested by the CAPM. However, controlling for idiosyncratic risk as well as for the Fama and French and Carhart factors also takes into account the possible links between different risk factors, as has been argued in Sections 2.3.3 as well as the robustness tests in 4.5.4.

In the next section, the data are going to be described in detail.

6.5.3 Data

In the following empirical analysis of liquidity and risk factor timing in Europe, I mainly consider the daily data on the quarterly rebalanced, free-float weighted risk factors as described in Chapter 3. The use of daily data in analyses of timing has become more common during the last years, see e.g. Bollen and Busse (2001), Swinkels and Tjong-a-Tjoe (2007), Matallin-Saez (2008), Sehgal and Jhanwar (2008), Budiono and Martens (2009) or Benos et al. (2010). Annaert and van Campenhout (2007) seem to be the first to empirically study daily data in a dynamic analysis of European mutual funds, but they do not analyze mutual fund performance itself but focus on style, i.e. risk factor, changes. According to Chance and Hemler (2001), the use of daily data aids to detect timing with respect to market and risk factor timers who frequently switch between asset classes. Bollen and Busse (2001) claim that statistical tests used in previous studies are weak as they are based on monthly data. In line with this, Goetzmann et al. (2000) argue that decisions with respect to market exposures are made more frequently than monthly. However, Patton and Ramadorai (2009) state that hedge funds rather than mutual funds are able to change factor exposures within a month. Overall, the use of daily data is intuitive as changes in the market excess return and in the other risk factor returns rather happen suddenly. This is also suggested by the financial crisis where days with even two-digit negative market returns occurred.

The mutual fund data set comprises the mutual fund data as they have been described in detail in Chapter 5 regarding mutual fund performance. It is much larger than that of e.g. Swinkels and van der Sluis (2006) who only consider a few international funds. I also take into account the equally weighted mutual fund portfolio containing all the individual funds of the mutual fund data set as introduced in Chapter 5. An equally weighted fund portfolio in the context of timing is e.g. considered in Daniel et al. (1997), Chan et al. (2002) or Cao et al. (2009b). Results on such a fund portfolio are useful for a first aggregate insight on time-varying risk exposures as well as aggregate timing abilities, as individual fund analyses are more extensive.

In the next section, the empirical results are given.

6.6 Empirical evidence

6.6.1 Unconditional timing results

The outcome of the unconditional Treynor-Mazuy timing tests is given in Table 6.1 for the different multifactor models. Here, more than 40 percent of the mutual funds possess a negative market timing ability in the different models, which is consistent with the results of e.g. Treynor and Mazuy (1966) or Henriksson and Merton (1981). A small number of mutual funds show negative size timing. However, with respect to valuation and momentum, in some of the different models more mutual funds are characterized by a positive than negative timing ability. However, this is not stable across different model specifications and upon inclusion of the liquidity risk factor. In the liquidity augmented CAPM around 28% of the mutual funds possess a significantly positive liquidity timing ability, whereas around 12% of the mutual funds are characterized by negative liquidity timing. The results are quite similar when additionally controlling for the Fama and French and Carhart factors. An additional inclusion of the idiosyncratic risk factor considerably diminishes the percentage of significant liquidity timers, but further tests are necessary to defer a conclusion on the link between both risk factors from it. Overall, the evidence given here displays a rather negative market timing ability and some slightly positive liquidity timing ability, whereas evidence on other risk factor timing is not stable and only significant for a small fraction of the mutual funds.

The Henriksson-Merton results are also given, see Table 6.2. The timing results are again indicative of negative market and size timing by the fund managers, thus confirming the Treynor-Mazuy results. However, the results with respect to the other risk factors are partly different as some evidence of positive valuation and momentum timing in the Fama-French and Carhart models seems to have vanished. For the Henriksson-Merton methodology the fraction of liquidity timers is much smaller and no concise conclusion in favor of positive compared to negative liquidity timers is given. Moreover, now, some funds possess a positive as well as negative idiosyncratic risk factor timing ability compared to the rather negative timing ability found before.

For both the Treynor-Mazuy and the Henriksson-Merton tests the average adjusted R^2 in the liquidity augmented CAPM is approximately 55% which is quite high. The average adjusted R^2-statistics in the other models are quite similar and the average F-statistics for testing the joint significance of the coefficients are also very high. Hence, the joint significance of the coefficients is not rejected.

Overall the unconditional timing tests are inconclusive regarding risk factor timing, apart from market and size timing, and the results on liquidity timing are not stable across both methods. Thus, one can not derive a clear conclusion, as the results are not consistent for these widely used timing tests and different model specifications. As this may be caused by the unconditional methods not adequately taking into account dynamics in risk exposures in an adequate way, this will be explored next.

6.6.2 Aggregate analysis of time-varying risk exposures

It is now investigated whether the risk exposures of the mutual funds are time-varying, as already indicated by the robustness tests in Chapter 5. First, I conduct Chow break tests,

Table 6.1: Timing results: Treynor and Mazuy

This table gives the fraction of funds with significant Treynor and Mazuy (1966) timing coefficients at the 5%-significance level based on individual mutual fund regressions. The average adj. R^2- and F-statistics are also given. Regressions are performed considering the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). Sample period: October 1, 2002 to September 30, 2009.

Fraction of funds with sign. timing coeff.	MARKET EXC. RET.	SIZE	VALUAT.	MOM.	ILLIQU.	IDIOS. RISK	Avg. adj. R^2	Avg. F-stat.
CAPM							0.548	3097.268
Sign. neg.	40.72%							
Sign. pos.	0.38%							
FF							0.586	1127.692
Sign. neg.	30.49%	7.20%	3.03%					
Sign. pos.	1.14%	0.38%	15.72%					
Carhart							0.590	866.102
Sign. neg.	33.90%	6.25%	5.11%	8.33%				
Sign. pos.	1.70%	0.57%	13.26%	5.49%				
Liquidity augm. CAPM							0.551	1585.142
Sign. neg.	41.67%				12.12%			
Sign. pos.	0.38%				27.46%			
Liquidity augm. CAPM with idios. risk							0.555	1078.487
Sign. neg.	42.05%				3.79%	4.92%		
Sign. pos.	0.76%				7.01%	0.95%		
Liquidity augm. CAPM with FF factors							0.589	863.811
Sign. neg.	30.30%	6.25%	4.36%		6.06%			
Sign. pos.	1.14%	0.57%	3.98%		27.46%			
Liquidity augm. CAPM with Carhart factors							0.592	706.526
Sign. neg.	35.61%	5.87%	6.63%	7.58%	5.68%			
Sign. pos.	1.14%	0.76%	1.14%	11.74%	24.81%			

Table 6.2: Timing results: Henriksson and Merton

This table gives the fraction of funds with significant Henriksson and Merton (1981) timing coefficients at the 5%-significance level based on individual mutual fund regressions. The average adj. R^2- and F-statistics are also given. Regressions are performed considering the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). Sample period: October 1, 2002 to September 30, 2009.

Fraction of funds with sign. timing coeff.	MARKET EXC. RET.	SIZE	VALUAT.	MOM.	ILLIQU.	IDIOS. RISK	Avg. adj. R^2	Avg. F-stat.
CAPM							0.547	3096.993
Sign. neg.	47.73%							
Sign. pos.	0.19%							
FF							0.584	1125.536
Sign. neg.	24.81%	5.87%	1.33%					
Sign. pos.	0.10%	0.57%	4.92%					
Carhart							0.588	863.549
Sign. neg.	26.89%	3.41%	1.33%	4.55%				
Sign. pos.	0.00%	0.57%	2.08%	0.57%				
Liquidity augm. CAPM							0.549	1583.729
Sign. neg.	45.27%				7.58%			
Sign. pos.	0.00%				2.84%			
Liquidity augm. CAPM with idios. risk							0.554	1076.251
Sign. neg.	47.16%				6.25%	3.03%		
Sign. pos.	0.00%				3.41%	5.30%		
Liquidity augm. CAPM with FF factors							0.586	862.655
Sign. neg.	27.65%	5.68%	2.08%		3.79%			
Sign. pos.	0.38%	0.38%	1.89%		4.17%			
Liquidity augm. CAPM with Carhart factors							0.590	702.888
Sign. neg.	28.22%	2.46%	0.38%	4.55%	4.36%			
Sign. pos.	0.19%	0.95%	1.52%	0.38%	3.21%			

Table 6.3: Structural break tests: Equal-weighted mutual fund portfolio
This table gives the results of the Chow and Quandt likelihood ratio (QLR) tests for different model specifications and the equal-weighted mutual fund portfolio. Sample period: October 1, 2002 to September 30, 2009.

	F-stat. (Chow-test)	QLR-stat.
CAPM	117.275***	136.946***
FF	89.760***	105.414***
Carhart	77.036***	89.328***
Liquidity augm. CAPM	76.755***	90.021***
Liquidity augm. CAPM with idios. risk	55.614***	62.845***
Liquidity augm. CAPM with size	84.465***	99.098***
Liquidity augm. CAPM with FF factors	71.634***	83.410***
Liquidity augm. CAPM with Carhart factors	64.301***	73.923***

see Swinkels and van der Sluis (2006), and Quandt likelihood ratio (QLR) tests as tests on the stability of the regression coefficients. Both methods focus on rather discrete shifts over time before applying the Kalman filter methodology which also allows for smooth time changes.[50] As the Chow breakpoint test requires knowing the break date, subperiods by dividing the sample period into halves as in Section 5.4.6 are formed. Second, the QLR statistic, a modified Chow test as described in detail in Stock and Watson (2007) pp. 567, is used as it tests for breaks at unknown dates. It gives the maximum of individual Chow F-statistics and tests for breaks at all possible dates in the test period. The test period has symmetrically been trimmed by 15% as suggested by Stock and Watson (2007) pp. 567. The results on both tests are given in Table 6.3 which reports the F-statistics on both tests. It displays the results for the aggregate equal-weighted fund portfolio with respect to the different model specifications given above. Both test statistics for each model specification reject the null hypothesis of no structural break over the sample period. Hence, the relevance of a time-varying analysis using the Kalman filter approach is emphasized and the reliability of the Treynor-Mazuy and Henriksson-Merton results above is questionable, as both methods are not prone to structural breaks and dynamics in the data.

Next, the Kalman filter is applied to get a better sense of the time-variation of the risk

[50] An overview on alternative test methods to test for parameter stability is given in Wells (1994), Bollen and Whaley (2009) or Annaert and van Campenhout (2007). These are for example the CUSUM-based tests which test the cumulative sum (CUSUM) of recursive residuals or the changepoint regression. Wells (1996) pp. 27 additionally proposes to test for heteroskedasticity in regression residuals to detect parameter instability. However, this is not so useful with respect to daily data which are often characterized by such heteroskedasticity.

factor sensitivities, which takes into account not only discrete but also smooth changes in risk factor exposures. First, the results are given for the equal-weighted mutual fund portfolio, providing a first impression on the importance of time-varying risk exposures and later on also timing, see e.g. Chan et al. (2002). Table 6.4 gives the summary statistics of the time-varying risk exposures. First, in the liquidity augmented CAPM, the average market and liquidity exposures are positive on average and the minimum and maximum numbers suggest that the exposures vary a lot over time, especially for the liquidity factor where exposures range from -1.444 to 1.104. In contrast to the unconditional results in Chapter 5, the conditional results reveal a considerably positive illiquidity exposure which is consistent with the focus on smaller, probably rather illiquid funds. This is more intuitive than the former unconditional result on the equal-weighted mutual fund portfolio having slightly negative exposure to liquidity risk. For smaller funds increasing sensitivity to smaller, probably rather illiquid securities is sensible as their investment positions in single securities are smaller in absolute value. Thus, they probably induce less price impact on more illiquid securities which may be attractive investments as they offer higher expected returns. In this context, in the presence of time-varying risk exposures the use of unconditional methods may lead to biased results. So, it is useful to complement the analysis of Chapter 5 by the dynamic analysis in this chapter. The considerable variation in the time-series of the risk exposures confirms that a time-varying analysis is justified, see Table 6.4.

This is also confirmed in Figure 6.1 which displays the time-varying market and liquidity risk exposures over time. On aggregate, the mutual funds seem to have reduced the market exposure over time, especially in the second subperiod which also contains the financial crisis. However, this figure also displays a puzzle as the fund managers seem to have reduced the market beta to zero, while market risk should be difficult to hedge for fund managers as the previous chapter has shown. Later on, backtests will address this issue. Moreover, the liquidity risk exposure of the aggregate mutual fund portfolio seems to be characterized by a lot of variation over time, which strengthens the importance of the time-varying analysis as well. The negative outlier at the start of the sample period results from the Kalman filter procedure as the Kalman filter needs a short training period before it becomes stable.[51]

Next, I analyze the liquidity augmented CAPM including additional risk factors, like idiosyncratic risk or size. The minimum and maximum results and standard deviations of the time-varying risk exposures again suggest that there is enough time variation in

[51] Later on, a backtest ignoring the training period of the Kalman filter is conducted to check for the robustness of the results.

the risk exposures to justify a dynamic analysis. The results on the market exposure, i.e. the beta, are quite similar across the different models for the equal-weighted mutual fund portfolio. There is a large positive mean exposure on size and a small negative mean exposure on valuation, both stable across the models. Thus, in line with the results in Chapter 5 well-known risk factors like e.g. size are also relevant in a time-varying context. In contrast, the dynamic liquidity results are dependent on the model and thus not so stable. The average liquidity risk exposure is reduced by taking into account idiosyncratic risk as well as the Carhart factors and it even becomes negative when including size as well as the Fama and French factors. As this may be linked to the argumentation of e.g. Liu (2006) on the possible connection between the Fama and French factors and the liquidity factor as outlined in Section 4.5.4, later on, backtesting more deeply the results for these other risk factors is useful. One can also observe that the equal-weighted mutual fund portfolio is again –due to its small fund bias– characterized by a considerably positive size exposure but a much smaller average market exposure. In line with the unconditional results, it possesses a quite large positive exposure to idiosyncratic risk which suggests that the smaller funds load on a considerable portion of this risk factor. In contrast to the unconditional tests, the aggregate fund portfolio now has a small exposure towards growth stocks, which is probably related to the focus on stocks with smaller market capitalization being rather startup or strongly growing firms, but also a small exposure to past loser stocks. With respect to the equal-weighted fund portfolio the effects of liquidity and size can not properly be disentangled as the sign of the average liquidity risk factor is dependent including the size factor or not. Because of the possible small fund bias of the equal-weighted fund portfolio, an additional analysis of individual mutual funds seems to be necessary, as is considered next.

6.6.3 Aggregate timing analysis

The obvious time-variation in risk factor exposures motivates an in-depth dynamic timing analysis on whether the dynamics in factor exposures, which have been identified in this section, are caused by true timing abilities of the mutual fund managers. Hence, the results of the dynamic timing test are now given for the equal-weighted fund portfolio.

The tables 6.5, 6.6, 6.7 and 6.8 give the results on the Kalman filter based dynamic timing analysis.[52] In the liquidity augmented CAPM, the coefficients on the market excess return are positive but only significant with respect to the second lead, whereas the timing

[52]The constants of the timing regression in Equation 6.16 are given but not interpreted in detail, as they are of no specific economic relevance in contrast to e.g. Jensen's alpha.

Table 6.4: Time-varying risk factor exposures: Equal-weighted mutual fund portfolio
This table gives summary statistics of the time-varying risk factor exposures estimated by the Kalman filter for the equal-weighted mutual fund portfolio and different model specifications of the liquidity augmented CAPM. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: October 1, 2002 to September 30, 2009.

	Mean	Median	Maximum	Minimum	Std. dev.
Liquidity augm. CAPM					
MARKET EXC. RET.	0.226	0.065	0.654	-0.406	0.291
ILLIQU.	0.215	0.191	1.104	-1.444	0.288
Liquidity augm. CAPM with idios. risk					
MARKET EXC. RET.	0.158	0.037	0.643	-0.402	0.249
ILLIQU.	0.076	0.082	0.310	-1.577	0.104
IDIOS. RISK	0.140	0.159	0.517	-0.613	0.060
Liquidity augm. CAPM with size					
MARKET EXC. RET.	0.245	0.082	0.856	-0.388	0.339
ILLIQU.	-0.153	-0.177	0.248	-1.681	0.142
SIZE	0.669	0.678	0.937	-0.622	0.134
Liquidity augm. CAPM with FF factors					
MARKET EXC. RET.	0.240	0.055	0.988	-0.460	0.353
ILLIQU.	-0.110	-0.124	0.228	-1.795	0.147
SIZE	0.523	0.523	1.826	-0.946	0.368
VALUATION	-0.011	-0.022	0.878	-0.427	0.118
Liquidity augm. CAPM with Carhart factors					
MARKET EXC. RET.	0.238	0.046	1.068	-0.469	0.356
ILLIQU.	0.070	0.016	2.019	-1.890	0.420
SIZE	0.458	0.428	2.390	-1.116	0.356
VALUATION	-0.007	-0.020	1.885	-0.359	0.156
MOMENTUM	-0.019	-0.027	0.554	-0.134	0.046

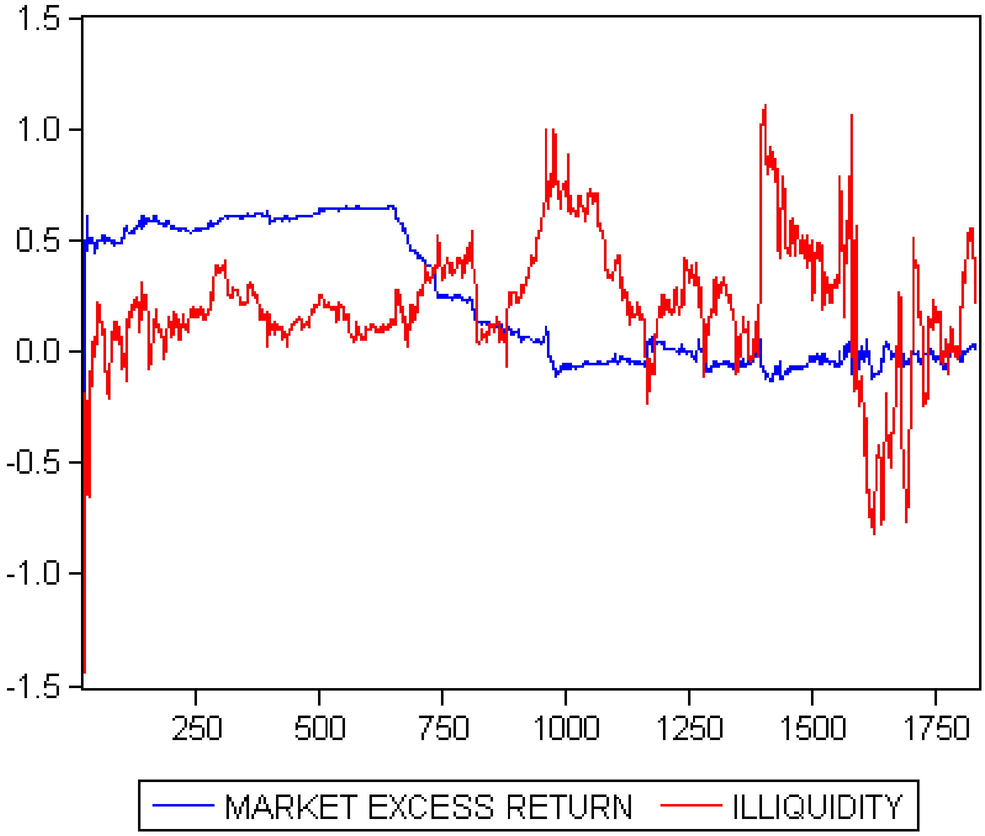

Figure 6.1: Time-varying risk factor exposures in the liquidity augmented CAPM

This graph shows the time-varying risk factor exposures of the market excess return and the liquidity risk factor in the liquidity augmented CAPM for the equal-weighted mutual fund portfolio and the overall number of 1808 daily observations. The time-varying risk exposures have been estimated by the Kalman filter. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: October 1, 2002 to September 30, 2009.

coefficients on liquidity are rather negative and insignificant. Hence, there is only small evidence in favor of aggregate market timing –here in the sense of forecasting– and rather negative evidence of liquidity timing, conditioning and forecasting. As the coefficient on the current market excess return is insignificant, there is no aggregate timing ability. When controlling for idiosyncratic risk and size separately, there is more evidence in favor of an existing market timing ability as the coefficients are significantly positive even at the 5%-level for different leads and lags. The coefficients on liquidity timing are in both models rather negative and insignificant as well as those on idiosyncratic risk. However, there is some evidence on successful size forecasting as the forecasting coefficients are positive and significant for several leads of the size risk factor. Including the Fama and French and Carhart factors, some results slightly change as the significance of the coefficients with respect to size timing has almost disappeared and also the sign of the coefficients partly becomes negative. The coefficients on valuation and momentum are also rather negative and insignificant. Overall, based on this evidence, there is not much evidence of successful liquidity timing and no or only unstable evidence of other risk factor timing, as well as conditioning and forecasting.

The findings in Table 6.9 regarding the adjusted R^2-statistics for the timing regressions show that the goodness-of-fit of the models is very small and that only a negligible fraction of the daily variation in the time-varying risk factor exposures can be explained by the linear dynamic timing model which considers the factor returns as explanatory variables. Thus, evidence on timing, conditioning as well as forecasting is rather weak for funds in the aggregate. However, goodness-of-fit is not much smaller than in daily market timing tests given under consideration of time-varying risk exposures in Matallin-Saez (2008) where it ranges between less than 1% and 10%. At least, the F-statistics which test the joint significance of the coefficients are for some models significant.

It can be noted that the evidence of perverse market timing found when using the unconditional Treynor-Mazuy and Henriksson-Merton methods has been removed when taking into account time-variation in risk exposures. In line with Ferson and Schadt (1996) who do not find evidence of perverse market timing using a conditional evaluation method in order to consider time-variation in betas, I also detect no perverse market timing anymore based on the dynamic testing approach, which seems to be a more sensible result. Perverse timing would not be rational as the respective fund managers would always invest opposite to what would be optimal with respect to the evolution of the risk factor performance. Over longer time periods, rational investors would penalize negative performance by redemptions of their funds' holdings as confirmed for poorly performing German equity funds over the 2003 to 2008 period by Jank and Wedow (2010). In contrast to the unconditional Treynor-Mazuy results, evidence of liquidity timing has disappeared. However, the adjusted R^2-statistics of the dynamic timing tests are very low. An assortment of backtests will later on try to backtest this issue.

Overall, the aggregate results suggest that there is no risk factor timing and that the time-varying risk factor exposures can not be explained by past, present and future factor returns, being in line with the results on an equally-weighted mutual fund portfolio and the Fama and French factors given in Chan et al. (2002). As this result may be different for individual mutual funds and as the equal-weighted fund portfolio may have a small fund bias, in the next section an individual fund analysis is conducted.

6.6.4 Individual analysis of time-varying risk exposures

Now, I give the results with respect to individual mutual funds. I estimate the Kalman filter only for those 254 mutual funds which have been existing over the overall sample period due the training period of the Kalman filter. During this training period, very large positive and negative values can occur before the state series becomes stable as the Kalman filter starts from an initial value –i.e. the diffuse prior– for each state variable, see also Figure 6.1. By restricting the mutual fund sample in this way, I construct a consistent data set of individual mutual funds, where, in later backtests, it is possible to control for these distorted observations.

Table 6.10 gives the summary statistics of the filtered states for the liquidity augmented CAPM. On the top of the table, mean, median, maximum and minimum as well as standard deviation refer to the time-series of the risk exposures. On the left hand side of the table, the cross-sectional summary statistics of these time series statistics are given for these 254 mutual funds. Here, all of the 254 Kalman filter estimations successfully converge. For the market excess return, the summary statistics in Table 6.10 suggest a time-variation in the risk factor exposures. This becomes obvious with respect to the dispersion of the time-series mean and median of the market risk exposures and the minimum and maximum market betas across the individual mutual funds. At the extremes of the beta dispersion are a time-series maximum estimated beta of 3.626 and a minimum beta of -4.141.[53] Some mutual funds possess a high standard deviation of the beta which is also an obvious sign of time variation in the risk factor exposures around the cross-sectional mean beta of 0.613. Overall, as expected, the average market beta is now larger than it

[53]However, such a negative market beta is only given for single mutual funds, while the summary statistics for the equal-weighted fund portfolio confirm that mutual funds in the aggregate can not hedge market risk. As the negative market betas may be due to estimation errors, it will be controlled later on whether results are strongly affected by estimation quality.

Table 6.5: Risk factor timing: Liquidity augm. CAPM and liquidity augm. CAPM with idios. risk

Same caption as in Table 6.6 applies. The results are given for the liquidity augmented CAPM and the liquidity augmented CAPM with idios. risk.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augm. CAPM												
MARKET EXC. RET.: Coeff.	0.226	0.531	0.575	0.621	0.696	0.687	0.735	0.763	0.873	0.689	0.656	0.661
T-stat.	11.684***	1.088	1.213	1.273	1.447	1.443	1.533	1.548	1.671*	1.412	1.349	1.419
ILLIQU.: Coeff.	0.223	-2.253	-2.557	-2.964	-3.264	-2.879	-2.451	-0.601	0.532	-0.400	-1.283	-1.245
T-stat.	11.583***	-1.058	-1.156	-1.313	-1.476	-1.417	-1.286	-0.295	0.252	-0.205	-0.732	-0.813
Liquidity augm. CAPM with idios. risk												
MARKET EXC. RET.: Coeff.	0.158	0.643	0.694	0.705	0.711	0.693	0.716	0.855	0.890	0.723	0.682	0.678
T-stat.	9.618***	1.586	1.741*	1.738*	1.775*	1.733*	1.804*	2.069**	2.064**	1.805*	1.708*	1.798*
ILLIQU.: Coeff.	0.080	-0.064	-0.150	-0.363	-0.444	-0.393	-0.420	0.169	0.012	-0.031	-0.033	-0.137
T-stat.	14.405***	-0.106	-0.237	-0.587	-0.774	-0.753	-0.880	0.274	0.020	-0.057	-0.066	-0.299
Idios. Risk: Coeff.	0.141	-0.202	-0.277	-0.242	-0.232	-0.220	-0.197	-0.200	-0.048	-0.103	-0.097	-0.085
T-stat.	39.762***	-1.174	-1.485	-1.349	-1.258	-1.161	-1.026	-1.052	-0.303	-0.649	-0.667	-0.509

Table 6.6: Risk factor timing: Liquidity augm. CAPM with size

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM including size. The time-varying risk exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively, testing against a null hypothesis of a zero coefficient. Sample period: October 1, 2002 to September 30, 2009.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augm. CAPM with size												
MARKET EXC. RET.: Coeff.	0.245	0.795	0.813	0.816	0.799	0.806	0.846	1.077	1.146	0.998	0.880	0.908
T-stat.	10.921***	1.343	1.411	1.381	1.381	1.421	1.497	1.768*	1.784*	1.649*	1.489	1.610
ILLIQU.: Coeff.	-0.148	-1.067	-1.171	-1.350	-1.406	-1.258	-1.167	-0.875	-1.007	-1.026	-0.934	-0.929
T-stat.	-16.526***	-1.226	-1.298	-1.473	-1.598	-1.560	-1.522	-1.005	-1.131	-1.239	-1.236	-1.269
SIZE: Coeff.	0.669	1.270	1.125	1.323	1.187	1.229	1.230	1.296	1.720	1.582	1.627	1.838
T-stat.	80.592***	1.579	1.471	1.618	1.482	1.525	1.473	1.660*	2.082**	2.025**	2.089**	2.231**

Table 6.7: Risk factor timing: Liquidity augm. CAPM with Fama and French factors

This table gives the timing coefficients $b_{i,k,t-j}$ and respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM including the Fama and French (FF) factors. The time-varying risk exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively, testing against a null hypothesis of a zero coefficient. Sample period: October 1, 2002 to September 30, 2009.

E.-w. m. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augm. CAPM with FF factors												
MARKET EXC. RET.: Coeff.	0.240	0.942	1.024	1.064	1.134	1.155	1.126	1.236	1.247	1.034	0.947	1.032
T-stat.	10.276***	1.427	1.570	1.593	1.699*	1.730*	1.665*	1.825*	1.765*	1.549	1.443	1.641
ILLIQU.: Coeff.	-0.105	-0.857	-0.790	-0.955	-1.097	-0.924	-1.005	-0.868	-0.914	-0.847	-0.875	-0.950
T-stat.	-11.722***	-0.926	-0.810	-0.965	-1.175	-1.074	-1.228	-0.954	-0.998	-0.989	-1.145	-1.290
SIZE: Coeff.	0.524	-1.770	-1.321	-0.568	-0.522	-1.923	-1.990	0.463	1.355	1.302	0.957	2.825
T-stat.	22.353***	-0.693	-0.494	-0.214	-0.203	-0.727	-0.717	0.181	0.473	0.501	0.421	1.100
VALUATION: Coeff.	-0.010	-0.531	-0.695	-0.538	-0.454	-0.448	-0.517	-0.453	-0.399	-0.076	-0.091	-0.233
T-stat.	-1.388	-1.411	-1.910*	-1.469	-1.339	-1.293	-1.321	-1.058	-0.862	-0.169	-0.215	-0.560

Table 6.8: Risk factor timing: Liquidity augm. CAPM with Carhart factors
Same caption as in Table 6.7 applies. The results are given for the liquidity augmented CAPM including the Carhart factors.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augm. CAPM with Carhart factors												
MARKET EXC. RET.: Coeff.	0.237	0.804	0.875	0.925	1.036	1.112	1.098	1.119	1.271	0.989	0.862	1.044
T-stat.	10.089***	1.221	1.365	1.402	1.575	1.689*	1.621	1.663*	1.778*	1.470	1.325	1.630
ILLIQU.: Coeff.	0.078	-2.174	-3.418	-3.188	-3.535	-2.924	-3.465	0.247	-0.946	0.394	-1.602	-2.060
T-stat.	2.924**	-0.640	-0.981	-0.898	-1.039	-0.952	-1.188	0.080	-0.306	0.131	-0.615	-0.902
SIZE: Coeff.	0.456	-0.645	-0.115	1.511	1.338	-0.718	-0.906	0.994	2.165	2.046	2.470	4.357
T-stat.	19.793***	-0.269	-0.050	0.633	0.576	-0.279	-0.327	0.405	0.794	0.871	1.155	1.738*
VALUATION: Coeff.	-0.008	-0.441	-0.720	-0.812	-0.691	-0.628	-0.483	-0.413	-0.371	-0.042	-0.294	-0.147
T-stat.	-0.800	-0.837	-1.480	-1.578	-1.510	-1.403	-0.905	-0.757	-0.626	-0.072	-0.612	-0.255
MOMENTUM: Coeff.	-0.020	-0.226	-0.153	-0.098	-0.053	-0.072	-0.120	-0.197	-0.270	-0.252	-0.140	-0.295
T-stat.	-7.607***	-1.326	-1.121	-0.702	-0.392	-0.602	-0.907	-1.256	-1.307	-1.380	-1.064	-1.420

Table 6.9: Risk factor timing results for the equal-weighted mutual fund portfolio: Adj. R^2- and F-statistics

This table gives the adj. R^2- and F-statistics for the timing regression Equation 6.16 for each risk factor k. The time-varying risk exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: October 1, 2002 to September 30, 2009.

	adj. R^2	F-statistic
Liquidity augm. CAPM		
MARKET EXC. RET.	0.25%	1.421
ILLIQUIDITY	0.48%	1.786**
Liquidity augm. CAPM with size		
MARKET EXC. RET.	0.51%	1.838**
ILLIQUIDITY	0.55%	1.903**
SIZE	2.32%	4.882***
Liquidity augm. CAPM with idios. risk		
MARKET EXC. RET.	0.73%	2.208**
ILLIQUIDITY	-0.39%	0.359
IDIOS. RISK	0.87%	2.431***
Liquidity augm. CAPM with FF factors		
MARKET EXC. RET.	0.88%	2.452***
ILLIQUIDITY	0.14%	1.226
SIZE	-0.15%	0.749
VALUATION	1.51%	3.512***
Liquidity augm. CAPM with Carhart factors		
MARKET EXC. RET.	0.68%	2.120**
ILLIQUIDITY	0.07%	1.120
SIZE	0.10%	1.156
VALUATION	1.18%	2.949***
MOMENTUM	3.46%	6.858***

has been for the equal-weighted mutual fund portfolio which seems to overweight small funds. The results in Table 6.10 are thus more in line with the individual fund results in Chapter 5.

The summary statistics suggest a smaller average exposure towards liquidity risk as the average exposure is 0.173 in contrast to 0.613. There is one fund which is characterized by a very high estimated maximum liquidity exposure of more than 10 whereas the other funds exhibit rather moderate liquidity exposures. In contrast to the unconditional analysis in Chapter 5 where there have been more funds with a significantly negative than positive exposure towards liquidity risk, the evidence in Table 6.10 rather suggests the opposite, which is probably induced by the dynamic Kalman filter based methodology. Consistent with the aggregate results, a dynamic analysis is important in the presence of time-varying risk exposures as the dispersion in the summary statistics and the high standard deviation regarding the liquidity risk factor underpins.[54] In line with the dynamic equal-weighted mutual fund portfolio results, the liquidity risk exposure is on average positive. Overall, the summary statistics in Table 6.10 give evidence of time-varying risk factor exposures with respect to the market excess return and liquidity, being in line with the structural break test and the Kalman filter results for the aggregate, equal-weighted mutual fund portfolio.

Next, it is checked whether the dynamics in the risk factor exposures for the individual funds are due to timing, conditioning and forecasting activities.

6.6.5 Individual timing analysis

This section gives the timing results for the 254 individual mutual funds. The results given in Table 6.11 show that with respect to the market excess return, only around 6% to 12% of individual mutual funds possess significantly positive timing, conditioning or forecasting coefficients at the 10%-significance level, but there is also a comparable number of funds characterized by negative and thus perverse market timing, conditioning and forecasting activities. Hence, one should pay special attention to not invest in one of those funds with negative daily market timing. The results regarding liquidity timing, conditioning and forecasting of the individual mutual funds are even less pronounced. Only a few, often less than ten mutual funds possess significantly positive timing coefficients at the different leads and lags at the 10%-level. There is also evidence of a very small amount of mutual

[54]The high standard deviations for some mutual funds with respect to the liquidity risk factor result from a large variation of the liquidity exposure during the financial crisis. In later backtests, it will be checked whether this results from estimation errors in the state variables which are estimated by the Kalman filter and whether this influences the timing results.

Table 6.10: Individual mutual funds: Summary statistics of risk factor exposures

This table gives cross-sectional summary statistics of the time-varying risk factor exposures as estimated by the Kalman filter for individual mutual funds and the liquidity augmented CAPM. The Kalman filter specification follows Equations 6.18 and 6.19. Number of individual mutual funds: 254. Sample period: October 1, 2002 to September 30, 2009.

Individual mutual funds		Time-series mean exp.	Time-series median exp.	Time-series maximum exp.	Time-series minimum exp.	Time-series std. dev. of exp.
MARKET EXC. RET.	CROSS-SECT. MEAN	0.613	0.631	1.033	-0.682	16.16%
	CROSS-SECT. MIN.	-0.072	-0.063	-0.029	-4.141	1.38%
	CROSS-SECT. 25th %	0.496	0.491	0.909	-1.211	9.32%
	CROSS-SECT. MEDIAN	0.680	0.706	1.074	-0.508	13.95%
	CROSS-SECT. 75th %	0.889	0.931	1.215	0.124	19.50%
	CROSS-SECT. MAX.	1.144	1.132	3.626	0.907	50.47%
ILLIQU.	CROSS-SECT. MEAN	0.173	0.172	1.109	-1.983	27.53%
	CROSS-SECT. 25th %	0.070	0.055	0.604	-2.876	18.70%
	CROSS-SECT. MEDIAN	0.181	0.174	0.876	-1.453	25.81%
	CROSS-SECT. 75th %	0.290	0.295	1.122	-0.555	33.29%
	CROSS-SECT. MAX.	0.500	0.522	10.980	-0.025	173.68%

funds with negative liquidity timing. It seems that the mutual fund managers are not able to take advantage of successfully managing dynamics in liquidity risk, although previous chapters have suggested that liquidity risk is important in asset pricing as a systematic risk factor and as a source of additional return as it directly influences the individual mutual fund's holdings. Overall, the number of funds with significant timing is even smaller when one considers the 5%-significance level. The small goodness-of-fit results in Table 6.12 and the average F-statistics also suggest that the timing model is not successful in explaining the time-variation of the daily risk factor exposures. The average F-statistics for market timing are slightly higher than those on liquidity risk but still not in favor of the joint significance of the estimated coefficients.

To summarize, by modeling the risk exposures as latent state vectors in a Kalman filter setup, one is able to introduce time variation without knowing the concrete information sets of the mutual fund managers analyzed. As the mutual fund managers' information sets may deviate from those of the mutual fund investors, e.g. if the asset management companies possess more sophisticated and specialized research departments, this offers an adequate method of analysis without having access to the fund managers' information sets. However, it is still unclear whether the small number of mutual funds with significant risk factor timing abilities also show a better risk-adjusted performance. Thus, next, those mutual funds in Table 6.11 which possess a positive market or liquidity timing coefficient are more closely investigated with respect to their risk-adjusted performance in the liquidity augmented CAPM. The results for the fifteen individual mutual funds with significantly positive market timing abilities are given in Table 6.13, but none of these funds possesses a positive alpha, even if the goodness-of-fit of the liquidity augmented model is quite high for most of these funds. However, only for one mutual fund, i.e. the EMIF European Value, the performance is significantly negative, whereas for the remaining ones the performance is not statistically significant. The only mutual fund in Table 6.11 which is characterized by a significantly positive liquidity timing ability, i.e. the Threadneedle (Lux)-Pan European Equities AE, also shows a negative but insignificant performance. Hence, one can not conclude that positive risk factor timing materializes in higher returns and higher alpha, see Bollen and Busse (2001). Thus, it may be that daily timing strategies, which are most probably costly in terms of complexity and transaction costs, are not followed by fund managers on purpose as for them timing is known to not necessarily result in higher performance. This might provide for a rational explanation for the rather missing timing abilities of fund managers as documented by the daily evidence above.

However, in order to further examine the previous results, next, different backtests need

Table 6.11: Risk factor timing: Individual mutual funds and the liquidity augmented CAPM

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 5% and 10%-significance levels testing against a null hypothesis of a zero coefficient. Overall number of funds: 254. Sample period: October 1, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	30	27	25	17	27	30	18	20	20	18	15
MARKET EXC. RET.: sig. pos.	221	15	18	21	30	17	19	29	28	22	26	21
ILLIQU.: sig. neg.	26	8	8	8	12	9	6	8	3	3	5	3
ILLIQU.: sig. pos.	212	1	3	3	2	1	2	10	12	6	2	1
5%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	21	16	14	9	13	17	11	14	12	11	7
MARKET EXC. RET.: sig. pos.	221	5	9	9	14	9	10	14	17	8	15	11
ILLIQU.: sig. neg.	25	6	4	4	5	6	2	5	0	0	3	0
ILLIQU.: sig. pos.	211	0	0	1	0	0	0	2	3	1	1	0

Table 6.12: Risk factor timing for the liquidity augmented CAPM: Adj. R^2- and F-statistics

This table gives the adj. R^2 and F-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. Overall number of funds: 254. Sample period: October 1, 2002 to September 30, 2009.

Adj. R^2- stat.	Mean	Median	Max.	Min.
MARKET EXC. RET.	0.38%	0.02%	8.18%	-0.59%
ILLIQU.	-0.06%	-0.20%	3.12%	-0.60%
F-stat.	**Mean**	**Median**	**Max.**	**Min.**
MARKET EXC. RET.	1.647	1.044	15.563	0.039
ILLIQU.	0.914	0.668	6.257	0.032

Table 6.13: Timing and alpha for the liquidity augmented CAPM

This table gives the annualized alphas, the respective t-statistics and the adj. R^2 with respect to the liquidity augmented CAPM. The dependent variables equal those mutual funds possessing a significantly positive market or liquidity timing coefficient regarding the 10%-significance level, as given in Table 6.11. Regressions are performed using the HAC-consistent covariance estimator of Newey and West (1987). Sample period: October 1, 2002 to September 30, 2009.

Mutual fund	Alpha p.a.	Alpha (t-stat.)	Adj. R^2
AXA Europa	-2.90%	-0.783	0.354
BAWAG PSK Europa Blue Chip Stock A	-0.25%	-0.034	0.001
DWS Invest European Equities LC	-0.36%	-0.093	0.558
EMIF Europe Value B C (Load)	-3.78%	-1.905*	0.857
E.ON Aktienfonds DWS	1.52%	0.327	0.255
G&P UNIVERSAL AKTIENFONDS A	-4.05%	-0.696	0.295
Investec Pan European Equity A Acc Net	-3.43%	-1.142	0.526
Morgan Stanley European Equity Alpha Fund A EUR	-1.31%	-0.608	0.682
MSMM Pan European Equity B	-0.77%	-0.627	0.935
Petercam Equities Europe Cap	-0.05%	-0.023	0.876
Principal GI European Equity A Acc	0.14%	0.033	0.213
Selector Mgt Fund - Selector European Value A2	0.15%	0.029	0.342
SWC (CH) EF Europe	-1.30%	-0.983	0.931
Threadneedle (Lux)-Pan European Equities AE	-2.16%	-0.696	0.447
UniEuropa A	-1.41%	-0.685	0.719

to be investigated.

6.6.6 Different robustness tests

First, I conduct backtests for a restricted sample period where the first 50 time series observations are excluded in estimating the timing regression of Equation 6.16. This specification ignores those observations of the sample period which are most probably influenced by the starting values of the Kalman filter before the estimated state series converge. First, I conduct this backtest on the timing results of Table 6.5 for the liquidity augmented CAPM and the equal-weighted mutual fund portfolio, see Table A.24 in Section A.7 of the appendix. Overall, it seems that the results with respect to market and liquidity timing are not changed much, as the timing coefficients are still insignificant, and unreported very small adjusted R^2- and F-statistics confirm the former results.

The descriptive statistics in Table A.25 of the time-varying risk factors across the individual mutual funds for the restricted sample period suggest that the mean, median and maximum summary statistics are not changed much. However, the minimum beta statistics are slightly increased, whereas the standard deviation statistics are slightly decreased compared to those in Table 6.10. Hence, by ignoring the training period of the Kalman filter, the negative outliers during the first observations of the sample are removed. The timing results for the individual mutual funds in Table 6.11 are backtested ignoring the training period of the Kalman filter as well, see Table A.26. The results with respect to positive market timing, conditioning and forecasting rather seem to have improved for almost all coefficients for the shorter observation period. For example, at lag 3, now, 50 instead of 30 of the mutual funds possess a significant regression coefficient. However, with respect to liquidity, the overall timing, conditioning and forecasting results have not improved much. Table A.27 gives the adjusted R^2- and F-statistics for the restricted sample period, which are still on average very low for the market excess return, and are even smaller regarding liquidity timing. As the maximum numbers suggest, there are only individual mutual funds with a better goodness-of-fit of around 8% and a joint significance of the coefficients.

Second, I conduct a backtest on the individual fund results in Table 6.10 in order to control for idiosyncratic risk, which is a still unexplored aspect in the context of risk factor timing and which is possibly linked to liquidity, see Section 2.3.3. In Table A.28 in the appendix, the results are given for the overall as well as restricted sample period. The mean exposures are relatively unchanged regarding market and liquidity risk but the standard deviations are now much higher. A possible explanation may be that the

Kalman filter has more problems to estimate this more complex model for individual mutual funds. The mean exposure to idiosyncratic risk is quite similar to that to liquidity risk and inclusion of idiosyncratic risk does not considerably change the mean exposure to liquidity risk. Hence, idiosyncratic risk seems to be also an important risk factor, being in line with the results of Chapter 5 where idiosyncratic risk has been an important determinant of mutual fund performance in addition to liquidity. In Table A.28, when ignoring the first 50 observations of the sample period, again, the summary statistics of the minimum exposures are slightly increased and the standard deviation summary statistics are slightly decreased.

Tables A.29, A.30 and A.31 display the results for risk factor timing of the individual mutual funds in the liquidity augmented CAPM with idiosyncratic risk.[55] Again, only a few mutual funds possess a significant timing, conditioning and forecasting coefficient regarding the market, liquidity and idiosyncratic risk factors for the overall and the restricted period results. One has to note that, e.g. for the restricted sample period, some evidence of successful market timing for individual funds has disappeared and seems to be captured now by successful idiosyncratic risk timing. This is possibly linked to the positive correlation between the market risk and idiosyncratic risk amounting to 0.419. However, the variance inflation factors are not considerably different from one. The summary statistics of the adjusted R^2- as well as median F-statistics in Table A.31 confirm the on average small goodness-of-fit and do not support the joint significance of the coefficients for the overall and the restricted sample period. As the aggregate results on the equal-weighted fund portfolio do not display stable timing of other risk factors like e.g. size or valuation, I do not give the individual mutual fund timing results for other multifactor models, considering the deterioration in estimation quality and the much higher computational burden when estimating such more complex models for a large number of individual mutual funds.

Third, in Tables A.32, A.33 and A.34 in the appendix robustness tests based on different model specifications as in the backtests of Chapter 4 and 5 are given. With respect to the equal-weighted fund portfolio and the liquidity augmented CAPM, I consider risk factors derived from style indices with 1%- and 99%-cut-off-rates, risk factors derived from equal-weighted style indices, the liquidity risk factor derived from the detrended Amihud measure and a data sample ignoring those 13 observations where liquidity has been characterized by very high outliers as suggested by the three sigma rule, see e.g. Wells (1996) p. 106. The results are most significantly different for the specification

[55] Only the results with respect to the 10%-level are given as the results with respect to the 5%-level apply analogously to those before.

with detrended liquidity. Here, there is now more evidence of successful market timing, conditioning and forecasting while there is also evidence of significantly negative liquidity timing –in the sense of liquidity forecasting. Regarding the other model specifications, the market timing coefficients are only significantly positive for two to three lags and leads, whereas liquidity timing is still insignificant and rather negative, similar to the results before. In Table A.34, the adjusted R^2-statistics again suggest that the time-varying risk factor exposures can not be linearly linked to the respective factor returns. The F-statistics are at least significant with respect to some model specifications.

Fourth, I consider different numbers of leads and lags in the timing regression of Equation 6.16. Table A.35 in the appendix gives the results for one, three as well as five lags and leads of the risk factors in the liquidity augmented CAPM for the equal-weighted mutual fund portfolio.[56] The coefficients of determination, the F-statistics as well as the Akaike information criterion (AIC) and Schwarz Bayesian criterion (SBC) statistics are given as well. For the different models the overall result is confirmed that there is no evidence of successful market and liquidity timing as suggested by the missing statistical significance of the coefficients and the very small coefficients of determination and F-statistics. For market timing, the Akaike and Schwarz criteria are lowest for the model only including 1 lead and lag, whereas for liquidity timing, the lowest Akaike and Schwarz criteria are found for the model with 5 leads and lags. Hence, it is not clear which number of leads and lags in the model should be preferred. However, it seems to be feasible to include more leads and lags in order to better capture timing abilities based on more periods of information on the risk factor return.

Next, I consider a backtest where the risk factor states, which are used as dependent variables in the timing regression, are estimated by the Kalman smoother instead of the Kalman filter. The results in Table A.36 in the appendix for the liquidity augmented CAPM and the equal-weighted mutual fund portfolio are similar to those before as the coefficients indicative of market timing are positive and insignificant, the coefficients on liquidity are again negative and insignificant and the goodness-of-fit and F-statistics are again small. Thus, no timing abilities at all can be detected when considering smoothed states.

Sixth, I consider subperiods by dividing the sample period into halves as it has already been described in the robustness tests in Chapters 4 and 5 in order to test the relevance of liquidity and market timing before and including the financial crisis. During the first subperiod, the market timing coefficients are rather negative, but insignificant, see Table

[56]The model including five leads and lags corresponds to the model which has already been presented above.

A.36. There is no evidence of liquidity timing. The coefficients of determination, i.e. the adjusted R^2, are negative and the F-statistics are even smaller than for the overall sample period. During the second subperiod, significantly negative market timing coefficients are indicative of perverse daily market timing, conditioning and forecasting and there is again no significant liquidity timing. The adjusted R^2-statistics on market and liquidity timing are again very small and the F-statistics for liquidity timing are small as well, but the coefficients on negative market timing are jointly significant at the 10%-level. In the aggregate, the fund managers have not been able to protect their portfolio holdings from the market downturn during the financial crisis and, at a daily frequency, they did not properly react to information on or expectations about market movements. However, this may be related to the small fund bias of the equal-weighted fund portfolio. Smaller funds may be characterized by less sophisticated fund management as linked to smaller assets under management as well as less favorable compensation conditions.

Figure 6.1 presented above has been characterized by a puzzle with respect to the market exposure of the equal-weighted mutual fund portfolio over time. During the time period of the crisis it shows that the fund managers have considerably reduced the market risk of their portfolios, but usually fund managers rather can not hedge market risk. As this may be due to the possible shortcomings of the equal-weighted fund portfolio, I also give the results for the equal-weighted mutual fund portfolio as well as cross-sectional averages of the summary statistics for the individual mutual funds for the two subperiods. In Table A.37 in the appendix, one can observe that the mean and median risk factor exposures are only significantly different for the equal-weighted mutual fund portfolio but not for the individual mutual funds. The individual fund portfolio result hence shows that the fund managers have not diminished the risk exposure for the second subperiod including the crisis, confirming that there is no timing activity by the fund managers. Hence, as the equal-weighted fund portfolio may produce misleading results, it is useful to take into account both the equal-weighted fund portfolio as well as individual mutual funds in the analysis.

Seventh, in the backtests given in Tables A.38 and A.39 in the appendix it is tested whether the individual mutual fund timing results are influenced by the estimation quality of the Kalman filter. The on average small adjusted R^2 may be caused by poorly measured or estimated variables which may cause the very high standard deviation of the time-varying risk factor exposures in the Kalman filter estimations for some mutual funds. That is why I now cut off the top decile and top quintile of the root mean square error distribution of the filtered states before estimating the timing ability for the liquidity augmented CAPM. The so constructed samples include 222 and 197 mutual funds, respectively. Comparing the results without the poorly estimated mutual funds, see Tables A.38 and A.39 in the appendix, with the results without this adjustment, one perceives that regarding the market timing coefficients, the number of mutual funds with significantly negative timing coefficients slightly has decreased, whereas evidence of significantly positive market timing coefficients considerably has increased. However, regarding liquidity timing, the number of mutual funds with significantly positive and negative liquidity timing coefficients is now even smaller than before. Hence, evidence of liquidity timing can not be improved by empirically investigating only those mutual funds where the filtered states have less estimation error. The adjusted R^2 and F-statistics in Table A.40 suggest that both statistics can on average be minimally improved by excluding the mutual funds with the highest estimation error for market but not with regard of liquidity timing.

Eighth, I test whether the assumption that the manager ability alpha is constant influences the timing, conditioning and forecasting results. Alpha may not be stable over time when e.g. other fund managers copy a successful asset management strategy which forces a fund's alpha to decrease over time. Another example may be that increasing scale makes it more difficult for a mutual fund manager to realize specific strategies on the market which causes a decreasing alpha over time as well. Furthermore, during periods of crisis, it is much more difficult for a fund manager to realize a constant performance, as the strategies usually applied might not be adequate anymore and market turbulences have a large impact on the outcome of the asset management strategies. Moreover, it is worth to consider whether time variation in factor betas might be overstated by forcing alpha to be constant and it needs to be checked whether this influences the timing results found above. In this backtest, the equal-weighted mutual fund portfolio and a random walk process for alpha is considered. In Equations 6.18 and 6.19, the alpha of mutual fund i is now additionally considered to evolve based on the following random walk process

$$\alpha_{i,t} = \alpha_{i,t-1} + \xi_{i,t}. \tag{6.21}$$

The resulting alpha is varying over time as Graph A.2 in the appendix suggests. There, the time-variation of alpha during the financial crisis reflects the uncertainty and difficulty to implement a constant risk adjusted return. Table A.45 in the appendix shows the timing results for the liquidity augmented CAPM and the equal-weighted fund portfolio. For market timing, conditioning and forecasting the results are even stronger considering time-variation in alpha. At different leads and lags the coefficients are significant and the F-statistic is significant as well. The adjusted R^2 is not large but of a similar size compared to those without considering time-variation in alpha. The results for liquidity are not changed much with respect to the coefficients and the very low adjusted R^2. Overall, assuming that alpha is constant over time does not overstate but may rather slightly understate the results with respect to the market excess return and does not change the illiquidity results.

Last, as many timing studies examine monthly data and as monthly data are not as much influenced by estimation errors and microstructure issues like stale pricing or the bid-ask bounce, it may be useful to consider monthly timing in further backtests, as given in the appendix. Table A.41 displays the market and liquidity risk factor states which are estimated by the Kalman filter for the equal-weighted fund portfolio. The average exposure with respect to liquidity is quite unchanged, whereas the average exposure on the market factor is now much larger. With respect to the monthly data, the minimum and maximum numbers as well as standard deviations again suggest a substantial time variation in the monthly risk exposures. The observation that the minimum numbers are now positive suggests that during the training period of the Kalman filter there are no negative outliers in contrast to using daily data. Thus, one expects smoother changes in risk factors, which is confirmed by Figure A.1 in the appendix. Here, the evolution of the illiquidity exposure is quite similar to the daily result, but the market exposure is decreasing much faster for the monthly compared to the daily figure. The timing results for the equal-weighted mutual fund portfolio in Table A.42 suggest that there is now strong evidence in favor of adequate market timing conditional on the information for the first two lags of the market factor. However, some leading factor coefficients are now negative. Furthermore, there is now significant evidence of negative liquidity timing and forecasting. The adjusted R^2-statistics are now larger than 20% and the F-statistics are in favor of the joint significance of the coefficients.

With respect to individual mutual funds, one has to consider that the number of monthly observations of 84 months is not so large and that many funds started to exist only after the start of the observation period. Only around one half of the funds, i.e. 273, is characterized by data which cover the overall observation period. The monthly results on individual funds in Table A.43 suggest that, evidence of positive market timing, conditioning and forecasting is found regarding much more mutual funds than with daily data. For example, 123 of the 273 mutual funds investigated possess a significant coefficient on the market factor at the second lag. Regarding liquidity timing, evidence of negative liquidity timing and forecasting is stronger than with the daily data. The summary statistics of the adjusted R^2- and F-statistics in Table A.44 with respect to market timing are on average much higher now. However, these statistics are on average not improved for liquidity timing, with the exception of single mutual funds where the adjusted R^2 is as high as 55.97%. It is obvious that the goodness-of-fit is now higher for the monthly backtests compared to the daily timing tests. There may arise two possible explanations. First, estimation error in the daily data is so high that a good model fit is impossible. However, this is checked by the backtests where I have accounted for the mean square error in the Kalman filter estimation. A second explanation would be that no daily timing ability exists as the information on dynamics in risk factor returns is too frequent to be properly processed and implemented in timing activities. Monthly data on changes in risk factors are more easily interpreted as they do not contain as much 'noise' information unrelated to sustainable developments in risk factors. A sensible explanation would be that not every daily news and information should lead to portfolio rebalancing as this is increasing transaction costs and may lead to a deviation from the underlying overall fund strategy.

Based on the more robust monthly timing results, I conclude that there is some evidence of monthly positive market timing for quite a large subset of mutual funds when taking into account the time-variation in risk exposures, but that there is no concise evidence of liquidity timing. Next, timing on hedge funds is analyzed.

6.6.7 Monthly backtests on hedge funds

The last robustness test examines whether at least hedge funds are able to time liquidity in addition to market risk as they have more easily access to dynamic strategies than mutual funds. Hedge funds are allowed to use leverage, short positions and derivative instruments and their returns have different characteristics than those of mutual funds like e.g. higher downside tail risks (see e.g. Agarwal and Naik (2004)) or higher moment market risks (see e.g. Agarwal et al. (2008)), calling for adjusted performance evaluation methods, see among others Fung and Hsieh (1997). Liquidity is also an important risk factor to hedge funds, see evidence in Sadka (2010) and Boyson et al. (2010), why hedge fund managers should be interested in timing liquidity risk. A first observation in this direction is made by Li and Patton (2007) who, by analyzing the autocorrelation of hedge fund returns as a measure of illiquidity, find evidence of time variation in the degree of liquidity of hedge fund investments. To my knowledge, apart from the above mentioned study of Cao et al. (2009a) liquidity timing of hedge funds is still a relatively unexplored issue, also with respect to European hedge fund data. However, Billio et al. (2009) find that, in periods of crisis, liquidity risk is a common risk factor to hedge funds. Thus, this backtest extends insights on liquidity timing as well as on the issue of market timing by hedge funds, where there is only some evidence of negative market timing by Fung et al. (2002). The following Kalman-based analysis on hedge fund returns is also motivated by related research of Bollen and Whaley (2009), Racicot and Théoret (2009) and Monarcha (2009) on applying the Kalman filter on hedge funds.

In this robustness test, I examine monthly data on a class of European hedge fund indices provided on the website of the hedge fund data provider Eurekahedge at www.eurekahedge.com. I consider the following European hedge fund strategy indices in addition to the Eurekahedge European hedge fund index which covers all hedge fund strategies: Arbitrage, CTA / managed futures, distressed debt, event driven, fixed income, long / short equities, macro, multi-strategy and relative value, see more details in Section A.9 in the appendix. These indices are characterized by a European focus which means that at least 90% of the regional mandate of a hedge fund part of the index must be in the European region. The detailed index methodology is described at www.eurekahedge.com. Using monthly data on hedge funds is more reliable than daily data as hedge funds are not required to report daily and as some hedge fund strategies may hold illiquid positions for which daily market prices can not reliably be estimated, see Li and Kazemi (2007) and Li et al. (2009).

The summary statistics of the hedge fund indices are given in Table A.46 in Section A.8 of the appendix. The average annualized returns suggest that most of the aggregate hedge fund strategies are characterized by a positive performance of around six to eight percent per year. The overall European hedge fund index provides for a mean return of 8.33% per annum. A quite unfavorable performance is offered by the arbitrage and the relative value hedge fund indices, whereas a very high positive performance is achieved by the macro and the multi-strategy hedge fund indices. However, these strategies are also among those with the highest standard deviation which is substantially high for the macro hedge fund index. The other strategies are characterized by less standard deviation, but also by less return suggesting a positive risk return relationship. All indices are skewed to the left, suggesting that hedge funds provide relatively well for positive returns, but that large negative returns may also be possible, which is in line with the usually considerable tail risk in hedge fund returns, and most hedge fund indices possess a high excess kurtosis. Almost all hedge fund indices are characterized by a distribution which is not normal and unreported Jarque-Bera tests reject the null of normal distribution for all indices apart from the CTA / managed futures index. The non-normality of hedge fund data is, among others, caused by the use of options as well as dynamic trading strategies. Overall, the summary statistics are in line with other empirical findings on hedge fund returns, see Brooks and Kat (2002).

The timing results in Table A.47 suggest positive market conditioning and forecasting for the overall European hedge fund index. The coefficients on the market excess return at the second and third lag as well as the coefficient for the fifth lead are significant at the 5%-level. The adjusted R^2 of 11.4% and the significant F-statistic suggest that the time-varying market exposures of the overall hedge fund index can be slightly linked to the dynamics in market performance, but to a smaller degree compared to monthly mutual fund market timing. Evidence of liquidity timing is again disappointing as the coefficients are not significant, which also possess differing signs, and the goodness-of-fit and the F-statistics are very low. In Tables A.48 to A.56 of the appendix, the timing results differ vastly across the hedge fund strategies with respect to the sign and significance of the timing coefficients as well as the goodness-of-fit. Substantial evidence of negative market timing and conditioning is found for the arbitrage hedge fund index, but this hedge fund index is also characterized by a positive forecasting ability up to the fifth lead. One also observes substantial evidence of negative conditioning and forecasting for the fixed income hedge fund index. Some positive market timing coefficients can be detected for the distressed debt hedge fund index and the long / short equities hedge fund index. The remaining hedge fund indices possess significantly negative and positive timing, conditioning and forecasting coefficients only with respect to single leads and lags and are characterized by worse goodness-of-fit.

Overall, evidence of positive and negative market timing seems to be stronger with respect to some hedge fund strategy indices than it has been with respect to mutual funds. This is sensible as hedge funds are much more flexible regarding the dynamic application of investment strategies and the different strategy subindices try to reflect these different investment approaches. The investor only has to choose the right strategy for her dynamic risk factor timing preferences. If these preferred timing characteristics of the hedge funds do not pay off in form of higher performance, as it is the case with the arbitrage hedge fund index, other decision criteria should be emphasized when choosing a hedge fund. However, it may be an issue that evaluating the timing of hedge funds against risk factors derived from equities leaves out that hedge funds have access to a more diversified portfolio of asset classes and investment strategies, which might be addressed in further research. The complexity of the possible investment strategies, i.e. e.g. derivatives and leverage, makes also failure of market timing probably more severe, as underpinned by the larger downside risks. Moreover, self-reporting biases imply that a hedge fund labeling a specific strategy may in reality follow a different one. However, overall, monthly mutual fund market timing abilities seem to be slightly more pronounced than monthly aggregate hedge fund timing abilities. Hedge funds have rather not been able to adequately manage these instruments during the recent turbulent periods in order to profit from timing. This is in line with Fung et al. (2002) who finds rather disappointing market timing ability results for hedge funds.

Liquidity timing is also analyzed. The overall European hedge fund index is not characterized by liquidity timing, conditioning and forecasting abilities. The coefficients on liquidity are insignificant and the signs on the coefficients are partly positive as well as negative, while the coefficient of determination, i.e. the adjusted R^2, is even negative. Regarding the strategy subindices, some positive liquidity forecasting can be found for the arbitrage hedge fund index with a goodness-of-fit of 10.7%. However, this does not positively pay back as the negative per annum mean return of this hedge fund strategy in Table A.47 suggests. This may be due to the significantly negative market timing coefficient of this hedge fund strategy. It seems that either the positive forecasting abilities with respect to the market and liquidity factors can not balance out this negative influence on average performance or that other aspects of the strategy of the respective hedge funds, e.g. derivatives, negatively pay back. Positive liquidity timing and forecasting can also be detected for the fixed income hedge fund index, which is also characterized by a quite good per annum performance of 6.41% (median 11.15%). Negative liquidity forecasting is achieved by the relative value hedge fund index. This index is also the second worst index with respect to mean and median per annum return which confirms the economic relevance of successful liquidity timing. The remaining indices are characterized by partly significant liquidity coefficients but the goodness-of-fits are even negative based on the adjusted R^2-statistics. Thus, these other strategies do not apply successful liquidity timing.

If an investor is concerned by the issue of systematic liquidity risk in his portfolio, she should choose one of those hedge funds or hedge fund strategies which dynamically manages this liquidity risk in an adequate way. One has to note that the macro hedge fund index is neither possessing special market nor liquidity timing abilities, but still has the highest performance of all hedge fund strategies. This suggests that successful market and liquidity timing can be a useful tool to improve expected return, but that hedge funds are open to so many different investment strategies and instruments that such risk factor timing is not their only option. However, as the results suggest, hedge fund managers should be aware of avoiding perverse factor timing in order to not diminish their performance.

6.7 Conclusion

In this chapter, the perspective has been switched from an unconditional to a dynamic analysis of mutual fund returns. First unconditional timing tests suggest that there is some perverse timing ability with respect to the market risk factor and some other risk factors. However, the results on structural break tests and Kalman filter results show that time-variation in the risk exposures of the mutual funds investigated can be found. Then, an attempt has been carried out to link these time-varying risk exposures to the evolution of the risk factor returns in order to test for timing or forecasting as well as conditioning activities.

Overall, the results show that there are only single mutual funds with significantly positive timing, conditioning and forecasting abilities at a daily frequency. This holds for an equal-weighted mutual fund portfolio as well as for a large set of individual mutual funds with a European investment focus and is backtested with respect to various different model specifications. Hence, the information in the past, current and future factor returns is either not successfully interpreted and implemented by the fund managers in their risk exposure decisions or fund managers form false expectations about future risk factor returns. A comparison of market timing abilities across two subperiods indicates that adequate market timing is even more difficult during periods of market turmoil, while the results regarding liquidity timing during the financial crisis are inconclusive. However, the ability to protect portfolio holdings from overall market downturns is one of the main abilities which investors would like to have provided by mutual fund managers. Thus, mutual fund managers in the aggregate fail on this issue.

The weak evidence on daily risk factor timing is also confirmed for the relatively unexplored liquidity and idiosyncratic risk factors. No successful liquidity timing can be detected in contrast to what would have been suggested by the research of Vayanos (2004) and Huang (2008) during periods of crisis. I conclude that mutual fund managers miss a source of additional abnormal return by not successfully exploiting the dynamics in systematic liquidity, but also idiosyncratic risk as well as the other risk factor returns in their portfolio decisions. In this way, it is recommendable to increase the awareness of mutual fund managers on the dynamics in systematic liquidity risk as well as other risk factors. Overall, the evidence on European data is consistent with the evidence of most U.S. studies on non-existing or unstable risk factor timing by mutual fund managers and the results in Chan et al. (2002) or Benos et al. (2010).

At least, evidence of perverse, i.e. negative, risk factor timing found in the unconditional timing tests can be removed by taking into account the time-variation of the risk exposures as such a behavior would be punished by investors by redeeming money from these mutual funds. This would, due to the smaller assets under management, force the respective mutual fund managers to optimize their strategies or even make the respective mutual fund disappear from the market. Hence, in this context, the consideration of time-varying risk exposures has proven to be useful. Moreover, the results are more in favor of dynamic market timing when switching from a daily to a monthly data frequency, but this is not the case for monthly liquidity timing. Thus, the overall results suggesting that a daily horizon is probably too frequent when evaluating timing is in contrast to Goetzmann et al. (2000) who find that a monthly evaluation of timing is too infrequent. This result may be linked to higher estimation error, transaction costs as well as more difficult information processing for a daily frequency, including also a lot of information noise not linked to the long-term investment strategy of the fund.

Additional research investigated monthly hedge fund timing as hedge funds are much more flexible in dynamic portfolio management decisions. For the overall European hedge fund index some market timing ability can be found, but there is no evidence of liquidity timing abilities. Only some individual hedge fund strategy subindices, like for example the arbitrage hedge fund index, are characterized by quite successful liquidity forecasting and timing strategies. This suggests that hedge fund investors may obtain certain dynamic risk factor management characteristics, but they need to choose one of those hedge fund strategies which most probably provides for this.

7 Summary and conclusion

In this thesis, different aspects of equity styles, style indices and liquidity have been examined for a European data set. The focus has been on the still relatively unexplored European capital market as motivated by recent enhancements in capital market integration. The performance and characteristics of a new set of European style indices presented in Chapter 3 in this thesis as well as risk factors derived from these style indices demonstrate that most of the underlying trading strategies may positively pay off for European investors. Moreover, the empirical results document that risk factors derived from this novel set of European style indices, like especially liquidity risk, influence prices of European equities and mutual funds.

As has been shown by the empirical evidence in Chapter 4, systematic liquidity displays a risk relevant to European investors as it seems to be a determinant of the stochastic discount factor for a set of European stocks. Moreover, a liquidity mimicking factor constructed from the Stoxx 600 universe demands a significantly positive liquidity risk premium. The evolution of common liquidity over the time period examined displays a rise in market illiquidity during the financial crisis similar to non-European results. The results show that, during the second half of the sample period, including the financial crisis, the role of liquidity risk in addition to market risk as e.g. a determinant of asset prices has considerably strengthened. Thus, due to its state-dependent nature, liquidity is of special hedging concern to investors in the European capital market. As the link to periods of financial stress suggests, it is very important to keep market liquidity high in order to avoid that crises like the recent financial crisis are aggravated. Otherwise, higher liquidity risks would lead to even higher expected returns and, in this way, to even lower current asset prices, thus worsening such crises.

As the capital markets in Europe have become increasingly integrated during the last years, it became even more difficult to diversify away systematic market and liquidity risks. Hence, a successful liquidity risk management has become even more important issue regarding investment decisions. A significant interest of investors should be to successfully manage and time exposures to such undiversifiable liquidity risks. In line with this, liquidity risk is not only relevant to individual investors but also to asset managers which are agents commissioned by investors. As suggested by the empirical relevance of systematic liquidity in Europe and in line with Brunnermeier and Pedersen (2009) and Chordia et al. (2005a), regulatory and central bank efforts should focus on avoiding the drying-out of common liquidity on European capital markets. In this context, Fernandez-Amador et al. (2011) find that an expansionary monetary policy of the European Central Bank leads to an increase of stock market liquidity in several European markets. However, related efforts should also take into account that flooding of capital markets with liquidity might cause new market distortions, like e.g. a boom in real estate investments, or impact bond markets due to effects on interest rates.

The results in Chapter 5 have demonstrated that liquidity is a relevant risk factor in mutual fund performance evaluation as well, as a substantial number of individual funds exhibit significant factor loadings with respect to the liquidity but also the idiosyncratic risk factors. This evidence is as strong as that with respect to the established valuation and momentum factors, while market excess return and size are still dominant risk factors. As a substitution of the valuation by the liquidity factor may offer a valid alternative to the established factor models of for example Fama and French (1992, 1993), the evidence in this thesis also provides for new insights on improving currently widely used models of performance evaluation. Due to the observation that managers on average seem to prefer liquid stock holdings, this result confirms the state dependent role of liquidity found in Chapter 4: fund managers are more concerned about holding illiquid assets during periods of crises when overall liquidity deteriorates. The analysis of the individual net performance of mutual funds with European investment focus in Chapter 5 reveals that for most funds the performance is statistically indistinguishable from zero. In light of the huge amount of assets under management in the mutual fund industry, it could be that investors show behavioral biases, where they are ex ante over-optimistic about the active management ability of fund managers as suggested by the negative average risk-adjusted abnormal return provided by a broad set of mutual funds as well as a negligible number of funds with positive alpha. Another explanation could be that available liquidity, e.g. being the cause of growth in private pension plans, need to be invested, while other investment opportunities and asset classes are rather relatively unavailable or unattractive. Furthermore, deficiencies in models of performance measurement, like e.g. in the presence of style investors like in Stutzer (2008), call for further research on this issue.

In Chapter 6, I also test for the dynamic abilities of mutual fund managers with respect to liquidity and risk factor timing. A first unconditional timing analysis, which only provides for implausible results, has been complemented by a conditional timing analysis based on the Kalman filter, as there is considerable time variation in the mutual funds' risk exposures. Applying this more sophisticated conditional evaluation method, there is no evidence of perverse market timing anymore and some biases of the unconditional analysis in Chapter 5 have been reduced as well. For example, in contrast to the unconditional results, the conditional results reveal a considerably positive illiquidity exposure of the equal-weighted mutual fund portfolio which is consistent with its focus on smaller funds. The overall results of the dynamic analysis in Chapter 6 suggest that liquidity is still ignored in timing decisions regarding mutual and hedge funds, apart from a very small number of individual funds. Results with respect to other risk factors are not more promising. Combining static as well as dynamic methods when evaluating mutual fund managers' timing abilities demonstrates that asset managers provide only for disappointing dynamic abilities in managing systematic risk factors.

Moreover, it has been demonstrated that mutual funds with existing timing abilities do not necessarily show a higher performance. For investors, it is hence very difficult to select those mutual funds which simultaneously possess positive selectivity as well as risk factor timing abilities. Budiono and Martens (2009) find that only choosing mutual funds based on abnormal returns or on timing abilities with respect to one risk factor leads to a low ex post performance for the investor. This suggests that choosing the best mutual fund is even more challenging, especially when one considers that there are even less mutual funds with risk factor timing compared to market timing abilities. When one also prefers a mutual fund with low expenses, it even becomes more difficult to find an adequate mutual fund as the backtests in Chapter 5 on net as well as gross performance suggest. Rational private as well as institutional investors might as a consequence look for alternative investments. Passive investment products like exchange traded funds do not offer special selectivity or timing abilities, especially not with respect to liquidity risk, but relatively low total expense ratios make them quite attractive. That is why one expects future competition among different investment products to further increase. However, the focus of analysis in this thesis has been on daily data. As there is more evidence on dynamic mutual fund abilities when estimations are conducted at a monthly frequency, asset managers seem to be unable to quickly process daily information on risk factors and to adjust their risk factor exposures in an adequate way. At least, the findings show that specific groups of hedge funds offer market or liquidity timing abilities at a monthly frequency, but investors must be aware of choosing the right hedge fund possessing the respective characteristics from the quite disperse set of hedge funds and hedge fund strategies offered.

Furthermore, evidence in this thesis provides for new insights on the relationship between liquidity and idiosyncratic risk. Even in case liquidity and idiosyncratic risk are jointly considered as risk factors, the importance of these two risk factors is neither diminished by considering them jointly nor by considering them in addition to other risk factors, see the results in Chapter 4 as well as 5 and 6. Overall, both risk factors seem to capture different aspects in the cross-section of returns. Hence, it seems to be useful to include both as risk factors in financial multifactor models. In light of the argumentation of O'Hara (2003) and Kamara et al. (2008), the results that both liquidity and idiosyncratic risk are relevant risk factors in the cross-section of stock returns are rather supportive of the hypothesis that liquidity captures the effects of transaction costs in the cross-section of returns, whereas idiosyncratic risk is related to the price discovery process. This conclusive interpretation is confirmed by the results in Easley et al. (2002) who find that the probability of informed trading as a proxy measure for asymmetric information contains information beyond other liquidity-related variables like e.g. the bid-ask spread with respect to the cross-section of stock returns. O'Hara (2003) argues that the influence of liquidity and price discovery on asset prices may not be properly disentangled as one suspects proxies of liquidity to rather capture risks of price discovery than the transaction costs of liquidity. This argumentation may be linked to Spiegel and Wang (2006) who conclude that different approaches to measure liquidity might influence the results on the link between liquidity and idiosyncratic risk, which, as well as a longer time period of analysis for my pan-European data set, is an issue of further research. Moreover, further research has still to be conducted on whether alternative inventory based explanations (see e.g. Spiegel and Wang (2006)) or funding based explanations (see Brunnermeier and Pedersen (2009)) may be more sensible approaches in order to understand more clearly what really links liquidity and idiosyncratic risk.

Overall, the results in this thesis have not only demonstrated the importance of systematic liquidity in the context of crises, asset pricing and performance measurement, but have also emphasized the relevance of other risk factors derived from the remaining set of European style indices. These results are important to mutual fund managers, as well as to institutional investors and private investors who have to choose a mutual fund, especially in light of the increasing relevance of private retirement pension plans. It has been shown that liquidity and idiosyncratic risk simultaneously affect stock returns and that common liquidity suffered during the financial crisis. Based on this evidence, the results are also relevant to (i) market makers in European financial markets, as suggested by inventory models of market making, (ii) European investors like traders and speculators which are influenced by possibly increased transaction costs and margin requirements, as suggested by e.g. Brunnermeier and Pedersen (2009), and (iii) investors which are influenced by the existence of privately informed investors, i.e. a better informed counterparty, see O'Hara (2003). Moreover, the results contributing to the still relatively scare pan-European empirical evidence are also consistent with the majority of other empirical U.S. studies.

In further research, it may be examined what motivates some mutual fund managers, mainly those of smaller funds, to prefer to have a negative exposure towards idiosyncratic risk. Probably, this result is connected to the mutual fund managers having reduced exposures to this risk factor during the financial crisis. Moreover, some evidence for volatility clustering in the return series may call for further research on whether results are considerably changed by considering potential autoregressive conditional heteroskedasticity in the data. Future research may test whether risk factor timing abilities are influenced by nonlinearities, i.e. better timing abilities in e.g. up markets than down markets, and whether this may improve the goodness-of-fit of daily timing tests. An increased focus on nonlinearities is also useful for further research on hedge fund data as nonlinear methods of performance evaluation of hedge funds became widely applied. As Billio et al. (2009) find that hedge funds exhibited an increase in idiosyncratic volatility during the 2007 / 2008 global financial crisis, further research on hedge funds could take into account the timing abilities with respect to idiosyncratic risk. Further research might also focus on whether the importance of dynamic timing abilities has increased compared to the importance of the selectivity component of active fund management.

A further issue of research, which has still to be examined with respect to Europe and in the context of the financial crisis, is commonality in liquidity in light of different asset classes and asset allocation. This thesis has focused on commonality in liquidity with respect to equity markets, as proxied mainly by the constituent stocks of well-known European stock indices. However, O'Hara (2003) addresses that commonality in liquidity may be diversified across different kinds of assets, see also the research of Chordia et al. (2005b) on the cross-market dynamics in liquidity between stock and bond markets. Hence, an investigation of other asset classes, like e.g. bond markets, as well as potential diversification and flight to quality effects would be an interesting issue of further research for the data set as well as time period examined in this thesis. As liquidity measures only provide for liquidity proxies, further research may backtest the results of this thesis with respect to different liquidity measures as well. However, even if the results presented above are only based on one specific liquidity measure, they underpin the role of systematic liquidity risk from different points of view, with respect to different investments, i.e. stocks, mutual and hedge funds, and for a still relatively unexplored European data set. Thus, liquidity is an aspect possessing considerable economic relevance as emphasized by the results in this thesis, which one expects to be a significant issue of financial research efforts for the next years.

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A Appendix

A.1 Correlations: Free-float and equal-weighted indices

Table A.1: Correlations: Free-float weighted indices

Free-float weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
MARKET	1.000	0.998	0.960	0.892	0.944	0.931	0.921	0.966	0.902	0.994	0.949
LARGE CAP	0.998	1.000	0.939	0.892	0.936	0.922	0.921	0.972	0.896	0.994	0.944
SMALL CAP	0.960	0.939	1.000	0.850	0.933	0.924	0.875	0.896	0.880	0.945	0.923
GROWTH	0.892	0.892	0.850	1.000	0.762	0.756	0.885	0.847	0.902	0.876	0.894
VALUE	0.944	0.936	0.933	0.762	1.000	0.958	0.806	0.892	0.838	0.937	0.885
BOT. SIX MONTH MOM.	0.931	0.922	0.924	0.756	0.958	1.000	0.755	0.878	0.850	0.927	0.874
TOP SIX MONTH MOM.	0.921	0.921	0.875	0.885	0.806	0.755	1.000	0.897	0.822	0.915	0.868
BOT. IDIOS. RISK	0.966	0.972	0.896	0.847	0.892	0.878	0.897	1.000	0.803	0.963	0.895
TOP IDIOS. RISK	0.902	0.896	0.880	0.902	0.838	0.850	0.822	0.803	1.000	0.883	0.920
BOT. ILLIQU.	0.994	0.994	0.945	0.876	0.937	0.927	0.915	0.963	0.883	1.000	0.928
TOP ILLIQU.	0.949	0.944	0.923	0.894	0.885	0.874	0.868	0.895	0.920	0.928	1.000

Table A.2: Correlations: Equal-weighted indices

Equal-weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
MARKET	1.000	0.979	0.995	0.950	0.976	0.966	0.931	0.963	0.978	0.978	0.987
LARGE CAP	0.979	1.000	0.955	0.939	0.948	0.937	0.917	0.958	0.953	0.994	0.955
SMALL CAP	0.995	0.955	1.000	0.941	0.974	0.966	0.924	0.951	0.975	0.956	0.987
GROWTH	0.950	0.939	0.941	1.000	0.877	0.874	0.952	0.900	0.949	0.933	0.930
VALUE	0.976	0.948	0.974	0.877	1.000	0.977	0.863	0.936	0.948	0.948	0.968
BOT. SIX MONTH MOM.	0.966	0.937	0.966	0.874	0.977	1.000	0.817	0.914	0.953	0.940	0.961
TOP SIX MONTH MOM.	0.931	0.917	0.924	0.952	0.863	0.817	1.000	0.910	0.905	0.910	0.909
BOT. IDIOS. RISK	0.963	0.958	0.951	0.900	0.936	0.914	0.910	1.000	0.900	0.956	0.944
TOP IDIOS. RISK	0.978	0.953	0.975	0.949	0.948	0.953	0.905	0.900	1.000	0.952	0.969
BOT. ILLIQU.	0.978	0.994	0.956	0.933	0.948	0.940	0.910	0.956	0.952	1.000	0.950
TOP ILLIQU.	0.987	0.955	0.987	0.930	0.968	0.961	0.909	0.944	0.969	0.950	1.000

A.2 Summary statistics: Monthly rebalanced and different momentum, cut-off-rate and illiquidity indices

Table A.3: Summary statistics: Monthly rebalanced indices

Free-float weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
Mean p.a.	6.10%	5.35%	9.18%	3.93%	6.85%	5.03%	5.88%	4.15%	7.28%	5.10%	12.73%
Median	0.07%	0.06%	0.12%	0.09%	0.07%	0.07%	0.09%	0.05%	0.09%	0.05%	0.12%
Std. dev. p.a.	20.92%	21.18%	20.81%	19.12%	28.83%	30.57%	20.21%	18.41%	27.70%	21.96%	20.56%
Skewness	-0.032	0.023	-0.238	0.051	0.200	0.195	-0.080	0.014	0.176	0.100	0.102
Excess Kurtosis	7.292	7.516	6.036	6.532	8.448	9.582	5.708	9.658	6.540	8.140	10.067
Equal-weighted	MARKET	LARGE CAP	SMALL CAP	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
Mean p.a.	9.38%	7.33%	10.18%	6.60%	10.40%	9.23%	8.53%	9.05%	10.85%	7.13%	9.23%
Median	0.12%	0.09%	0.12%	0.11%	0.09%	0.11%	0.12%	0.08%	0.12%	0.09%	0.14%
Std. dev. p.a.	20.90%	21.25%	21.06%	18.83%	26.16%	27.52%	18.34%	17.06%	21.48%	21.34%	25.69%
Skewness	-0.220	-0.061	-0.271	-0.401	-0.095	0.004	-0.375	-0.192	-0.312	-0.013	-0.254
Excess Kurtosis	6.536	7.268	6.119	5.523	6.835	7.808	5.415	9.915	7.228	7.380	5.674

Table A.4: Summary statistics: Momentum indices

	Quarterly rebalanced				Monthly rebalanced				Semiannually rebalanced			
Free-float weighted	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.
Mean p.a.	7.55%	3.80%	3.33%	4.33%	8.08%	5.03%	5.03%	5.88%	5.60%	6.35%	4.03%	6.15%
T-stat.	0.677	0.488	0.296	0.592	0.731	0.648	0.442	0.781	0.546	0.769	0.380	0.829
P-value (t-stat.)	0.498	0.626	0.767	0.554	0.465	0.517	0.658	0.435	0.585	0.442	0.704	0.407
Median	0.08%	0.08%	0.06%	0.08%	0.06%	0.08%	0.07%	0.09%	0.05%	0.07%	0.05%	0.09%
Std. dev. p.a.	29.97%	20.94%	30.32%	19.64%	29.74%	20.84%	30.57%	20.21%	27.64%	22.21%	28.40%	19.95%
Skewness	0.007	-0.065	0.078	-0.123	-0.007	-0.140	0.195	-0.080	0.184	0.073	0.090	-0.151
Exc. kurt.	10.406	5.041	8.202	5.836	10.435	4.621	9.582	5.708	8.256	9.004	6.975	6.024
	Quarterly rebalanced				Monthly rebalanced				Semiannually rebalanced			
Equal-weighted	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. THREE MONTH MOM.	TOP THREE MONTH MOM.	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.
Mean p.a.	11.18%	7.33%	8.73%	7.80%	10.13%	7.90%	9.23%	8.53%	9.68%	7.38%	8.10%	8.23%
T-stat.	1.127	1.017	0.867	1.162	1.009	1.113	0.901	1.250	1.066	0.962	0.859	1.183
P-value (t-stat.)	0.260	0.309	0.386	0.245	0.313	0.266	0.368	0.212	0.286	0.336	0.390	0.237
Median	0.11%	0.10%	0.09%	0.12%	0.12%	0.13%	0.11%	0.12%	0.11%	0.12%	0.10%	0.12%
Std. dev. p.a.	26.65%	19.40%	27.10%	18.05%	26.98%	19.10%	27.52%	18.34%	24.43%	20.65%	25.38%	18.73%
Skewness	-0.182	-0.316	-0.029	-0.437	-0.186	-0.360	0.004	-0.375	0.079	-0.342	0.000	-0.549
Exc. kurt.	8.330	4.768	7.059	5.515	9.260	4.392	7.808	5.415	6.101	7.900	5.829	6.659

Table A.5: Summary statistics: Illiquidity indices

	Monthly rebalanced				Quarterly rebalanced			
Free-float weighted	BOT. MTHLY. AVERAGE	TOP MTHLY. AVERAGE	BOT. MTHLY. DETR.	TOP MTHLY. DETR.	BOT. QTRLY. AVERAGE	TOP QTRLY. AVERAGE	BOT. QTRLY. DETR.	TOP QTRLY. DETR.
Mean p.a.	5.10%	12.73%	4.55%	6.35%	5.13%	11.33%	5.70%	7.33%
T-stat.	0.626	1.664	0.743	0.580	0.631	1.499	0.909	0.673
P-value (t-stat.)	0.531	0.096*	0.458	0.562	0.528	0.134	0.364	0.501
Median	0.05%	0.12%	0.06%	0.10%	0.05%	0.10%	0.07%	0.11%
Std. dev. p.a.	21.96%	20.56%	16.46%	29.41%	21.84%	20.33%	16.88%	29.26%
Skewness	0.100	0.102	0.093	-0.171	0.087	0.078	0.182	-0.154
Exc. kurt.	8.140	10.067	10.951	11.316	8.188	9.205	12.313	10.198
	Monthly rebalanced				Quarterly rebalanced			
Equal-weighted	BOT. MTHLY. AVERAGE	TOP MTHLY. AVERAGE	BOT. MTHLY. DETR.	TOP MTHLY. DETR.	BOT. QTRLY. AVERAGE	TOP QTRLY. AVERAGE	BOT. QTRLY. DETR.	TOP QTRLY. DETR.
Mean p.a.	7.13%	10.85%	8.73%	7.10%	7.05%	10.98%	8.65%	9.33%
T-stat.	0.897	1.359	1.536	0.704	0.875	1.411	1.531	0.950
P-value (t-stat.)	0.370	0.174	0.125	0.481	0.382	0.158	0.126	0.342
Median	0.09%	0.12%	0.09%	0.12%	0.08%	0.13%	0.09%	0.12%
Std. dev. p.a.	21.34%	21.48%	15.30%	27.11%	21.66%	20.93%	15.20%	26.37%
Skewness	-0.013	-0.312	-0.245	-0.385	-0.002	-0.328	-0.276	-0.252
Exc. kurt.	7.380	7.228	8.703	8.350	7.509	6.554	8.861	7.435

Table A.6: Summary statistics: Indices (1%- and 99%-cut-off-rates)

Free-float weighted	GROWTH	VALUE	BOT. SIX MONTH MOM.	TOP SIX MONTH MOM.	BOT. IDIOS. RISK	TOP IDIOS. RISK	BOT. ILLIQU.	TOP ILLIQU.
Mean p.a.	3.45%	7.88%	9.63%	7.60%	4.73%	6.58%	4.48%	10.80%
T-stat.	0.414	0.728	0.947	1.128	0.708	0.638	0.567	1.432
P-value (t-stat.)	0.679	0.467	0.343	0.259	0.479	0.523	0.571	0.152
Median	0.08%	0.07%	0.11%	0.12%	0.06%	0.10%	0.06%	0.11%
Std. dev. p.a.	22.46%	29.08%	27.36%	18.12%	17.95%	27.70%	21.22%	20.28%
Skewness	0.994	0.199	-0.073	-0.462	-0.020	0.131	0.093	0.015
Exc. kurt.	27.350	8.326	6.841	5.192	9.279	5.962	8.168	9.424
Equal-weighted	**GROWTH**	**VALUE**	**BOT. SIX MONTH MOM.**	**TOP SIX MONTH MOM.**	**BOT. IDIOS. RISK**	**TOP IDIOS. RISK**	**BOT. ILLIQU.**	**TOP ILLIQU.**
Mean p.a.	7.13%	10.23%	9.45%	7.58%	9.10%	9.85%	6.65%	10.23%
T-stat.	1.033	1.039	0.927	1.123	1.483	1.029	0.830	1.321
P-value (t-stat.)	0.302	0.299	0.354	0.262	0.138	0.304	0.407	0.187
Median	0.11%	0.10%	0.11%	0.12%	0.09%	0.13%	0.07%	0.12%
Std. dev. p.a.	18.55%	26.47%	27.39%	18.12%	16.51%	25.75%	21.55%	20.82%
Skewness	-0.450	-0.117	-0.077	-0.462	-0.251	-0.212	0.003	-0.334
Exc. kurt.	5.697	6.602	6.817	5.198	9.765	5.462	7.569	6.654

Table A.7: Summary statistics: Risk factor portfolios (1%- and 99%-cut-off-rates)

Free-float weighted	VALUATION	SIX MONTH MOM.	IDIOS. RISK	ILLIQUIDITY
Mean p.a.	4.43%	-2.03%	1.85%	6.33%
T-stat.	0.533	-0.327	0.292	2.121
P-value (t-stat.)	0.594	0.744	0.771	0.034**
Maximum p.d.	23.68%	6.02%	12.54%	8.57%
Minimum p.d.	-21.18%	-6.51%	-11.80%	-7.80%
Median	0.01%	0.02%	0.02%	0.03%
Std. dev. p.a.	22.29%	16.66%	17.08%	8.02%
Skewness	-0.135	-0.581	0.509	0.386
Excess Kurtosis	90.546	7.438	21.262	76.543
Equal-weighted	**VALUATION**	**SIX MONTH MOM.**	**IDIOS. RISK**	**ILLIQUIDITY**
Mean p.a.	3.10%	-1.87%	0.75%	3.58%
T-stat.	0.609	-0.302	0.153	1.381
P-value (t-stat.)	0.542	0.763	0.879	0.167
Maximum p.d.	5.17%	6.03%	5.01%	2.41%
Minimum p.d.	-5.83%	-6.51%	-4.03%	-2.69%
Median	0.01%	0.02%	0.03%	0.02%
Std. dev. p.a.	13.69%	16.68%	13.21%	6.79%
Skewness	0.178	-0.578	0.254	-0.453
Excess Kurtosis	8.671	7.393	4.214	4.126

A.3 Summary statistics of the Stoxx Europe 50 constituent stocks

Table A.8: Stoxx Europe 50 constituents: Summary statistics of individual simple stock returns. Sample period: October 1, 2002 to September 30, 2009.

Company Name	ISIN	SEDOL	Geom. avg. ret. p.a.	Min. ret. p.d.	Max. ret. p.d.	Std. dev. p.a.
ABB	CH0012221716	7108899	23.54%	-61.83%	45.79%	55.07%
ALLIANZ	DE0008404005	5231485	4.07%	-12.99%	19.49%	39.78%
ANGLO AMERICAN	GB00B1XZS820	B1XZS82	9.50%	-20.21%	22.69%	47.47%
ARCELORMITTAL	LU0323134006	B03XPL1	35.96%	-18.93%	20.07%	54.73%
ASSICURAZIONI GENERALI	IT0000062072	4056719	6.87%	-6.50%	8.28%	24.67%
ASTRAZENECA	GB0009895292	0989529	3.04%	-10.30%	12.80%	28.18%
AXA	FR0000120628	7088429	12.46%	-18.41%	21.28%	46.24%
BARCLAYS	GB0031348658	3134865	-0.51%	-24.53%	72.06%	59.05%
BASF	DE0005151005	5086577	13.78%	-12.12%	13.53%	30.23%
BAYER	DE000BAY0017	5069211	17.56%	-14.10%	38.13%	34.95%
BCO BILBAO VIZCAYA ARGENTARIA	ES0113211835	5501906	10.93%	-11.50%	12.04%	31.47%
BCO SANTANDER	ES0113900J37	5705946	15.20%	-11.94%	13.39%	33.00%
BG GRP	GB0008762899	0876289	16.29%	-11.63%	14.73%	34.90%
BHP BILLITON	GB0000566504	0056650	21.66%	-15.04%	22.21%	43.69%
BNP PARIBAS	FR0000131104	7309681	11.03%	-17.24%	20.77%	39.81%
BP	GB0007980591	0798059	2.58%	-8.32%	13.08%	27.49%
BRITISH AMERICAN TOBACCO	GB0002875804	0287580	14.51%	-10.13%	13.41%	25.75%
CREDIT SUISSE GRP	CH0012138530	7171589	10.93%	-15.50%	26.17%	42.67%
DAIMLER	DE0007100000	5529027	3.85%	-13.26%	19.59%	36.60%
DEUTSCHE BANK	DE0005140008	5750355	4.75%	-16.53%	24.99%	42.24%
DEUTSCHE TELEKOM	DE0005557508	5842359	5.42%	-12.41%	14.16%	28.18%
DIAGEO	GB0002374006	0237400	1.13%	-9.36%	11.85%	23.68%
E.ON	DE000ENAG999	4942904	12.57%	-10.19%	17.22%	29.99%
ENI	IT0003132476	7145056	8.24%	-9.63%	17.52%	27.53%
ERICSSON LM B	SE0000108656	5959378	19.72%	-24.21%	17.96%	48.92%
FRANCE TELECOM	FR0000133308	5176177	19.85%	-9.73%	16.52%	32.43%
GDF SUEZ	FR0010208488	B0C2CQ3	-2.63%	-13.08%	25.01%	36.80%
GLAXOSMITHKLINE	GB0009252882	0925288	-0.68%	-8.32%	10.98%	25.01%
GRP SOCIETE GENERALE	FR0000130809	5966516	8.23%	-15.56%	19.94%	41.20%
HSBC	GB0005405286	0540528	2.87%	-19.49%	16.12%	30.51%
IBERDROLA	ES0144580Y14	B288C92	13.02%	-12.58%	18.80%	28.54%
ING GRP	NL0000303600	7154182	2.37%	-27.48%	29.24%	53.99%
INTESA SANPAOLO	IT0000072618	4076836	11.39%	-22.69%	17.51%	38.03%
NESTLE	CH0038863350	7123870	6.24%	-6.04%	9.46%	19.33%
NOKIA	FI0009000681	5902941	-1.61%	-16.83%	14.58%	39.11%
NOVARTIS	CH0012005267	7103065	0.14%	-7.71%	11.29%	20.18%
RIO TINTO	GB0007188757	0718875	-7.76%	-36.63%	21.79%	50.04%
ROCHE HLDG P	CH0012032048	7110388	8.42%	-10.53%	9.73%	23.55%
ROYAL DUTCH SHELL A	GB00B03MLX29	B09CBL4	3.63%	-8.98%	14.00%	26.07%
RWE	DE0007037129	4768962	14.50%	-10.92%	15.32%	27.92%
SANOFI-AVENTIS	FR0000120578	5671735	1.13%	-10.34%	14.66%	27.81%
SAP	DE0007164600	4846288	16.12%	-15.26%	26.56%	34.27%
SIEMENS	DE0007236101	5727973	10.80%	-15.10%	18.06%	35.20%
TELEFONICA	ES0178430E18	5732524	16.95%	-9.10%	10.76%	23.39%
TESCO	GB0008847096	0884709	6.56%	-9.44%	12.64%	27.39%
TOTAL	FR0000120271	B15C557	6.90%	-9.19%	13.64%	27.41%
UBS	CH0024899483	B18YFJ4	-3.59%	-16.93%	30.38%	42.87%
UNICREDIT	IT0000064854	4232445	0.86%	-13.11%	19.18%	38.64%
UNILEVER NV	NL0000009355	B12T3J1	3.39%	-10.17%	8.76%	24.20%
VODAFONE GRP	GB00B16GWD56	B16GWD5	6.01%	-13.40%	12.73%	32.07%

A.4 GMM asset pricing tests: Robustness tests

Table A.9: Two-step GMM estimation and Stoxx Europe 50 constituent stocks: Different model specifications

This table gives the result of a two-step GMM estimation of different linearly specified SDFs across systems of individual Stoxx Europe 50 constituent stocks. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance tests and the J-statistics to test for model mis-specifications are given. Sample period: October 1, 2002 to September 30, 2009.

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY	SIZE	VALUATION	MOMENTUM	IDIOS. RISK
Coeff.	1.000	-1.053	0.356	-0.043			
P-value (t-stat.)	0.000	0.000	0.000	0.000			
J-stat.	122.457	P-value of J-stat.	1.000	Number of overidentif. restrict.	196	P-value of Wald test	0.000
Coeff.	1.000	-1.118	0.228				0.173
P-value (t-stat.)	0.000	0.000	0.004				0.000
J-stat.	86.130	P-value of J-stat.	1.000	Number of overidentif. restrict.	196	P-value of Wald test	0.000
Coeff.	1.000	-0.998	0.456			0.038	
P-value (t-stat.)	0.000	0.000	0.000			0.000	
J-stat.	131.455	P-value of J-stat.	1.000	Number of overidentif. restrict.	196	P-value of Wald test	0.000
Coeff.	1.000	-0.915	0.558	0.062	-0.051		
P-value (t-stat.)	0.000	0.000	0.000	0.471	0.466		
J-stat.	270.408	P-value of J-stat.	0.127	Number of overidentif. restrict.	245	P-value of Wald test	0.000

Table A.10: Two-step GMM estimation and price-to-book portfolios: Different model specifications

This table gives the results of a two-step GMM estimation of different linearly specified SDFs across systems of market capitalization and price-to-book sorted test portfolios. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance and the J-statistics to test for model mis-specification are given. Sample period: October 1, 2002 to September 30, 2009.

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY	SIZE	VALUATION	MOMENTUM	IDIOS. RISK
Coeff.	1.000	-0.997	0.055	-0.401			
P-value of t-stat.	0.000	0.000	0.172	0.000			
J-stat.	39.240	P-value of J-stat.	0.006	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	0.999	-0.506	2.074				-0.206
P-value of t-stat.	0.000	0.092	0.130				0.644
J-stat.	44.143	P-value of J-stat.	0.014	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	1.000	-0.727	1.381			-0.110	
P-value of t-stat.	0.000	0.006	0.006			0.264	
J-stat.	49.262	P-value of J-stat.	0.000	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	1.000	-0.922	0.042	-0.277	-0.089		
P-value of t-stat.	0.000	0.000	0.450	0.000	0.019		
J-stat.	48.259	P-value of J-stat.	0.003	Number of overidentif. restrict.	25	P-value of Wald test	0.000

Table A.11: Two-step GMM estimation and price-to-earnings portfolios: Different model specifications

This table gives the results of a two-step GMM estimation of different linearly specified SDFs across systems of market capitalization and price-to-earnings sorted test portfolios. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance and the J-statistics to test for model mis-specification are given. Sample period: October 1, 2002 to September 30, 2009.

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY	SIZE	VALUATION	MOMENTUM	IDIOS. RISK
Coeff.	1.000	-1.769	-0.905	-0.741			
P-value of t-stat.	0.000	0.000	0.074	0.000			
J-stat.	48.057	P-value of J-stat.	0.000	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	0.999	-0.956	1.072				-0.048
P-value of t-stat.	0.000	0.001	0.393				0.921
J-stat.	42.955	P-value of J-stat.	0.002	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	0.999	-0.592	1.754			-0.086	
P-value of t-stat.	0.000	0.016	0.000			0.405	
J-stat.	52.542	P-value of J-stat.	0.000	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.		1.000	-1.481	-0.659	-0.417	-0.141	
Prob.	0.000	0.000	0.189	0.379	0.720		
J-stat.	51.733	P-value of J-stat.	0.001	Number of overidentif. restrict.	25	P-value of Wald test	0.000

Table A.12: Two-step GMM estimation and dividend yield portfolios: Different model specifications

This table gives the results of a two-step GMM estimation of different linearly specified SDFs across systems of market capitalization and dividend yield sorted test portfolios. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance and the J-statistics to test for model mis-specification are given. Sample period: October 1, 2002 to September 30, 2009.

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY	SIZE	VALUATION	MOMENTUM	IDIOS. RISK
Coeff.	1.000	-0.965	0.113	-0.356			
P-value of t-stat.	0.000	0.000	0.018	0.000			
J-stat.	45.584	P-value of J-stat.	0.001	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	0.999	-0.564	0.724				0.173
P-value of t-stat.	0.000	0.070	0.586				0.702
J-stat.	57.480	P-value of J-stat.	0.000	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	1.000	-0.418	1.453			-0.161	
P-value of t-stat.	0.000	0.011	0.000			0.063	
J-stat.	61.753	P-value of J-stat.	0.000	Number of overidentif. restrict.	20	P-value of Wald test	0.000
Coeff.	1.000	-0.951	0.053	-0.303	-0.044		
Prob.	0.000	0.000	0.218	0.000	0.068		
J-stat.	48.921	P-value of J-stat.	0.003	Number of overidentif. restrict.	25	P-value of Wald test	0.000

Table A.13: Iterated GMM results: Two-factor model

This table gives the results of an iterated GMM estimation of a linearly specified two-factor SDF for systems of market capitalization and price-to-earnings (P/E) sorted test portfolios. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance tests and the J-statistics to test for model mis-specifications are given. Sample period: October 1, 2002 to September 30, 2009.

P/E sorted test portfolios	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Coeff.	0.994	-0.544	17.595
P-value (t-stat.)	0.000	0.503	0.000
P-value of Wald test	0.000		
J-stat.	34.542		
P-value of J-stat.	0.003		
Number of overidentif. restrict.	15		

Table A.14: GMM: Different robustness tests

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Equal-weighted factors			
Coeff.	1.000	-1.277	0.961
Prob.	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	130.758		
P-value of J-stat.	0.828		
Number of overidentif. restrict.	147		
Detrended liquidity factor			
Coeff.	1.000	-0.902	0.018
Prob.	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	54.602		
P-value of J-stat.	1.000		
Number of overidentif. restrict.	147		
Without orthogonality conditions			
Coeff.	1.004	-3.507	-15.482
P-value (t-stat.)	0.000	0.023	0.041
P-value of Wald test	0.063		
J-stat.	37.461		
P-value of J-stat.	0.886		
Number of overidentif. restrict.	49		
1%- and 99%-cut-off-rates			
Coeff.	0.999	-0.684	1.361
P-value (t-stat.)	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	149.428		
P-value of J-stat.	0.429		
Number of overidentif. restrict.	147		
SDF prices riskless asset and traded factors			
Coeff.	1.000	-0.917	0.537
P-value (t-stat.)	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	145.656		
P-value of J-stat.	0.713		
Number of overidentif. restrict.	156		
Monthly rebalanced factors			
Coefficient	1.000	-1.077	0.124

Table A.14 – continued from previous page

	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
P-value (t-stat.)	0.000	0.000	0.001
P-value of Wald test	0.000		
J-stat.	126.800		
P-value of J-stat.	0.884		
Number of overidentif. restrict.	147		
Without outliers			
Coefficient	1.000	-1.155	0.294
P-value (t-stat.)	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	99.797		
P-value of J-stat.	0.999		
Number of overidentif. restrict.	147		

Table A.15: GMM test portfolio results: First subperiod

This table gives the results of a two-step GMM estimation of a linearly specified two-factor SDF on the different test portfolios for the first subperiod. The test portfolios are sorted on market capitalization as well as on either price-to-book, price-to-earnings or dividend yield characteristics. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance tests and the J-statistics to test for model mis-specification are given. Number of overidentifying restrictions: 15. The first subperiod comprises 906 observations from October 1, 2002 to March 31, 2006.

Price-to-book sorted test portf.	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Coeff.	1.000	-0.981	-1.810
P-value (t-stat.)	0.000	0.009	0.254
P-value of Wald test	0.005		
J-stat.	34.590		
P-value of J-stat.	0.003		
Price-to-earnings sorted test portf.	**CONST.**	**MARKET EXCESS RETURN**	**ILLIQUIDITY**
Coeff.	0.998	0.490	2.940
P-value (t-stat.)	0.000	0.416	0.213
P-value of Wald test	0.320		
J-stat.	29.030		
P-value of J-stat.	0.016		
Div. yield sorted test portf.	**CONST.**	**MARKET EXCESS RETURN**	**ILLIQUIDITY**
Coeff.	1.000	-0.908	-1.593
P-value (t-stat.)	0.000	0.025	0.342
P-value of Wald test	0.006		
J-stat.	27.527		
P-value of J-stat.	0.025		

Table A.16: GMM test portfolio results: Second subperiod

This table gives the results of a two-step GMM estimation of a linearly specified two-factor SDF on the different test portfolios for the second subperiod. The test portfolios are sorted on market capitalization as well as on either price-to-book, price-to-earnings or dividend yield characteristics. The following orthogonality and pricing error condition $\mathbf{g}_T = E_T[\mathbf{u}_t \otimes \mathbf{f}_t]$ is considered with $\mathbf{f}_t$ also including a constant. The estimations take into account a heteroskedasticity and autocorrelation consistent weighting matrix considering the quadratic kernel of Andrews (1991) and the Newey and West (1994) bandwidth method. Moreover, the results on Wald joint significance tests and the J-statistics to test for model mis-specification are given. Number of overidentifying restrictions: 15. The second subperiod comprises 903 observations from April 3, 2006 to September 30, 2009.

Price-to-book sorted test portf.	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Coeff.	1.000	-0.591	1.256
P-value (t-stat.)	0.000	0.000	0.000
P-value of Wald test	0.000		
J-stat.	20.043		
P-value of J-stat.	0.170		
Price-to-earnings sorted test portf.	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Coeff.	1.000	-0.785	1.115
P-value (t-stat.)	0.000	0.001	0.016
P-value of Wald test	0.000		
J-stat.	22.800		
P-value of J-stat.	0.088		
Div. yield sorted test portf.	CONST.	MARKET EXCESS RETURN	ILLIQUIDITY
Coeff.	1.000	-0.557	1.150
P-value (t-stat.)	0.000	0.001	0.000
P-value of Wald test	0.000		
J-stat.	26.365		
P-value of J-stat.	0.034		

A.5 Individual mutual funds: Descriptive statistics

Table A.17: Individual mutual funds: Summary statistics

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
AAM Selection European Equities A	-15.03%	7.90%	-7.72%	31.54%	378
Aberdeen Global - European Equity A Acc	3.23%	9.79%	-10.09%	20.96%	1808
ACATIS AKTIEN EUROPA FONDS UI A1	0.81%	8.39%	-5.85%	20.53%	982
Agressor	7.60%	6.93%	-5.96%	15.04%	1808
AIG Global Funds - AIG Europe A	1.68%	8.56%	-7.64%	20.11%	1500
AIG Global Funds - AIG Europe Focus Equity A1	-22.90%	8.14%	-6.77%	30.09%	464
Albatros Aktien Europa OP	4.23%	7.05%	-7.27%	17.37%	1808
Alken Fund - European Opportunities-R	1.29%	9.66%	-9.44%	25.78%	966
All Europe	2.32%	7.06%	-4.94%	14.84%	1808
AllianceBernstein-European Growth Portfolio A EUR	1.88%	9.88%	-9.04%	22.51%	1808
AllianceBernstein-European Strategic Value A EUR	-22.88%	9.47%	-11.40%	35.34%	647
AllianceBernstein-European Value Portfolio A EUR	3.90%	9.59%	-11.47%	24.26%	1808
Allianz PIMCO Euro StocksPLUS Total Return -A- EUR	-3.08%	10.80%	-14.03%	25.52%	1140
Allianz RCM Aktien Europa - A - EUR	4.00%	9.91%	-12.00%	21.30%	1808
Allianz RCM Deep Value Europe - A - EUR	4.23%	9.39%	-12.87%	21.71%	1808
Allianz RCM Europe Alpha Plus - AT - EUR	5.15%	9.20%	-12.02%	25.55%	1808
Allianz RCM Europe Equity Growth - W - EUR	9.45%	7.40%	-9.30%	20.66%	1808
Allianz RCM European Equity - A - EUR	13.20%	5.03%	-4.91%	25.42%	230
Allianz RCM European Equity Dividend - AT - EUR	61.90%	4.76%	-2.92%	19.13%	145
Allianz RCM High Dividend Discount - A - EUR	-1.43%	7.31%	-10.68%	18.71%	1248
Allianz RCM High Dividend Europe - I - EUR	-5.43%	8.49%	-11.13%	23.85%	989
Allianz RCM New Stars Europe - A - EUR	-13.13%	7.51%	-11.10%	30.63%	704
Allianz RCM Vermoegensbildung Europa - A - EUR	3.98%	10.52%	-14.99%	23.13%	1808
Allianz RCM Wachstum Europa - A - EUR	7.75%	8.13%	-9.64%	22.00%	1808
All-Star Europe A	-5.68%	7.43%	-5.82%	16.68%	985
AMC Professional Fund - Pro Active Europe Equity A	-0.30%	7.37%	-8.16%	20.19%	1259
AMC Professional Fund - Pro Europe Equity A	6.55%	10.23%	-8.51%	22.37%	1691
AMG Europa Infra A	-6.70%	8.75%	-4.99%	20.51%	677
Anima European Equity B	-1.96%	8.48%	-6.56%	18.85%	1017
Antaios German Deep Value Fund	53.08%	11.52%	-4.73%	25.61%	138
apo Trend Selekt INKA	-0.65%	8.65%	-11.32%	22.56%	1808
Aquila International F-Acatis Europn Equity (EUR)	5.03%	15.03%	-10.93%	19.97%	1394
AriDeka CF	2.42%	10.23%	-12.51%	22.00%	1808
Arnica European Opportunity Fund	-16.48%	5.99%	-7.55%	19.44%	542
Artemis Intl Pan European Equity A EUR Acc	-20.60%	9.86%	-9.45%	26.54%	723
Aviva Investors Pan European Equity A	-3.73%	8.62%	-8.69%	19.27%	738
Aviva Investors Pan European Equity Focus A EUR	-2.98%	9.08%	-9.88%	32.86%	288
Aviva Investors Sustainable Future Pan Euro Eq A	-8.30%	7.43%	-7.40%	21.23%	738
AXA Europa	2.63%	9.23%	-11.72%	20.95%	1808
AXA Rosenberg Pan European Enhanced Idx Eq Alpha A	3.80%	9.59%	-7.85%	19.92%	1545
AXA Rosenberg Pan European Equity Alpha B EUR	3.18%	10.10%	-8.53%	20.90%	1808
AXA WF Framlington Europe Dividend AC	-11.63%	9.46%	-8.09%	26.41%	754
AXA WF Framlington Europe IC	16.23%	8.10%	-5.90%	29.31%	248
AXA WF Framlington Europe Opportunities AC	5.15%	11.14%	-8.75%	21.36%	1808
AXA WF Framlington Europe Talents AC GBP	-9.55%	8.36%	-7.87%	21.70%	892
AZ Fund 1 European Trend A AZ FUND	1.35%	10.04%	-8.50%	20.44%	1808
B & P Vision - Q-Selection Europe	-23.00%	6.39%	-4.95%	23.30%	524
Balius Sector Rotation Fund - Europe B	-9.88%	7.65%	-7.09%	29.34%	389
BARDUSCH GEHRSITZ UNIVERSAL AKTIENFONDS	-10.55%	18.81%	-16.03%	32.18%	1071
Baring Europa USD	5.38%	11.38%	-10.49%	23.23%	1808
Base Investments Sicav Equities Europe	0.06%	22.17%	-14.79%	24.17%	1496
BAWAG PSK Europa Blue Chip Stock A	2.09%	9.39%	-9.09%	21.53%	1808
BAWAG PSK Europa Dividende Plus T	-1.41%	7.38%	-5.71%	25.02%	256
BAWAG PSK Europa Stock A	3.28%	10.19%	-8.43%	21.99%	1808
BayernInvest Aktien Sustainable Value Europa-Fonds	-16.43%	8.66%	-6.84%	25.72%	621
BayernInvest Aktien Value Europa-Fonds	-3.78%	7.17%	-5.94%	18.31%	1050
BayernLB Europa Fonds AL	2.83%	8.33%	-11.71%	20.79%	1808
BayernLB Vermoegensverwaltungsfonds Aktien TL1	-17.15%	6.92%	-9.01%	19.31%	388
BCGE Synchrony Europe Equity	3.93%	5.71%	-4.25%	15.28%	1808
Bellevue Funds (Lux) BB Entrepreneur Europe B EUR	44.65%	8.92%	-8.01%	24.38%	109
Berenberg Systmt Approach - European STOCKPICKER A	-19.13%	10.15%	-8.76%	29.41%	591
Best Europe Concept OP	2.27%	8.33%	-6.13%	14.78%	1572
BFC Masterfund Aktien Europa	0.87%	7.12%	-12.61%	19.01%	1290
bfw europe quant selection fund	-17.80%	9.53%	-8.20%	28.95%	719
BGF European Enhanced Equity Yield Fd A2 EUR	-17.08%	6.97%	-10.24%	25.67%	507
BGF European Focus Fund A2 EUR	5.00%	9.13%	-10.39%	24.14%	1022
BGF European Fund A2 EUR	6.78%	8.15%	-10.26%	20.24%	1808
BGF European Growth Fund A2 EUR	6.03%	7.35%	-9.08%	19.06%	1798
BGF European Value Fund A2 EUR	5.05%	8.92%	-10.79%	21.74%	1808
BL Equities Europe Cap	5.23%	8.65%	-6.48%	17.20%	1808
BNY Mellon Pan European Equity A EUR	6.23%	9.77%	-10.46%	19.58%	1808
Brandes European Equities EUR A	4.93%	7.71%	-8.68%	20.04%	1603
BSF European Opportunities Extension Strat A2 EUR	-7.20%	6.70%	-7.90%	24.89%	537
BWI-EuroProfil	4.85%	8.09%	-8.95%	19.23%	1808
BZ Senior Equity Fund	3.43%	7.90%	-5.63%	16.81%	1334

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
CAAM Funds Gems Europe CC	-19.20%	10.37%	-8.37%	32.48%	483
CAAM Funds Minimum Variance Europe CC	26.98%	1.99%	-2.10%	12.63%	110
CAAM Funds Restructuring Equities C	-23.10%	9.68%	-8.38%	30.41%	505
CAAM Funds Select Europe C C	23.80%	6.35%	-4.90%	23.93%	214
Cadmos Fund Management-Guile Europ Engagement Fund	-9.23%	10.53%	-7.89%	27.43%	760
Cap Grande Europe	-25.70%	6.20%	-7.63%	21.71%	609
Capital at Work - European Equities at Work C	5.98%	13.49%	-8.82%	21.26%	1808
Carlson Fund - Europe	3.38%	8.94%	-11.79%	21.90%	1808
Carmignac Euro - Investissement	7.35%	6.31%	-6.66%	13.18%	1769
Carmignac Portfolio Grande Europe A	8.13%	8.42%	-7.54%	15.05%	1808
Carnegie Fund - European Equity	5.00%	7.26%	-8.14%	17.60%	1808
Cazenove Pan Europe B EUR	7.68%	9.32%	-9.85%	17.97%	1742
CB - Accent (Lux) European Equity Fund B	2.49%	10.88%	-8.64%	22.40%	1808
CCR Croissance Europe	7.75%	8.33%	-7.24%	18.07%	1808
CCR Valeur R	10.28%	9.12%	-7.02%	20.71%	1808
Centifolia Europe C	4.23%	8.02%	-5.69%	16.21%	1419
CIF European Equity B EUR	3.43%	6.36%	-9.05%	19.15%	1808
CIF European Growth And Income Fund B EUR	4.45%	7.33%	-9.04%	18.74%	1786
CIIM European Stock Portfolio	-4.70%	8.41%	-7.84%	26.54%	793
Clariden Leu (Lux) European Equity Fund B	2.83%	9.75%	-8.01%	20.88%	1808
CMIG European Enhanced Equity	3.65%	10.13%	-12.17%	22.85%	1339
CMT - European Market Maximum Yield	-4.03%	7.85%	-6.44%	24.02%	473
COLLEGIUM Portfolio II	-10.05%	9.76%	-9.85%	24.65%	581
Comgest Europe	4.18%	7.12%	-5.50%	15.44%	1808
Comgest Growth Europe Cap	4.10%	7.35%	-6.03%	15.38%	1808
cominvest Best-in-One Europe I P	4.08%	5.53%	-4.59%	14.11%	1808
cominvest EuropaVision P	0.83%	8.60%	-9.30%	22.30%	1808
cominvest Fondak Europa P	-9.88%	9.46%	-10.10%	26.80%	787
cominvest Fondiropa	0.05%	9.65%	-9.89%	22.84%	1808
cominvest Selektion Dividende P	-4.20%	8.78%	-11.14%	22.99%	1484
Connect Equity Europe ex Switzerland Red	-12.70%	9.50%	-8.24%	34.25%	379
Constantia Spezial Equity T	-12.50%	14.55%	-11.34%	23.55%	962
C-QUADRAT Active European Equity T	4.35%	4.30%	-4.69%	11.82%	1808
Credit Suisse Equity (CH) European Opportunities	3.88%	12.39%	-11.81%	27.47%	1808
Credit Suisse Equity (Lux) Style Invest Europe B	4.80%	9.79%	-8.02%	20.05%	1642
Credit Suisse MACS European Dividend Value P	-17.85%	10.08%	-8.34%	31.17%	459
CS Aktien Plus	3.28%	11.37%	-8.61%	22.04%	1808
CS Equity (Lux) Dividend Europe Aberdeen B	3.10%	9.76%	-8.37%	20.09%	1621
CS Equity (Lux) European Blue Chips Aberdeen B	2.43%	9.56%	-8.29%	20.80%	1808
CS MF (Lux) Equity Europe Aberdeen B	6.73%	6.53%	-7.71%	14.37%	1701
CSIF Europe ex CH Enhanced D	-1.24%	9.12%	-8.56%	24.66%	1055
CSIMF Universe F	-11.10%	7.60%	-7.27%	20.80%	710
CSSP Equities-Europe ex CH (CHF)	4.80%	11.15%	-8.44%	22.86%	1808
CW-MatrixCreativ	1.71%	9.29%	-10.52%	18.45%	1808
Danske Invest Europe A	6.38%	9.68%	-10.39%	21.00%	1808
Danske Invest High Dividend A	5.08%	8.61%	-10.78%	19.18%	1808
Degussa Aktien Universal-Fonds	2.36%	10.07%	-8.94%	21.39%	1808
DEGUSSA BANK AKTIEN EURO-GLOBAL UI	-3.08%	10.35%	-9.61%	24.08%	1808
Deka-DividendValue Europa CF	-4.40%	8.99%	-11.36%	21.68%	1109
Deka-EuropaSelect	2.39%	10.25%	-8.63%	20.65%	1808
Deka-EuropaValue CF	3.05%	9.24%	-12.21%	20.60%	1808
Deka-Institutionell Aktien Europa	4.03%	9.59%	-10.85%	22.91%	1808
DekaLux-Europa TF A	-0.64%	9.39%	-11.41%	22.33%	1808
Deutsche Postbank Europafonds Aktien	4.38%	7.74%	-8.91%	17.25%	1808
Dexia Equities B Europe C	-5.15%	10.35%	-8.53%	23.90%	984
Dexia Equities B European Large Caps C	-6.28%	10.17%	-9.01%	25.23%	983
Dexia Equities B European Sector Rotation C C	4.23%	9.61%	-7.98%	21.44%	1808
Dexia Equities L Europe C C	1.87%	10.27%	-8.60%	21.18%	1808
Dexia Equities L Europe High Dividend C C	-15.93%	13.43%	-8.27%	30.00%	567
Dexia Equities L Europe Innovation CC	-4.98%	8.93%	-7.55%	29.48%	323
Dexia Equities L Europe Value C C	-22.78%	10.05%	-9.05%	35.09%	500
Dexia Quant Equities Europe C C	5.23%	9.49%	-8.06%	19.97%	1683
Dexia Sustainable Europe C	1.66%	10.50%	-8.80%	21.67%	1808
Digital Funds Stars Europe Acc	10.83%	7.81%	-6.92%	18.33%	1808
DKB Europa Fonds TNL	2.58%	8.26%	-11.69%	20.79%	1808
DKB Zukunftsfonds TNL	-16.68%	7.50%	-8.60%	25.86%	541
DKO-Lux-Aktien Europa	-1.05%	19.75%	-15.64%	30.34%	1808
DWS Europaeische Aktien Typ O	4.33%	11.02%	-10.90%	23.81%	1808
DWS Eurovesta	4.65%	10.54%	-11.73%	23.11%	1808
DWS Invest European Equities LC	5.30%	9.50%	-10.40%	22.06%	1808
DWS Invest European Select Plus LC	-37.00%	7.86%	-11.83%	32.03%	443
DWS Sterne Europas	-3.73%	9.49%	-12.04%	24.99%	1099
DWS Top 50 Europa	5.70%	9.05%	-9.48%	20.58%	1808
DWS Zuerich Invest Aktien Europa	2.68%	10.15%	-10.33%	17.37%	1808
DZ Int Portfolio - Zuwachs	1.05%	9.63%	-8.78%	20.81%	1808
E.ON Aktienfonds DWS	6.43%	10.19%	-7.72%	18.74%	1808
Echiquier Major	2.95%	7.49%	-6.09%	18.51%	1177
Echiquier Selection	-13.00%	5.47%	-13.30%	18.16%	617
Ecology Stock FOCUS	3.50%	0.68%	-0.76%	2.21%	279
Edmond de Rothschild Europe Value A	4.98%	9.94%	-8.12%	17.64%	1808
EFG Equity Funds Europe	0.93%	6.55%	-5.66%	14.78%	1290

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
EMIF Europe Growth B C (Load)	3.48%	9.39%	-7.57%	20.24%	1808
EMIF Europe Value B C (Load)	3.83%	11.69%	-11.12%	25.15%	1808
Equity-MinRisk-Invest	-1.41%	8.49%	-6.71%	16.69%	1030
ESPA BEST OF EUROPE T	3.45%	6.59%	-5.72%	14.80%	1808
ESPA STOCK EUROPE-ACTIVE EUR T	0.00%	10.03%	-9.29%	21.38%	1443
ESPA STOCK EUROPE-VALUE T	3.70%	10.95%	-8.78%	23.64%	1778
ESPA STOCK NEW-EUROPE ACTIVE T	-10.20%	9.50%	-9.92%	29.61%	944
Ethos - Eq Europe ex CH indexed Corp Governance-E	-7.90%	9.38%	-8.43%	26.44%	907
Ethos - Eq Europe ex CH-E	-5.83%	9.02%	-8.00%	24.63%	980
Europa-INVEST	1.47%	9.43%	-11.08%	19.77%	1808
Europe Rendement C	6.98%	8.98%	-7.40%	17.19%	1808
European Equity Minimum Varianz AMI	-8.55%	6.72%	-6.03%	17.30%	603
F&C European Equity A	-0.16%	8.79%	-10.07%	21.85%	1808
Falcon Best Select Europe	0.74%	5.34%	-8.29%	14.51%	1259
Falcon European Equity Fund T	5.33%	9.38%	-7.98%	20.94%	1808
FAST - Europe A EUR Acc	11.20%	9.15%	-7.38%	19.61%	1290
Federated Unit Trust Europa-Aktien LVM	2.30%	9.77%	-7.90%	19.80%	1808
Fidelity Funds - Euro Special Situations A EUR	-12.18%	8.94%	-9.68%	32.12%	438
Fidelity Funds - European A Acc EUR	-5.75%	8.71%	-8.43%	22.20%	981
Fidelity Funds - European Aggressive A EUR	3.98%	12.76%	-14.50%	24.00%	1808
Fidelity Funds - European Dynamic Growth A EUR	7.13%	7.73%	-6.61%	18.45%	1808
Fidelity Funds - European Growth A EUR	6.05%	8.54%	-7.93%	19.53%	1808
Fidelity Funds - European Larger Cos A EUR	5.65%	8.92%	-7.36%	19.12%	1808
Fidelity Funds - Fidelity Selection Europe	5.35%	8.53%	-7.70%	19.02%	1808
Fidelity Funds - Inst European Larger Cos I EUR	3.65%	8.90%	-7.31%	19.65%	1345
Fidelity Inst Pan-European Acc	6.65%	8.53%	-8.98%	19.40%	1808
Fidelity Inst Select European Equities Acc	5.98%	8.95%	-9.62%	20.47%	1808
FIDES Europa	9.88%	4.11%	-4.51%	9.97%	1808
Finter Fund European Equities	6.43%	8.28%	-8.34%	21.32%	1808
First Private Europa Aktien ULM A	4.88%	8.88%	-7.35%	19.92%	1808
Focus Europa P	5.33%	9.91%	-6.97%	18.31%	1224
Focused Fund - Eq Europe Flexible I B	0.64%	5.25%	-3.56%	10.19%	1478
Focused Fund - Eq Europe Flexible II B	-0.73%	9.98%	-9.33%	18.88%	1382
Fortis L Equity Best Selection Europe Cap	2.70%	9.08%	-7.25%	19.65%	1389
Fortis L Equity Europe Cap EUR	3.13%	9.99%	-8.44%	21.19%	1808
Fortis L Equity Growth Europe Cap EUR	4.25%	9.39%	-9.84%	20.46%	1808
Fortis L Equity High Dividend Europe Cap EUR	-24.18%	9.79%	-8.61%	30.92%	510
Fortis L Equity Socially Responsible Europe Cap	2.70%	10.01%	-8.05%	20.96%	1808
Fortis L Opportunities Europe Cap	-1.89%	9.22%	-9.06%	21.98%	1248
Franklin European Growth A Acc	6.53%	6.57%	-5.28%	17.04%	1808
Franklin Mutual European A Acc EUR	5.70%	6.65%	-6.81%	13.62%	1808
Fructifonds Valeurs Europeennes C	2.60%	9.95%	-8.36%	20.31%	1808
FT Europa Dynamik Fonds	5.35%	8.43%	-8.84%	21.83%	1808
FT UnternehmerWerte	-8.20%	7.58%	-7.45%	23.75%	719
G&P UNIVERSAL AKTIENFONDS A	1.71%	9.74%	-7.83%	16.67%	1808
GAM Star European Equity EUR Acc	5.55%	8.77%	-7.72%	18.89%	1808
Gartmore SICAV Pan European EUR A	3.08%	9.03%	-12.67%	20.90%	1808
GEN INV European Value Equities A CAP	3.28%	9.59%	-8.13%	20.86%	1464
GEN INV Futur D CAP	-14.08%	8.91%	-7.59%	29.23%	420
GEN INV High Conviction Europe D CAP	0.26%	16.25%	-13.01%	20.58%	1509
Generali Komfort Dynamik Europa	3.98%	6.18%	-6.71%	16.14%	1808
Gerling Europa Aktien P (a)	-0.45%	18.91%	-47.21%	28.88%	1786
GIP InvestWorld - Europe Portfolio	1.23%	5.79%	-5.07%	12.48%	1808
GLG European Equity A	3.38%	9.28%	-7.03%	21.71%	1808
GLOBE CC AMI P	-7.18%	6.12%	-7.43%	13.57%	978
Going Public Equity Fund T	-11.78%	10.47%	-6.79%	19.98%	863
GOLDEN ROOF Europa	4.48%	5.26%	-6.11%	14.06%	1808
Goldman Sachs Europe CORE Equity Pf Base Cur EUR	6.28%	9.12%	-8.10%	20.75%	1808
Goldman Sachs Europe CORE Flex Pf Base Acc EUR	-10.00%	9.34%	-8.14%	25.82%	795
Goldman Sachs Europe Eq Tgt Alpha Pf Base Curr EUR	1.99%	9.87%	-8.18%	20.17%	1486
Goldman Sachs Europe Portfolio Base Curr EUR	4.33%	9.32%	-7.67%	20.01%	1808
Griffin European Opportunities A	4.20%	4.55%	-4.57%	9.58%	1808
Gutmann CEE Portfolio	-12.95%	10.22%	-11.96%	29.86%	750
Gutmann Europa-Portfolio	2.88%	10.04%	-7.94%	19.74%	1808
H & A Lux Equities - VALUE Invest B	6.45%	9.86%	-9.01%	20.79%	1808
H & A Lux Unternehmerfonds I B	-16.83%	9.53%	-7.58%	27.86%	581
HANSAeuropa	4.78%	9.30%	-11.64%	20.19%	1808
Hansen & Heinrich Universal Fonds	-4.50%	6.54%	-4.79%	15.00%	699
Henderson HF Pan European Alpha A2 EUR	1.19%	7.01%	-7.69%	19.96%	729
Henderson HF Pan European Equity A2	8.38%	7.53%	-8.36%	17.86%	1808
Henderson HF Pan European Equity Dividend A2 EUR	3.38%	9.06%	-10.46%	19.91%	1312
Hidden Pearl Value Fund T	13.98%	0.92%	-0.66%	5.10%	98
HI-DividendenPlus Europa-Fonds	-1.43%	8.61%	-7.44%	22.46%	1224
hp&p://-Euro-Select-Universal-Fonds	14.85%	9.23%	-5.55%	20.05%	1808
HSBC GIF European Equity AD EUR	3.05%	7.35%	-9.75%	20.09%	1808
HSBC GIF European Equity High Dividend AC EUR	1.23%	6.82%	-11.91%	23.43%	1302
HSBC Intl Sel MultiAlpha Europe Eq I Acc EUR	-7.20%	9.51%	-7.98%	34.25%	306
HSBC Trinkaus Aktien Europa Dynamik INKA	-1.77%	9.32%	-9.53%	16.94%	1808
HSBC Trinkaus LAPLACE European Equity A	-10.23%	7.92%	-8.54%	32.27%	269
HSBC Trinkaus Top Europa INKA AC	0.01%	10.17%	-13.25%	20.62%	1808
HuserInvest Funds - Huser New Horizon	38.93%	4.11%	-4.45%	25.09%	78

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
IAM - European Equity Fund	4.30%	9.81%	-7.85%	20.67%	1808
IFP Quanteviour European Equitites (EUR) A	-7.15%	12.17%	-9.65%	32.58%	775
Ignis Intl Argonaut European Alpha EUR I Acc	1.24%	8.79%	-10.45%	21.35%	977
Ignis Intl Argonaut European Div Inc EUR IAcc	-2.63%	8.74%	-9.89%	20.74%	977
Ignis Intl Pan European I EUR Acc	-20.18%	10.25%	-10.40%	30.39%	507
Ikano European Equity F	4.05%	9.33%	-8.58%	21.41%	1808
IndiGO - European Equity I	54.90%	2.09%	-2.96%	18.24%	64
Industria - A - EUR	3.50%	8.50%	-9.86%	20.38%	1808
ING (L) Invest Europe Growth P Cap	0.11%	9.36%	-8.45%	21.08%	1259
ING (L) Invest Europe High Dividend P Cap	0.44%	8.90%	-7.88%	20.75%	1237
ING (L) Invest Europe Opportunities P Cap	-5.98%	13.09%	-11.82%	30.67%	723
ING (L) Invest European Equity P Cap	4.40%	10.63%	-9.77%	22.91%	1808
ING (L) Invest European Sector Allocation P Cap	3.45%	9.90%	-9.11%	21.31%	1808
INKA Tertius	-7.25%	8.13%	-9.86%	26.13%	741
Invesco Europa Core Aktienfonds	5.98%	7.43%	-7.94%	18.26%	1808
Invesco European Growth Equity A	3.30%	7.16%	-8.73%	18.71%	1357
Invesco Pan European 130/30 Equity A EUR Acc	-20.18%	7.19%	-10.86%	28.35%	516
Invesco Pan European Equity A	5.63%	8.26%	-10.30%	18.92%	1808
Invesco Pan European Equity Income A Acc	-9.85%	7.68%	-9.78%	20.38%	752
Invesco Pan European Structured Equity A	6.30%	7.45%	-8.59%	17.81%	1808
Invesco Top of Europe	2.36%	9.19%	-8.63%	20.37%	1808
Investec GSF Pan European Equity A Acc	1.56%	9.78%	-9.46%	21.31%	1808
Investec Pan European Equity A Acc Net	1.57%	9.19%	-9.62%	20.24%	1808
IQAM Equity Europe	1.67%	5.45%	-5.95%	16.94%	1420
IVI European EUR	-2.55%	7.29%	-6.00%	18.14%	928
Janus European Research A EUR Acc	36.45%	4.50%	-5.40%	26.13%	215
JOHCM European Retail GBP	8.15%	7.64%	-10.55%	19.90%	1654
JOHCM European Select Values Retail GBP	9.23%	6.01%	-8.64%	18.39%	1654
JPM Europe 130/30 A Acc EUR	-20.85%	6.47%	-9.39%	25.86%	586
JPM Europe Dynamic A Dist EUR	5.33%	6.13%	-9.46%	18.35%	1808
JPM Europe Dynamic Mega Cap A Acc EUR	-2.49%	7.36%	-10.19%	20.99%	1041
JPM Europe Equity A Dist EUR	3.23%	7.41%	-10.08%	19.70%	1808
JPM Europe Focus A Acc EUR	-7.23%	7.86%	-9.10%	23.16%	917
JPM Europe Recovery A Acc EUR	8.75%	4.91%	-7.83%	16.20%	1642
JPM Europe Select 130/30 A Acc EUR	-20.53%	7.43%	-9.73%	27.39%	586
JPM Europe Select Equity A Acc EUR	3.80%	8.55%	-9.52%	20.17%	1808
JPM Europe Strategic Dividend A Acc EUR	1.59%	6.68%	-8.89%	18.84%	1186
JPM Europe Strategic Growth A Dist EUR	4.45%	6.15%	-8.47%	17.10%	1808
JPM Europe Strategic Value A Dist EUR	4.50%	8.46%	-10.74%	21.49%	1808
JPM EuropeOne Fund A Acc EUR	-16.35%	7.62%	-9.42%	26.99%	548
JPM Highbridge Europe STEEP A Acc EUR	0.94%	7.37%	-7.89%	28.80%	425
Julius Baer EF Europe Growth-EUR B	-3.28%	8.39%	-7.57%	23.64%	946
Julius Baer EF Europe Leading-EUR B	3.43%	9.98%	-8.94%	21.98%	1808
Julius Baer EF Europe-EUR B	2.44%	9.48%	-8.27%	21.56%	1808
Julius Baer Quality Europe Equity Fund B	1.26%	9.32%	-8.82%	22.33%	1291
Jupiter JGF European Growth L EUR	7.00%	7.39%	-6.66%	18.09%	1808
Jupiter JGF European Opportunities L EUR	7.13%	8.02%	-8.52%	17.80%	1808
Jyske Invest European Equities	2.41%	9.84%	-11.86%	21.79%	1808
Kapitalfonds LK Aktien Europa - Unterfonds G	4.28%	5.41%	-6.12%	16.30%	1598
Kapitalfonds LK Europa Strategie-Unterfonds	5.00%	8.21%	-9.48%	19.11%	1808
Kapitalfonds LK European Value Dividend-Unterfds R	0.71%	6.31%	-7.80%	15.71%	1329
KarstadtQuelle.Allianz Aktien Europa	3.18%	8.58%	-19.16%	21.10%	1808
KASSELER BANK Union Select	5.28%	9.43%	-7.13%	18.06%	1808
Kathrein European Equity A	4.63%	9.04%	-6.71%	19.47%	1808
KBC Equity (L)-Europe	0.28%	9.69%	-8.63%	21.33%	1808
KBC Equity Buyback Europe Acc	4.23%	8.85%	-8.01%	20.15%	1808
KBC Equity Europe Acc	2.45%	10.40%	-9.13%	21.55%	1808
KBL Key-Europe	3.05%	6.63%	-5.59%	14.39%	1808
KBL Richelieu Europe	5.58%	5.96%	-5.49%	13.42%	1808
KE Funds - KE Pan European Equities Fund P	-4.60%	10.00%	-6.49%	17.27%	1076
KEPLER Europa Aktienfonds A	1.66%	9.72%	-8.71%	21.56%	1808
Klassik Aktien Europa A	3.03%	9.28%	-8.61%	21.68%	1808
Klassik Invest Aktien T	0.98%	10.22%	-8.16%	19.45%	1808
Konzept Europa plus	1.51%	10.00%	-11.68%	20.60%	1808
Lampe Aktien Europa	-27.35%	8.82%	-8.06%	30.27%	356
Lazard Pan European Equity EUR	5.18%	8.82%	-9.89%	18.74%	1808
LB(Swiss) Europe Equity	1.97%	10.30%	-8.26%	21.92%	1808
LBBW Aktien ED BWI	-4.00%	9.88%	-11.19%	24.89%	828
LBBW Alpha Dynamic	-20.50%	11.15%	-10.25%	31.01%	646
LBBW Generation 50 Plus BWI	-8.20%	7.96%	-9.60%	26.31%	396
LBBW Zyklus Strategie I	27.38%	5.61%	-3.26%	16.75%	195
LEA-Fonds DWS	6.33%	8.73%	-9.52%	19.76%	1808
Legg Mason Batterymarch European Eq A Dis A EUR	3.60%	11.01%	-8.59%	20.83%	1808
Legg Mason Pan-Europe Equity A Ord USD	1.35%	9.79%	-7.97%	21.24%	1808
LGT Equity Fund Europe (EUR) B	-21.90%	9.50%	-8.36%	33.60%	450
LGT Equity Fund Europe Sector Trends (EUR) B	65.18%	5.57%	-4.27%	25.79%	130
LGT Multi Manager Equity Europe (EUR) B	-10.70%	7.79%	-7.42%	23.93%	760
LIGA-Pax-Aktien-Union	5.13%	9.79%	-8.07%	20.62%	1808
LINGOHR-EUROPA-SYSTEMATIC-LBB-INVEST	5.28%	9.48%	-8.46%	20.71%	1549
LLB Aktien Europa (EUR)	3.65%	9.67%	-8.41%	21.59%	1808
LODH Invest - Alto Europe Equity P A	1.00%	9.45%	-7.95%	21.85%	1211

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
LODH Invest - Europe P A	3.10%	8.07%	-10.94%	20.00%	1808
Lux-Provest Werte-Invest-Aktiv	-5.30%	8.70%	-7.07%	18.01%	942
LVUI Muenster Total Return I	-11.95%	0.43%	-0.60%	2.99%	77
M&G European Special Situations A Inc	-14.08%	8.43%	-8.91%	29.50%	429
M&G European Strategic Value A Inc	-7.15%	8.69%	-9.41%	30.81%	429
M&G Pan European A Inc	7.43%	7.60%	-7.80%	20.24%	1808
M&G Pan European Dividend A Acc GBP	-2.98%	9.44%	-9.62%	33.18%	310
MainFirst - avant-garde Stock Fund A	3.53%	9.83%	-7.81%	20.65%	1400
MainFirst - Top European Ideas A	-15.78%	9.28%	-7.82%	28.63%	572
Mandarine Valeur R	-23.03%	11.45%	-10.80%	38.56%	458
Martin Currie GF Pan-European Alpha EUR	4.80%	6.79%	-7.57%	20.72%	1536
MEAG EuroInvest A	6.75%	9.99%	-8.50%	20.35%	1808
MEAG EuroKapital	3.13%	10.31%	-8.21%	21.28%	1808
Mediolanum Best Brands European Collection L A	2.30%	7.50%	-7.68%	17.96%	1808
Mediolanum Challenge European Equity L - A	2.46%	9.10%	-7.92%	20.50%	1808
Mesina-Aktienfonds-UBS (D)	3.78%	9.39%	-7.64%	22.02%	1791
Metropole Frontiere Europe	9.10%	9.08%	-9.73%	19.09%	1571
Metropole Selection	8.43%	7.64%	-6.69%	18.73%	1764
Metzler Aktien Europa	2.06%	9.27%	-7.85%	20.73%	1808
Metzler Europa Value	-2.90%	9.55%	-9.03%	25.79%	1010
Metzler European Focus Fund	-5.08%	8.50%	-9.12%	27.58%	447
Metzler European Growth	6.88%	9.43%	-6.71%	19.24%	1808
MFS Meridian Funds European Equity A1 EUR	5.03%	11.19%	-10.17%	21.21%	1808
MFS Meridian Funds European Growth A1 EUR	4.63%	10.72%	-9.54%	21.05%	1807
MFS Meridian Funds European Value A1 EUR	7.23%	9.68%	-8.33%	18.84%	1807
Mi-Fonds (CH) - EuropeStock A	-5.90%	9.56%	-8.21%	25.14%	926
Mi-Fonds (Lux) - EuropeStock B	2.26%	9.62%	-8.06%	21.94%	1808
Mirabaud Equities High Alpha Pan Europ A Cap EUR	-14.43%	8.02%	-6.83%	25.97%	464
Mirabaud Select Equities Europe A Cap	3.15%	4.74%	-5.37%	15.38%	1808
MK EUROAKTIV	0.59%	10.26%	-11.62%	23.00%	1808
Monega Fair Invest Aktien	-12.88%	9.21%	-11.32%	26.00%	760
Morgan Stanley European Equity Alpha Fund A EUR	3.05%	7.39%	-9.66%	18.11%	1808
Morgan Stanley Eurozone Equity Alpha A EUR	2.85%	8.47%	-10.85%	19.69%	1808
MORGEN EUROPA AKTIEN UNIVERSAL FONDS	7.63%	11.55%	-6.16%	22.83%	1277
MPC Competence - Europa Methodik AMI	5.03%	10.02%	-6.97%	21.21%	1496
MSMM Pan European Equity B	4.68%	9.16%	-8.32%	20.75%	1808
Multiadvisor Sicav - PRIVAT INVEST	7.73%	4.60%	-5.17%	10.81%	1808
MultiSelect Europa-Aktien I	4.18%	5.63%	-5.94%	16.11%	1808
Naspa-Europafonds Deka	2.68%	8.22%	-5.39%	17.73%	1808
Natixis Impact Europe Equities Fd R/A(EUR)	-2.90%	10.36%	-8.20%	36.48%	257
NESTOR Europa Fonds	3.40%	8.31%	-7.22%	18.84%	1808
Newton Pan European GBP Inc	6.25%	9.67%	-10.03%	19.70%	1808
NORAMCO QUALITY FUNDS EUROPE	4.53%	8.16%	-7.38%	19.60%	1808
Nordea 1 - European Alpha BP EUR	-22.15%	7.49%	-10.61%	29.87%	485
Nordea 1 - European Equity Fund BP EUR	3.00%	6.92%	-8.77%	20.10%	1808
Nordea Fund of Funds Choice Pan-European Eq BP EUR	-21.83%	5.68%	-4.42%	18.51%	468
NORDGLOBAL	5.40%	10.26%	-8.23%	18.77%	1808
NOUVELLE EUROPE II	3.88%	9.48%	-7.68%	17.61%	1808
Odyssee C	6.15%	4.86%	-5.96%	12.46%	1663
OekoWorld OekoVision Europe C	-25.18%	8.29%	-8.03%	27.42%	546
OFI Cible A C	-4.38%	8.47%	-8.88%	24.14%	968
OP Exklusiv Aktien Select	-12.65%	7.35%	-10.64%	26.61%	374
OP Value European Equities	2.50%	9.73%	-13.87%	22.84%	1808
Orsay Investissement E.S.G.	7.23%	8.68%	-6.32%	16.70%	1808
OYSTER European Opportunities EUR	7.08%	9.90%	-8.10%	20.00%	1808
OYSTER Funds Europe Dynamic EUR	2.26%	9.95%	-8.05%	19.23%	1632
Parvest Europe Alpha C	-0.87%	10.06%	-9.30%	23.84%	1115
Parvest Europe Dividend C	5.05%	9.98%	-9.01%	19.25%	1550
Parvest Europe Growth C	3.73%	9.76%	-8.06%	19.56%	1551
Parvest Europe LS30 C	-24.18%	9.84%	-9.43%	32.04%	495
Parvest Europe Sustainable Develpt C	-10.20%	10.06%	-8.37%	27.58%	684
Parvest Europe Value C	1.87%	9.91%	-9.73%	22.57%	1548
Pegase Investment - European Equities EUR	2.78%	7.78%	-16.04%	16.86%	1808
PEH Q-Europa	0.92%	5.48%	-6.53%	16.48%	1808
Performa Fund HNW European Equities	5.35%	8.26%	-7.42%	19.17%	1808
Performance Environnement A	6.13%	12.56%	-8.78%	18.98%	1321
Performance Responsable	-17.65%	5.66%	-6.79%	14.81%	724
Performance Vitae	-6.05%	6.71%	-4.42%	11.20%	1054
Petercam Equities Europe Cap	5.70%	10.02%	-7.73%	19.15%	1808
Petercam Equities Europe Dividend Cap	5.75%	9.08%	-8.68%	17.91%	1808
Petercam Equities Europe Recovery Cap	3.93%	9.19%	-9.77%	24.55%	1616
Petercam Equities Europe Sustainable Cap	4.38%	9.83%	-7.35%	17.65%	1743
Petercam L Equities Europe Triton B	-9.70%	8.12%	-9.70%	24.48%	1056
PF(LUX)-European Equity Selection-P Cap	3.78%	9.00%	-8.08%	21.57%	1808
PF(LUX)-European Sustainable Equities-P Cap	3.35%	9.00%	-7.74%	20.78%	1808
Pictet (CH) Inst-European ex-Swiss Eq Tracker-Z	-12.38%	9.61%	-8.26%	28.62%	697
Pioneer Funds Austria - Master Fonds Europe T	2.88%	6.68%	-7.02%	14.51%	1808
Pioneer Funds Austria - Select Europe Stock A	3.58%	9.47%	-8.01%	21.63%	1808
Pioneer Funds Core European Equity E	3.73%	9.96%	-8.96%	20.22%	1808
Pioneer Funds European Equity 130/30 E No Dis	-13.60%	9.44%	-8.15%	33.98%	404
Pioneer Funds European Equity Growth E No Dis EUR	-25.00%	8.93%	-7.00%	28.69%	362

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
Pioneer Funds European Equity Value E No Dis	-15.58%	10.34%	-8.52%	37.35%	362
Pioneer Funds European Quant Equity E No Dis EUR	0.13%	9.73%	-9.41%	21.81%	1376
Pioneer Funds European Research E	3.43%	9.77%	-8.22%	20.92%	1808
Pioneer Funds Top European Players E	4.10%	9.20%	-8.03%	20.49%	1808
Pioneer Investments Europe Value	3.65%	9.02%	-9.86%	22.00%	1808
Pioneer Investments GP EuropeanEquity C	3.10%	10.21%	-10.65%	20.64%	1808
Pioneer SF European Eq Market Plus A No Dis EUR	16.58%	7.55%	-7.71%	30.93%	227
PLEIADE European Equities	0.39%	11.96%	-23.13%	20.29%	1808
Popso Investment Fd Sicav - European Equity	1.82%	9.55%	-8.28%	21.24%	1808
Postbank Europa	3.00%	8.87%	-10.59%	23.02%	1808
PriFund European Equities A C EUR	7.38%	2.18%	-3.20%	8.98%	1808
Principal GI European Equity A Acc	5.00%	7.42%	-10.59%	21.29%	1808
PVK-Aktien-UBS (D)	3.08%	9.73%	-7.88%	20.73%	1808
RAB European Dynamic A GBP	-1.73%	12.41%	-13.43%	21.68%	1506
Raiffeisen Fonds - EuroAc B	1.51%	9.04%	-8.24%	21.71%	1808
Raiffeisen-Europa-Aktien A	3.60%	10.36%	-8.74%	21.83%	1808
Raiffeisen-TopDividende-Aktien T	-3.03%	8.28%	-7.60%	21.99%	1097
Ras Lux Equity Europe	3.18%	8.39%	-7.33%	19.59%	1808
Reyl (Lux) GF Europe Low Vol (EUR) B	-5.83%	2.01%	-2.03%	7.10%	389
Reyl (Lux) GF European Equities (EUR) B	8.55%	8.80%	-12.67%	19.31%	1721
RIC II Pan European Equity B	4.33%	8.99%	-8.44%	20.83%	1808
Robeco 130/30 European Equities D EUR	-15.70%	9.91%	-7.60%	28.42%	560
Robeco European Conservative Equities B EUR	-11.25%	7.58%	-6.07%	21.57%	556
Robeco European Equities D EUR	2.53%	9.60%	-8.87%	21.93%	1808
Robeco European Opportunities D EUR	-17.60%	10.22%	-13.10%	33.93%	739
RP Selection Europe	11.28%	5.28%	-6.33%	14.73%	1752
RR Analysis TopSelect Universal	-2.70%	4.43%	-3.79%	11.16%	973
Saint-Honore Europe Synergie A	-5.18%	7.38%	-6.83%	23.52%	727
SAM Sustainable Europe Active Fund B	2.60%	9.86%	-8.40%	22.00%	1313
SAM Sustainable Europe Fund B	-18.03%	8.63%	-7.48%	29.06%	582
Santander Europaeische Aktien OP	3.25%	9.23%	-11.53%	22.38%	1808
Sarasin Sustainable Equity - Europe	2.88%	10.17%	-8.23%	21.92%	1808
Schroder ISF European Active Value A Acc	-14.28%	8.97%	-12.31%	25.38%	881
Schroder ISF European Dividend Maximiser A Acc	-20.18%	9.49%	-11.95%	25.40%	512
Schroder ISF European Dynamic Growth A Acc	-3.60%	8.76%	-12.27%	21.94%	1054
Schroder ISF European Equity Alpha A Acc	8.30%	8.97%	-12.08%	18.41%	1721
Schroder ISF European Equity Yield A Acc	-5.98%	9.72%	-13.09%	20.87%	1046
Schroder ISF European Large Cap A Acc	4.33%	10.04%	-12.83%	20.40%	1808
Schroder ISF European Special Situations A Acc	-5.18%	7.89%	-10.50%	21.28%	903
SEB Ethical Europe	5.78%	8.10%	-12.16%	19.86%	1679
SEB Europafonds	4.05%	8.99%	-7.62%	22.06%	1808
SEB Fund 1 Europe A	3.53%	7.84%	-11.90%	21.04%	1808
SEB Sicav 2 Europe Chance/Risk	4.43%	8.40%	-11.59%	20.93%	1808
SEI SGMF Pan European Equity USD Inv	3.53%	9.86%	-9.06%	21.74%	1808
Selector Mgt Fund - Selector European Value A2	5.38%	8.31%	-8.86%	22.51%	1808
SGAM Fund Equities Concentrated Europe AC	-16.93%	10.12%	-10.49%	28.72%	700
SGAM Fund Equities Europe Environment A	-19.08%	11.32%	-8.41%	31.01%	446
SGAM Fund Equities Europe Expansion A C	-21.55%	9.16%	-8.33%	31.21%	472
SGAM Fund Equities Europe Opportunities AC	0.70%	8.39%	-7.67%	20.39%	1296
siemens/equity.western-europe	2.93%	9.62%	-8.45%	20.12%	1808
SKAG Euroinvest Aktien	2.47%	7.81%	-11.90%	22.00%	1808
Skandia European Best Ideas A1	-5.80%	8.46%	-10.38%	30.66%	381
Skandia European Equity A1	2.60%	9.04%	-11.44%	19.52%	1808
Skandia European Opportunities A1	3.23%	9.58%	-12.18%	20.30%	1344
Spaengler European Growth Trust T	4.30%	7.33%	-5.90%	15.62%	1808
Sparinvest-European Value EUR R	-14.18%	3.93%	-4.98%	18.50%	750
SSgA Europe Alpha Equity Fund I P	4.93%	9.77%	-8.43%	21.64%	1808
Stability Funds - 130/30 Europe P	-20.13%	6.12%	-6.77%	19.44%	555
Stability Funds - Core Satellite Strategie	-2.73%	1.59%	-1.69%	5.29%	379
Standard Life IG SICAV European Equities A	3.75%	7.43%	-10.85%	20.81%	1808
SWC (CH) EF Europe	4.48%	9.79%	-9.15%	22.52%	1808
SWC (CH) IF - Equity Europe Growth AST	-2.68%	10.42%	-8.43%	24.26%	968
SWC (CH) IF - Equity Europe Value AST	-4.90%	11.60%	-10.50%	30.43%	968
SWC (LU) EF Top Dividend Europe B	-2.28%	9.59%	-9.21%	26.17%	997
SWIP SICAV European I Acc	-24.00%	9.13%	-9.62%	28.67%	569
Swiss Life Funds (LUX) Eq Europe R	-10.75%	10.27%	-8.74%	36.62%	318
Swiss Rock (Lux) - Europ Equity / Aktien Europa A	-14.75%	9.77%	-7.96%	33.03%	408
T Rowe European Equity A EUR	-17.33%	8.06%	-9.56%	27.08%	623
T Rowe European Structured Research Equity I EUR	1.83%	7.89%	-10.03%	20.25%	1220
Templeton European A Acc EUR	4.05%	7.95%	-8.95%	19.30%	1808
Threadneedle (Lux)-European Quantitative Eq AE	-18.95%	8.72%	-9.38%	26.73%	646
Threadneedle (Lux)-Pan European Equities AE	3.28%	7.71%	-5.98%	17.96%	1808
Threadneedle Pan European Accelerando C1	5.38%	7.18%	-8.88%	19.22%	1349
Threadneedle Pan European C1	5.38%	9.07%	-9.27%	19.45%	1808
Threadneedle Pan European Eq Div Net Acc GBP	-7.08%	11.15%	-11.52%	27.93%	878
Tocqueville Value Europe P	4.20%	6.18%	-5.34%	14.40%	1743
Tower European Equity EUR	2.83%	11.15%	-10.18%	19.72%	1808
TT European Equity A EUR	6.60%	11.31%	-8.92%	22.23%	1808
UBAM Lingohr Europe Equity Value A	-0.30%	10.95%	-9.07%	22.45%	1808
UBP Multifunds - Europe Equity A	3.88%	5.52%	-4.58%	13.25%	1808
UBS (CH) Equity Fund - European Opportunity P	4.25%	8.51%	-7.92%	20.57%	1808

Table A.17 – continued from previous page

Name	Mean p.a.	Max. p.d.	Min. p.d.	Std. Dev. p.a.	Obs.
UBS (CH) Inst Fd - Eq Europe (ex Switzerland) B	-3.85%	9.37%	-8.91%	27.00%	950
UBS (CH) VVA - A1 (EUR)	6.25%	10.83%	-8.47%	24.09%	1808
UBS (D) Konzeptfonds Europe Plus	4.38%	6.57%	-6.06%	15.20%	1808
UBS (Lux) Eq Fd - European Growth (EUR) P-acc	-1.71%	8.94%	-7.33%	20.75%	1286
UBS (Lux) Eq Fd - European Opportunity (EUR) P-acc	5.33%	8.39%	-8.21%	20.61%	1808
UBS (Lux) Eq Fd 2 - Sustainable European Eq P-acc	-1.24%	9.64%	-7.80%	23.24%	1087
UBS (Lux) Eq S - European Quantitative (EUR) P-acc	-7.68%	10.07%	-7.94%	25.52%	869
UBS (Lux) Eq S - European Value (EUR) P-acc	0.93%	9.10%	-7.17%	20.71%	1285
UBS (Lux) Inst Fd - Key Sel European Equity AA	6.13%	9.08%	-8.51%	20.84%	1650
UBS (Lux) Key Sel 2-European Eq 130/30 P-acc	-0.32%	10.04%	-8.69%	39.02%	306
UBS (Lux) KSS-European Equities P-acc	3.10%	9.05%	-8.39%	21.20%	1779
Ulysse C	6.18%	6.92%	-6.42%	16.20%	1808
UniConClusio: EuropeanEquities A	4.03%	9.84%	-8.64%	21.13%	1808
UniDividendenAss A	3.53%	8.17%	-6.52%	16.94%	1433
UniDynamicFonds: Europa A	6.23%	10.30%	-6.90%	21.02%	1808
UniEuropa A	4.48%	10.49%	-9.34%	22.44%	1808
UniEuropa -net-	4.15%	10.03%	-8.63%	22.34%	1808
UNI-GLOBAL Beta Managed Minimum Variance Europe	6.20%	7.87%	-7.15%	16.41%	1808
UNI-GLOBAL Minimum Variance Europe	6.73%	7.56%	-6.30%	14.65%	1398
UniSelection: Europa I	4.75%	6.64%	-6.55%	14.86%	1808
UniValueFonds: Europa A	4.95%	10.80%	-9.17%	23.06%	1808
Value-Holdings Europe Fund	-18.33%	12.12%	-7.89%	26.63%	323
VB-BestSector-Invest	-14.93%	8.44%	-6.81%	31.32%	347
VF-Global Responsibility European Equity B-EUR	19.85%	7.25%	-5.81%	28.20%	224
Vitruvius European Equity B EUR	6.78%	6.09%	-4.98%	14.62%	1808
VM Equity Strategy Europe	-11.98%	7.53%	-6.49%	23.50%	536
VMP EuroBlue Systematic	-3.25%	9.02%	-6.53%	21.63%	709
Volksbank-Europa-Invest T	5.95%	10.27%	-9.12%	21.52%	1808
Vontobel Fund European Eq B EUR	1.15%	9.01%	-8.28%	21.76%	1808
Vontobel Fund European Value Eq B EUR	4.13%	10.32%	-6.72%	15.40%	1753
VPV-Spezial Pioneer Investments	6.58%	10.63%	-11.70%	21.04%	1808
W&W Intl Funds-Europa Aktien Premium II	0.62%	4.62%	-4.55%	11.10%	1195
W&W Quality Select Aktien Europa BWI EUR	2.98%	8.31%	-10.91%	20.20%	1808
WARBURG - VGR Aktien Europa - FONDS	-15.03%	10.67%	-8.33%	28.60%	705
Waverton European B EUR	-14.60%	8.46%	-7.81%	27.93%	646
Wegelin (Lux) Eq Active Indexing Europe EUR IX	-25.03%	8.30%	-8.47%	32.47%	466
Weisenhorn Europa	10.20%	9.14%	-7.14%	20.65%	1808
Westpeak Enhanced Europe Equities Fund S/A EUR	7.88%	8.43%	-5.95%	29.23%	234
Wiener Privatbank European Equity T	0.13%	8.19%	-7.30%	19.42%	1290
Willerequity Europe	-0.02%	10.19%	-8.80%	18.58%	1808
World Invest - Eurostar Equities	5.73%	10.39%	-11.03%	16.97%	1808
WVB Union Aktien Plus	4.53%	9.57%	-8.08%	20.69%	1808
XT EUROPA	3.68%	9.49%	-8.27%	20.57%	1808
ZIF Aktien Europa A1	-5.75%	9.76%	-8.71%	26.40%	920
ZKB Aktien Europa (ex CH) enh Klasse I	27.33%	5.96%	-4.97%	26.76%	203
3 Banken Europa Stock-Mix	1.44%	8.96%	-7.96%	18.89%	1592
3 Banken European Top-Mix	4.23%	8.06%	-5.69%	15.73%	1808
4Q-EUROPEAN VALUE FONDS UNIVERSAL	6.28%	8.62%	-8.05%	20.50%	1808

A.6 Mutual fund performance evaluation: Robustness tests

Table A.18: Robustness of mutual fund analysis: Different model specifications

This table gives various robustness analyses for the Carhart model with liquidity and idiosyncratic risk. Dimson corrected average summed regression coefficients on individual mutual funds are given considering the current risk factor and risk factors with one or three lags. The table also reports the number of significantly positive and negative coefficients on the risk factor exposures in individual mutual fund regressions with respect to different model specifications. The equal-weighted risk factors are derived from the equal-weighted equity style indices. Detrended illiquidity is calculated by moving average trading volume over the preceding 100 days. An outlier detection is performed by considering 1%- and 99%-cut-off-rates and by using the three sigma rule to ignore potential outliers in the liquidity and idiosyncratic risk variable, yielding 13 outliers regarding liquidity and 26 outliers regarding idiosyncratic risk. See also Wagner and Winter (2013). Sample period: October 1, 2002 to September 30, 2009.

		MARKET EXC. RET.		SIZE		VAL.		MOM. OR ALPHA		ILLIQU./DETR. ILLIQU.		IDIOS. RISK	
Summed coeff.	Dimson 1 lag	0.919		0.197		-0.008		0.041		0.065		-0.012	
	Dimson 3 lags	0.922		0.164		0.008		0.042		0.068		0.013	
	Number of funds with exp.	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level
Equal-weighted	Sig. neg.	2	0	212	204	151	124	38	30	117	104	129	106
	Sig. pos.	457	454	105	86	54	33	194	149	229	203	83	71
Detr. illiqu.	Sig. neg.	8	2	28	25	52	43	29	24	98	80	109	88
	Sig. pos.	454	453	423	408	150	113	225	170	121	95	55	43
1%- and 99%-cut-off-rates	Sig. neg.	1	1	29	25	35	31	28	25	119	92	107	90
	Sig. pos.	455	454	414	400	133	105	203	168	88	68	97	63
Illiqu. outliers	Sig. neg.	1	1	41	37	90	77	41	34	134	93	91	70
	Sig. pos.	456	455	399	389	108	78	173	122	93	79	100	80
Idios. risk outliers	Sig. neg.	20	2	30	24	72	64	30	20	131	80	100	87
	Sig. pos.	455	454	405	395	114	81	188	147	64	54	59	50

Table A.19: Alternative model tests: All models, equal-weighted mutual fund portfolio and equal-weighted risk factors

This table reports Davidson and MacKinnon (1981) J-test results in a comparison of alternative four and five factor models. The null hypothesis is that the fitted values of model A should not be a significant explanatory variable when added to model B, when model B is superior. The table shows the p-values of the fitted values when entering the alternative models. Comparisons are given with respect to the equal-weighted fund portfolio (EQUAL) and equal-weighted risk factors. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

FITTED VALUES	FROM CARHART:		FROM FF WITH LIQU.:		FROM FF WITH IDIOS. RISK:		FROM CARHART WITH IDIOS. RISK:	FROM CARHART WITH LIQU.:
	FITTED VALUES ENTER:							
	IN FF WITH IDIOS. RISK	IN FF WITH LIQU.	IN CARHART	IN FF WITH IDIOS. RISK	IN CARHART	IN FF WITH LIQU.	IN CARHART WITH LIQU.	IN CARHART WITH IDIOS. RISK
EQUAL	0.755	0.169	0.161	0.302	0.000***	0.000***	0.000***	0.306

FITTED VALUES	FROM CARHART:			FROM FFML:			FROM FFMI:			FROM FFLI:		
	FITTED VALUES ENTER:											
	IN FFML	IN FFMI	IN FFLI	IN CARHART	IN FFMI	IN FFLI	IN CARHART	IN FFML	IN FFLI	IN CARHART	IN FFML	IN FFMI
EQUAL	0.740	0.036*	0.342	0.162	0.256	0.239	0.000***	0.000***	0.269	0.000***	0.000***	0.278

Table A.20: Robustness: Monthly and weekly mutual fund data sample

This table gives monthly and weekly robustness results for the Carhart model with liquidity and idiosyncratic risk. The number of significant individual fund exposures as well as summary statistics of adjusted R^2- and F-statistics are displayed. Regressions are performed using the heteroskedasticity and autocorrelation consistent covariance estimator of Newey and West (1987). Monthly and weekly data samples are constructed from the daily data sample. Only the 273 mutual funds with a full monthly data sample of 84 observations have been considered for the monthly backtest. With respect to the weekly backtest, those 505 mutual funds have been considered which possess at least 60 observations. Sample period: October 2002 to September 2009.

		MARKET EXC. RET.		SIZE		VAL.		MOM.		ILLIQU.		IDIOS. RISK	
	Number of funds with exposure	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level
Monthly returns	Sig. neg.	0	0	9	6	64	46	18	12	3	2	57	43
	Sig. pos.	273	272	155	133	7	4	19	10	45	34	37	26
Weekly returns	Sig. neg.	0	0	19	17	66	51	21	14	70	44	131	69
	Sig. pos.	505	505	297	249	90	65	226	183	82	69	24	17
Monthly returns	Mean	Median	Maximum	Minimum	Weekly returns	Mean	Median	Maximum	Minimum				
adj. R^2	0.883	0.915	0.990	0.071	adj. R^2	0.796	0.849	0.996	0.102				
F-stat.	194.164	148.142	1400.314	2.064	F-stat.	479.254	248.742	6382.442	2.444				

Table A.21: J-test of Davidson and MacKinnon: Quintile fund groups

This table reports Davidson and MacKinnon (1981) J-test results in a comparison of alternative four and five factor models. The null hypothesis is that the fitted values of model A should not be a significant explanatory variable when added to model B, when model B is superior. The table shows the p-values of the fitted values when entering the alternative models. Comparisons are given with respect to beta, size and illiquidity sorted quintile (Q.) fund portfolios. Significance at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

FITTED VALUES	FROM CARHART:		FROM FF WITH ILLIQU.		FROM FF WITH IDIOS. RISK		FROM CARHART WITH IDIOS. RISK	FROM CARHART WITH ILLIQU.
	FITTED VALUES ENTER IN:							
	IN FF WITH IDIOS. RISK	IN FF WITH ILLIQU.	IN CARHART	IN FF WITH IDIOS. RISK	IN CARHART	IN FF WITH ILLIQU.	IN CARHART WITH ILLIQU.	IN CARHART WITH IDIOS. RISK
BETA Q. 1	0.592	0.438	0.468	0.494	0.648	0.614	0.038**	0.514
BETA Q. 2	0.061*	0.140	0.879	0.724	0.207	0.204	0.601	0.803
BETA Q. 3	0.076*	0.140	0.481	0.459	0.788	0.952	0.265	0.480
BETA Q. 4	0.000***	0.000***	0.508	0.720	0.162	0.048**	0.196	0.807
BETA Q. 5	0.389	0.509	0.143	0.079*	0.709	0.978	0.878	0.076*
SIZE Q. 1	0.005***	0.021**	0.168	0.128	0.587	0.584	0.931	0.118
SIZE Q. 2	0.000***	0.000***	0.674	0.337	0.000***	0.000***	0.000***	0.263
SIZE Q. 3	0.020**	0.019**	0.596	0.386	0.286	0.162	0.389	0.120
SIZE Q. 4	0.110	0.219	0.627	0.479	0.103	0.114	0.630	0.510
SIZE Q. 5	0.215	0.256	0.538	0.598	0.861	0.823	0.625	0.655
ILLIQU. Q. 1	0.642	0.332	0.063*	0.002***	0.004***	0.000***	0.000***	0.002***
ILLIQU. Q. 2	0.918	0.408	0.112	0.008***	0.010**	0.001***	0.000***	0.008***
ILLIQU. Q. 3	0.338	0.958	0.156	0.025**	0.049**	0.008***	0.024**	0.015**
ILLIQU. Q. 4	0.150	0.466	0.334	0.114	0.141	0.082*	0.017**	0.113
ILLIQU. Q. 5	0.635	0.597	0.261	0.221	0.233	0.371	0.001***	0.440

Table A.22: Individual fund exposure results: First subperiod

First subperiod: 380 funds		MARKET EXCESS RETURN		SIZE		VALUATION		MOMENTUM		ILLIQU.		IDIOS. RISK	
	Number of funds with exp.	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level
Carhart	Sig. neg.	0	0	27	25	67	49	70	43				
	Sig. pos.	355	350	294	293	36	29	81	68				
FF with Illiqu.	Sig. neg.	0	0	31	27	78	62			154	134		
	Sig. pos.	342	328	294	285	39	33			49	39		
FF with Idios. Risk	Sig. neg.	0	0	36	32	89	70					41	34
	Sig. pos.	331	324	292	282	34	27					98	81
Carh. with Illiqu.	Sig. neg.	0	0	30	23	62	43	70	45	156	135		
	Sig. pos.	340	325	291	285	33	28	78	67	41	31		
Carh. with Idios. Risk	Sig. neg.	0	0	34	32	83	51	62	37			36	27
	Sig. pos.	330	324	288	281	30	26	79	65			102	81
Carh. with Illiqu. & Idios. Risk	Sig. neg.	0	0	35	35	74	47	58	38	154	134	38	27
	Sig. pos.	323	322	283	274	30	25	75	61	42	32	97	79

Table A.23: Individual fund exposure results: Second subperiod

Second subperiod: 528 funds		MARKET EXCESS RETURN		SIZE		VALUATION		MOMENTUM		ILLIQU.		IDIOS. RISK	
	Number of funds with exp.	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level	10-%-level	5-%-level
Carhart	Sig. neg.	31	15	38	31	30	23	14	10				
	Sig. pos.	453	452	384	373	188	164	237	176				
FF with Illiqu.	Sig. neg.	55	46	43	38	119	102			127	98		
	Sig. pos.	451	451	378	361	156	122			39	31		
FF with Idios. Risk	Sig. neg.	3	0	28	25	131	119					155	119
	Sig. pos.	453	452	385	372	132	97					24	18
Carh. with Illiqu.	Sig. neg.	32	14	35	26	41	36	16	15	114	86		
	Sig. pos.	453	452	386	378	188	160	226	177	57	41		
Carh. with Idios. Risk	Sig. neg.	3	0	27	25	56	47	22	18			109	94
	Sig. pos.	453	452	395	377	189	151	216	163			38	29
Carh. with Illiqu. & Idios. Risk	Sig. neg.	0	0	29	26	58	53	22	18	88	64	108	86
	Sig. pos.	453	452	397	379	186	149	216	165	65	44	30	25

A.7 Dynamic mutual fund results: Robustness tests

Table A.24: Risk factor timing results: Convergence robustness test

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. In estimating Equation 6.16 the first 50 time-series observations are ignored in order to exclude the training period of the Kalman filter. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: December 12, 2002 to September 30, 2009.

Equal-weighted mutual fund portfolio	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.219	0.476	0.504	0.573	0.651	0.616	0.634	0.707	0.775	0.665	0.639	0.641
T-stat.	11.168***	0.952	1.044	1.147	1.314	1.267	1.277	1.408	1.462	1.327	1.301	1.337
ILLIQU.: Coeff.	0.229	-2.215	-2.684	-2.966	-3.231	-2.912	-2.461	-0.452	0.721	-0.305	-1.202	-1.151
T-stat.	11.828***	-1.029	-1.210	-1.301	-1.444	-1.414	-1.269	-0.218	0.337	-0.154	-0.673	-0.737

Table A.25: Individual mutual fund analysis: Summary statistics of risk factor exposures for the restricted sample period

This table gives cross-sectional summary statistics of the time-varying risk factor exposures estimated by the Kalman filter for individual mutual funds and the liquidity augmented CAPM. The summary statistics are given for percentiles of the mutual funds. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: December 12, 2002 to September 30, 2009.

		Time-series mean exp.	Time-series median exp.	Time-series maximum exp.	Time-series minimum exp.	Time-series std. dev. of exp.
MARKET EXC. RET. - without first 50 obs.	CROSS-SECT. MEAN	0.617	0.633	1.007	0.085	14.866%
	CROSS-SECT. MIN.	-0.065	-0.063	-0.029	-2.485	0.759%
	CROSS-SECT. 25th %	0.495	0.487	0.903	-0.183	8.212%
	CROSS-SECT. MEDIAN	0.684	0.706	1.054	0.114	13.636%
	CROSS-SECT. 75th %	0.903	0.933	1.196	0.395	18.919%
	CROSS-SECT. MAX.	1.139	1.126	3.626	1.009	48.053%
ILLIQU. - without first 50 obs.	CROSS-SECT. MEAN	0.182	0.175	1.034	-0.753	24.522%
	CROSS-SECT. MIN.	-0.170	-0.200	-0.060	-18.451	1.658%
	CROSS-SECT. 25th %	0.071	0.053	0.514	-0.741	15.414%
	CROSS-SECT. MEDIAN	0.196	0.176	0.839	-0.418	22.695%
	CROSS-SECT. 75th %	0.294	0.298	1.088	-0.267	30.243%
	CROSS-SECT. MAX.	0.507	0.524	10.980	0.054	174.297%

Table A.26: Risk factor timing results: Individual mutual funds, liquidity augmented CAPM and restricted sample period

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 5%- and 10%-levels testing against a null hypothesis of a zero coefficient. The first 50 observations of the overall sample period are ignored because of the training period of the Kalman filter. Overall number of funds: 254. Sample period: December 12, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	32	24	23	17	24	27	17	21	16	19	15
MARKET EXC. RET.: sig. pos.	221	26	33	42	50	37	40	49	42	42	37	42
ILLIQU.: sig. neg.	26	10	9	12	13	9	7	9	2	2	5	3
ILLIQU.: sig. pos.	214	4	3	3	3	2	2	13	18	7	2	1
5%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	21	14	14	9	14	18	8	15	13	10	9
MARKET EXC. RET.:sig. pos.	221	15	21	25	34	26	25	32	28	21	14	25
ILLIQU.: sig. neg.	26	7	3	5	5	6	2	5	0	0	2	0
ILLIQU.: sig. pos.	214	0	0	0	0	0	0	6	3	1	1	0

Table A.27: Risk factor timing results in the liquidity augmented CAPM for the restricted sample period: Adj. R^2- and F-statistics

This table gives the adj. R^2 and F-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. The first 50 observations of the overall sample period are ignored because of the training period of the Kalman filter. Overall number of funds: 254. Sample period: December 12, 2002 to September 30, 2009.

Adj. R^2- stat.		Mean	Median	Max.	Min.
MARKET EXC. RET.	Without first 50 obs.	0.57%	0.07%	8.01%	-0.63%
ILLIQU.	Without first 50 obs.	0.02%	-0.14%	3.39%	-0.60%
F-stat.		Mean	Median	Max.	Min.
MARKET EXC. RET.	Without first 50 obs.	1.947	1.119	14.865	0.005
ILLIQU.	Without first 50 obs.	1.044	0.784	6.591	0.050

Table A.28: Individual Kalman filter analysis: Summary statistics of risk factor states in the liquidity augmented CAPM with idiosyncratic risk

		Time-series mean exp.	Time-series median exp.	Time-series maximum exp.	Time-series minimum exp.	Time-series std. dev. of exp.
MARKET EXC. RET. - overall sample period	CROSS-SECT. MEAN	0.542	0.562	1.824	-1.928	29.01%
	CROSS-SECT. MIN.	-0.340	-0.350	-0.092	-22.205	1.19%
	CROSS-SECT. 25th %	0.384	0.362	0.953	-2.047	11.81%
	CROSS-SECT. MEDIAN	0.568	0.605	1.116	-0.607	17.82%
	CROSS-SECT. 75th %	0.843	0.914	1.416	-0.001	29.71%
	CROSS-SECT. MAX.	1.093	1.106	13.047	0.959	170.38%
MARKET EXC. RET. - without first 50 obs.	CROSS-SECT. MEAN	0.544	0.563	1.784	-1.369	28.19%
	CROSS-SECT. MIN.	-0.334	-0.341	-0.118	-22.205	1.07%
	CROSS-SECT. 25th %	0.388	0.359	0.922	-0.491	10.88%
	CROSS-SECT. MEDIAN	0.570	0.604	1.081	-0.113	17.16%
	CROSS-SECT. 75th %	0.853	0.917	1.324	0.220	29.04%
	CROSS-SECT. MAX.	1.092	1.105	13.047	0.959	171.27%
ILLIQU. - overall sample period	CROSS-SECT. MEAN	0.126	0.125	6.211	-8.209	79.31%
	CROSS-SECT. MIN.	-0.283	-0.284	0.098	-148.402	2.44%
	CROSS-SECT. 25th %	0.039	0.035	0.616	-4.546	20.06%
	CROSS-SECT. MEDIAN	0.141	0.127	0.925	-2.527	28.96%
	CROSS-SECT. 75th %	0.225	0.217	1.918	-0.681	43.89%
	CROSS-SECT. MAX.	0.471	0.420	192.639	0.001	1002.45%
ILLIQU. - without first 50 obs.	CROSS-SECT. MEAN	0.136	0.128	6.136	-7.133	77.01%
	CROSS-SECT. MIN.	-0.258	-0.274	-0.036	-148.402	2.00%
	CROSS-SECT. 25th %	0.045	0.040	0.506	-1.200	15.61%
	CROSS-SECT. MEDIAN	0.149	0.131	0.886	-0.532	26.03%
	CROSS-SECT. 75th %	0.234	0.220	1.857	-0.343	38.57%
	CROSS-SECT. MAX.	0.495	0.427	192.639	0.132	1008.43%
IDIOS. RISK - overall sample period	CROSS-SECT. MEAN	0.123	0.110	2.962	-2.404	33.81%
	CROSS-SECT. MIN.	-0.118	-0.104	0.042	-48.796	0.94%
	CROSS-SECT. 25th %	0.047	0.039	0.498	-1.733	8.72%
	CROSS-SECT. MEDIAN	0.123	0.105	1.018	-1.014	13.67%
	CROSS-SECT. 75th %	0.187	0.164	1.504	-0.360	21.06%
	CROSS-SECT. MAX.	0.396	0.416	45.711	0.015	319.52%

Table A.28 – continued from previous page

		Mean exp.	Median exp.	Maximum exp.	Minimum exp.	Std. Dev. of exp.
IDIOS. RISK - without first 50 obs.	CROSS-SECT. MEAN	0.126	0.111	2.659	-1.807	33.10%
	CROSS-SECT. MIN.	-0.118	-0.103	-0.031	-48.796	0.54%
	CROSS-SECT. 25th %	0.047	0.040	0.340	-0.435	6.89%
	CROSS-SECT. MEDIAN	0.124	0.108	0.513	-0.177	13.13%
	CROSS-SECT. 75th %	0.191	0.166	0.921	-0.071	20.25%
	CROSS-SECT. MAX.	0.422	0.435	45.711	0.181	322.79%

Table A.29: Risk factor timing results: Individual mutual funds, liquidity augmented CAPM with idiosyncratic risk and overall sample period

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM with idiosyncratic risk. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 10%-level testing against a null hypothesis of a zero coefficient. Overall number of funds: 254. Sample period: October 1, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	34	24	17	14	9	15	21	8	13	12	13	19
MARKET EXC. RET.: sig. pos.	215	8	15	14	16	6	7	26	19	11	11	9
ILLIQU.: sig. neg.	35	32	29	16	9	6	4	8	9	13	9	5
ILLIQU.: sig. pos.	183	5	7	4	2	2	4	10	13	9	3	5
IDIOS. RISK: sig. neg.	13	25	29	27	19	16	11	21	7	9	10	10
IDIOS. RISK: sig. pos.	220	5	6	5	8	7	6	5	23	26	11	10

Table A.30: Risk factor timing results: Individual mutual funds, liquidity augmented CAPM with idiosyncratic risk and restricted sample period

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM with idiosyncratic risk. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 10%-level testing against a null hypothesis of a zero coefficient. The first 50 observations of the overall sample period are ignored because of the training period of the Kalman filter. Overall number of funds: 254. Sample period: December 12, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	34	35	15	15	11	13	19	11	14	10	16	17
MARKET EXC. RET.: sig. pos.	216	7	10	8	15	8	9	22	14	8	7	13
ILLIQU.: sig. neg.	36	34	30	17	12	6	4	10	10	16	11	6
ILLIQU.: sig. pos.	187	5	5	3	2	2	5	14	22	12	3	5
IDIOS. RISK: sig. neg.	12	17	20	13	12	11	11	11	6	7	5	9
IDIOS. RISK: sig. pos.	217	14	13	18	23	16	16	14	35	33	14	18

Table A.31: Risk factor timing results in the liquidity augmented CAPM with idiosyncratic risk: Adj. R^2- and F-statistics

This table gives the adj. R^2 and F-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM with idiosyncratic risk. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. Two time periods are considered: The overall sample period versus a restricted sample period where the first 50 observations of the overall sample period are ignored because of the training period of the Kalman filter. Overall number of funds: 254. Sample period: October 1, 2002 to September 30, 2009.

Adj. R^2- stat.		Mean	Median	Max.	Min.
MARKET EXC. RET.	Overall sample period	0.09%	-0.02%	4.09%	-0.60%
	Without first 50 obs.	0.11%	-0.16%	3.77%	-0.62%
ILLIQU.	Overall sample period	-0.09%	-0.04%	5.52%	-0.61%
	Without first 50 obs.	0.17%	0.06%	6.03%	-0.63%
IDIOS. RISK	Overall sample period	0.63%	-0.04%	9.67%	-0.59%
	Without first 50 obs.	0.23%	-0.16%	8.18%	-0.62%
F-stat.		**Mean**	**Median**	**Max.**	**Min.**
MARKET EXC. RET.	Overall sample period	2.092	0.932	18.490	0.041
	Without first 50 obs.	1.177	0.742	7.245	0.014
ILLIQU.	Overall sample period	1.161	0.937	10.552	0.011
	Without first 50 obs.	1.287	1.087	11.221	0.018
IDIOS. RISK	Overall sample period	2.092	0.933	18.490	0.041
	Without first 50 obs.	1.377	0.745	15.192	0.014

Table A.32: Risk factor timing robustness tests 1: Equal-weighted fund portfolio

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Risk factors are derived from either the style indices based on 1%- and 99%-cut-off-rates or from equal-weighted style indices. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
1%- and 99%-cut-off-rates												
MARKET EXC. RET.: Coeff.	0.249	0.728	0.779	0.797	0.802	0.800	0.833	0.926	1.024	0.832	0.797	0.789
T-stat.	12.151***	1.403	1.534	1.531	1.564	1.583	1.650*	1.760*	1.833*	1.593	1.539	1.599
ILLIQU.: Coeff.	0.318	-0.004	-0.281	-0.339	-0.410	-0.426	-0.257	0.207	0.029	0.056	-0.070	-0.091
T-stat.	43.544***	-0.005	-0.352	-0.409	-0.518	-0.572	-0.372	0.268	0.037	0.075	-0.098	-0.138
Equal-weighted risk factors												
MARKET EXC. RET.: Coeff.	0.277	0.727	0.829	0.785	0.829	0.789	0.874	1.027	1.011	0.871	0.817	0.924
T-stat.	11.756***	1.357	1.577	1.465	1.533	1.463	1.511	1.835*	1.727*	1.563	1.478	1.632
ILLIQU.: Coeff.	0.361	-2.146	-2.263	-1.936	-1.561	-0.931	-1.182	-1.450	-1.069	-1.349	-1.879	-1.265
T-stat.	22.689***	-1.149	-1.179	-0.986	-0.852	-0.497	-0.608	-0.817	-0.615	-0.853	-1.154	-0.799

Table A.33: Risk factor timing robustness tests 2: Equal-weighted fund portfolio

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Detrended illiquidity is calculated by moving average trading volume over the preceding 100 days. An outlier detection is performed applying the three sigma rule for potential outliers in the liquidity variable, yielding 13 outliers regarding liquidity. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

E.-w. m. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Detrended illiquidity												
MARKET EXC. RET.: Coeff.	0.158	1.141	1.095	1.027	0.946	0.915	0.992	1.414	1.558	1.321	1.138	1.139
T-stat.	22.088***	2.016**	1.872*	1.805*	1.652*	1.615	1.683*	2.487**	2.701***	2.297**	1.933*	2.024**
ILLIQU.: Coeff.	0.156	-1.765	-1.564	-1.246	-0.503	-0.965	-1.118	-0.871	-1.136	-1.008	-0.823	-0.807
T-stat.	11.496***	-3.307***	-2.760***	-2.202**	-0.860	-1.824*	-2.014**	-1.726*	-2.001**	-1.937*	-1.609	-1.295
Without illiquidity outliers												
MARKET EXC. RET.: Coeff.	0.232	0.594	0.596	0.587	0.628	0.558	0.582	0.807	0.889	0.710	0.663	0.584
T-stat.	12.025***	1.247	1.308	1.268	1.323	1.177	1.255	1.679*	1.764*	1.480	1.375	1.266
ILLIQU.: Coeff.	0.202	-0.013	0.197	-0.514	-0.539	-0.064	-0.357	0.872	0.635	0.538	0.529	0.704
T-stat.	13.071***	-0.007	0.110	-0.277	-0.288	-0.036	-0.190	0.495	0.370	0.326	0.341	0.443

Table A.34: Risk factor timing robustness tests for the equal-weighted mutual fund portfolio: Adj. R^2- and F-statistics

This table gives the adj. R^2- and F-statistics of the timing regression as of Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: October 1, 2002 to September 30, 2009.

	Liquidity augm. CAPM	Adj. R^2	F-statistic
1%- and 99%-cut-off-rates			
	MARKET EXC. RET.	0.51%	1.839**
	ILLIQUIDITY	-0.49%	0.197
Equally weighted			
	MARKET EXC. RET.	0.55%	1.907**
	ILLIQUIDITY	0.14%	1.230
Detrended illiquidity			
	MARKET EXC. RET.	1.66%	3.764***
	ILLIQUIDITY	3.54%	7.001***
Without outliers			
	MARKET EXC. RET.	0.28%	1.462
	ILLIQUIDITY	-0.52%	0.161

Table A.35: Robustness tests on equal-weighted mut. fund portf.: Different leads and lags

	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MKT. EXC. RET.												
Coeff.	0.226	0.424	0.466					0.671				
T-stat.	11.698***	0.919	1.061					1.467				
Adj- R^2	0.00%	F-stat.	0.983	AIC	0.372	SBC	0.384					
ILLIQU.												
Coeff.	0.216	-1.649	-1.775					-0.358				
T-stat.	11.700***	-1.003	-1.073					-0.235				
Adj. R^2	0.00%	F-stat.	0.993	AIC	0.348	SBC	0.360					
MKT. EXC. RET.												
Coeff.	0.226	0.556	0.514	0.504	0.689			0.680	0.780	0.689		
T-stat.	11.696***	1.085	1.107	1.091	1.497			1.419	1.592	1.482		
Adj. R^2	0.11%	F-stat.	1.291	AIC	0.375	SBC	0.399					
ILLIQU.												
Coeff.	0.219	-2.202	-2.388	-1.947	-2.642			0.117	0.945	0.130		
T-stat.	11.679***	-1.073	-1.194	-0.996	-1.399			0.063	0.486	0.078		
Adj. R^2	0.19%	F-stat.	1.484	AIC	0.314	SBC	0.339					
MKT. EXC. RET.												
Coeff.	0.226	0.531	0.575	0.621	0.696	0.687	0.735	0.763	0.873	0.689	0.656	0.661
T-stat.	11.684***	1.088	1.213	1.273	1.447	1.443	1.533	1.548	1.671*	1.412	1.349	1.419
Adj. R^2	0.26%	F-stat.	1.421	AIC	0.377	SBC	0.413					
ILLIQU.												
Coeff.	0.223	-2.253	-2.557	-2.964	-3.264	-2.879	-2.451	-0.601	0.532	-0.400	-1.283	-1.245
T-stat.	11.583***	-1.058	-1.156	-1.313	-1.476	-1.417	-1.286	-0.295	0.252	-0.205	-0.732	-0.813
Adj. R^2	0.48%	F-stat.	1.786**	AIC	0.293	SBC	0.330					

Table A.36: Robustness tests on equal-weighted mut. fund portf.: Smoothed states and different subperiods

Smoothed	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MKT. EXC. RET.												
Coeff.	0.182	0.679	0.643	0.680	0.614	0.625	0.627	0.689	0.751	0.667	0.604	0.599
T-stat.	10.359***	1.434	1.377	1.400	1.307	1.350	1.391	1.462	1.524	1.412	1.307	1.346
Adj. R^2	0.34%	F-stat.	1.555									
ILLIQU.												
Coeff.	0.205	-1.132	-1.037	-0.995	-0.906	-0.685	-0.586	-1.031	-0.955	-0.881	-0.827	-0.802
T-stat.	13.174***	-0.687	-0.630	-0.597	-0.564	-0.459	-0.430	-0.625	-0.573	-0.556	-0.566	-0.614
Adj. R^2	-0.36%	F-stat.	0.421									
Subper. 1	**Const.**	**Current**	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lead 1**	**Lead 2**	**Lead 3**	**Lead 4**	**Lead 5**
MKT. EXC. RET.												
Coeff.	0.442	-0.839	-0.562	-0.710	-0.695	-0.776	-0.883	-0.720	-0.619	-0.708	-0.593	-0.721
T-stat.	20.700***	-1.272	-0.820	-1.036	-1.036	-1.125	-1.354	-1.137	-0.944	-1.136	-0.897	-1.169
Adj. R^2	-0.57%	F-stat.	0.539									
ILLIQU.												
Coeff.	0.112	0.242	0.612	-0.110	-0.421	-0.222	-0.492	0.122	0.028	0.202	0.217	-0.029
T-stat.	18.866***	0.244	0.533	-0.111	-0.524	-0.328	-0.741	0.140	0.034	0.282	0.348	-0.053
Adj. R^2	-0.93%	F-stat.	0.244									
Subper. 2	**Const.**	**Current**	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lead 1**	**Lead 2**	**Lead 3**	**Lead 4**	**Lead 5**
MKT. EXC. RET.												
Coeff.	-0.058	-0.202	-0.216	-0.181	-0.140	-0.115	-0.042	-0.151	-0.130	-0.113	-0.113	-0.033
T-stat.	-17.263***	-2.243**	-2.534**	-2.123**	-1.777*	-1.720*	-0.699	-2.069**	-1.744*	-1.792*	-1.866*	-0.501
Adj. R^2	0.72%	F-stat.	1.587*									
ILLIQU.												
Coeff.	0.395	-0.322	-0.746	-0.869	-0.819	-0.726	-0.553	0.215	-0.105	-0.363	-0.486	-0.236
T-stat.	13.500***	-0.140	-0.315	-0.359	-0.353	-0.350	-0.307	0.095	-0.045	-0.165	-0.246	-0.140
Adj. R^2	-1.16%	F-stat.	0.062									

Table A.37: Time-varying risk factor exposures: Different subperiods

This table gives summary statistics of the time-varying risk factor exposures estimated by the Kalman filter for the liquidity augmented CAPM. The summary statistics are given for the equal-weighted mutual fund portfolio. Cross-sectional summary statistics for the individual mutual funds are displayed as well. The Kalman filter specification follows Equations 6.18 and 6.19. First subperiod: October 1, 2002 to March 31, 2006. Second subperiod: April 3, 2006 to September 30, 2009.

	Mean	Median	Maximum	Minimum	Std. dev.
Equal-weighted mutual fund portfolio: 1st subperiod					
MARKET EXC. RET.	0.435	0.550	0.678	-0.428	0.252
ILLIQU.	0.106	0.131	0.153	-1.468	0.113
Equal-weighted mutual fund portfolio: 2nd subperiod					
MARKET EXC. RET.	-0.058	-0.050	0.184	-0.751	0.048
ILLIQU.	0.391	0.435	1.569	-0.079	0.324
Individual mutual funds: 1st subperiod					
MARKET EXC. RET.	0.598	0.683	1.151	-0.190	0.361
ILLIQU.	0.102	0.126	0.526	-1.647	0.274
Individual mutual funds: 2nd subperiod					
MARKET EXC. RET.	0.609	0.653	1.162	-0.065	0.348
ILLIQU.	0.186	0.227	0.588	-1.115	0.238

Table A.38: Risk factor timing results: Without top decile of root mean square error mutual funds

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 5%- and 10%-levels testing against a null hypothesis of a zero coefficient. The top decile of the mutual funds with the highest root mean square error of the filtered states in the Kalman filter analysis is ignored. Overall number of funds: 222. Sample period: October 1, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	28	24	23	16	24	27	17	21	16	19	14
MARKET EXC. RET.: sig. pos.	190	26	31	39	44	36	36	43	39	39	35	39
ILLIQU.: sig. neg.	25	7	7	9	10	6	4	4	1	2	4	3
ILLIQU.: sig. pos.	188	4	1	2	2	1	2	9	12	5	1	0
5%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	19	14	14	9	14	18	8	15	13	10	8
MARKET EXC. RET.: sig. pos.	190	15	20	24	32	25	24	31	28	21	14	24
ILLIQU.: sig. neg.	25	4	1	2	2	3	0	2	0	0	2	0
ILLIQU.: sig. pos.	187	0	0	0	0	0	0	5	1	0	0	0

Table A.39: Risk factor timing results: Without top quintile of root mean square error mutual funds

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 5%- and 10%-levels testing against a null hypothesis of a zero coefficient. The top quintile of the mutual funds with the highest root mean square error of the filtered states in the Kalman filter analysis is ignored. Overall number of funds: 197. Sample period: October 1, 2002 to September 30, 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	23	19	18	13	20	24	13	16	12	15	13
MARKET EXC. RET.: sig. pos.	165	26	30	38	42	36	36	41	37	38	34	38
ILLIQU.: sig. neg.	23	4	5	6	7	4	3	3	0	1	3	2
ILLIQU.: sig. pos.	165	4	1	2	2	1	2	9	12	5	1	0
5%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	32	14	10	12	8	11	15	6	10	9	7	8
MARKET EXC. RET.: sig. pos.	165	15	19	24	32	25	24	30	28	21	14	23
ILLIQU.: sig. neg.	23	3	1	2	2	2	0	1	0	0	2	0
ILLIQU.: sig. pos.	164	0	0	0	0	0	0	5	1	0	0	0

Table A.40: Risk factor timing results in the liquidity augmented CAPM for the root mean square error robustness tests: Adj. R^2- and F-statistics

This table gives the adj. R^2 and F-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. The top decile or the top quintile of the mutual funds with the highest root mean square error of the filtered states in the Kalman filter analysis is ignored. Overall number of funds: 222 (without top decile) or 197 (without top quintile). Sample period: October 1, 2002 to September 30, 2009.

Adj. R^2- stat.	Mean	Median	Max.	Min.
Without top decile				
MARKET EXC. RET.	0.61%	0.06%	8.01%	-0.63%
ILLIQU.	-0.07%	-0.19%	3.39%	-0.60%
Without top quintile				
MARKET EXC. RET.	0.64%	0.08%	8.01%	-0.63%
ILLIQU.	-0.06%	-0.16%	2.13%	-0.60%
F-stat.	Mean	Median	Max.	Min.
Without top decile				
MARKET EXC. RET.	2.016	1.093	14.865	0.005
ILLIQU.	0.899	0.706	6.591	0.050
Without top quintile				
MARKET EXC. RET.	2.057	1.128	14.865	0.005
ILLIQU.	0.900	0.749	4.474	0.050

Table A.41: Time-varying risk exposures: Equal-weighted mutual fund portfolio and monthly data sample

This table gives summary statistics of the time-varying risk factor exposures estimated by the Kalman filter for the equal-weighted mutual fund portfolio and the liquidity augmented CAPM. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Sample period: October 2002 to September 2009.

MARKET EXC. RET.	0.884	0.934	1.214	0.099	0.226
ILLIQU.	0.237	0.192	1.345	0.007	0.158

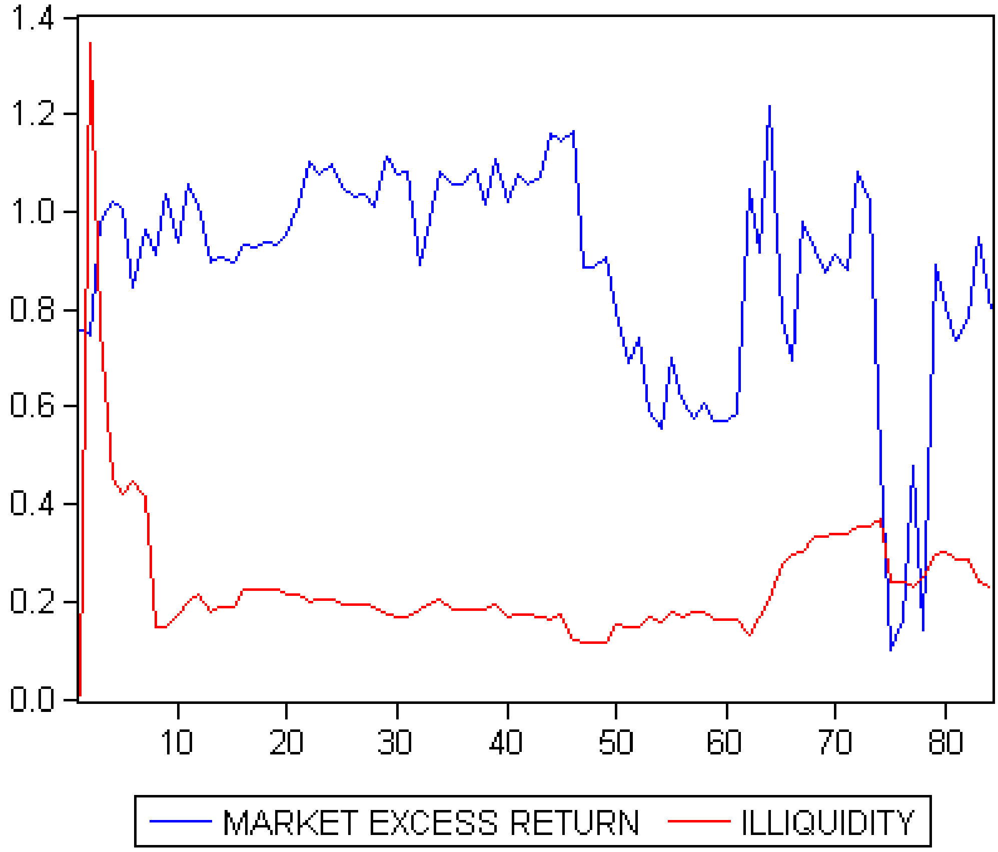

Figure A.1: Monthly time-varying risk factor exposures in the liquidity augmented CAPM

This graph shows the time-varying risk factor exposures of the market excess return and the liquidity risk factor in the liquidity augmented CAPM for the equal-weighted mutual fund portfolio which have been estimated by the Kalman filter. The Kalman filter specification follows Equations 6.18 and 6.19. Sample period: 84 monthly observations from October 2002 to September 2009.

Table A.42: Monthly timing results: Equal-weighted mutual fund portfolio

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augmented CAPM												
MARKET EXC. RET.: Coeff.	0.897	-0.283	1.422	1.535	0.614	0.713	0.402	-0.058	-0.508	-0.010	-0.353	0.217
T-stat.	21.978***	-0.511	2.940***	2.512**	1.073	1.160	0.864	-0.117	-1.112	-0.017	-0.584	0.348
Adj. R^2	0.236	F-stat.	3.055***									
ILLIQU.: Coeff.	0.247	-1.014	-1.013	-0.498	0.108	0.227	-0.170	-0.615	-0.633	-1.328	-1.428	-0.599
T-stat.	11.986***	-1.873*	-1.923*	-0.978	0.212	0.586	-0.440	-1.229	-0.975	-2.385***	-2.826	-1.373
Adj. R^2	0.211	F-stat.	2.772***									

Table A.43: Monthly timing results: Individual mutual funds and the liquidity augmented CAPM

This table gives the number of significant t-statistics of the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. Significance of the timing coefficients is given for the 5%- and 10%-levels testing against a null hypothesis of a zero coefficient. The monthly data sample comprises 84 monthly observations. Overall number of funds which have a complete data set of 84 observations: 273. Sample period: October 2002 to September 2009.

10%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	0	48	23	19	9	4	14	47	28	20	29	28
MARKET EXC. RET.: sig. pos.	254	15	79	123	50	41	107	16	7	13	26	66
ILLIQU.: sig. neg.	21	41	30	6	2	5	14	15	31	50	67	33
ILLIQU.: sig. pos.	168	3	2	2	3	10	3	5	21	3	5	16
5%-signif. level	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: sig. neg.	0	36	14	13	5	3	12	28	18	13	23	19
MARKET EXC. RET.: sig. pos.	254	10	51	103	30	25	74	5	5	7	23	45
ILLIQU.: sig. neg.	17	19	9	3	1	2	5	6	19	30	41	16
ILLIQU.: sig. pos.	160	1	1	2	2	4	1	2	8	2	1	5

Table A.44: Monthly timing results in the liquidity augmented CAPM: Adj. R^2- and F-statistics

This table gives the adj. R^2 and F-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM. The time-varying risk factor exposures for the individual mutual funds have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Overall number of funds which have a complete data set of 84 observations: 273. Sample period: October 2002 to September 2009.

Adj. R^2-stat.	Mean	Median	Max.	Min.
MARKET EXC. RET.	23.64%	21.47%	69.23%	-11.25%
ILLIQU.	-0.19%	-3.15%	55.97%	-17.07%
F-stat.	Mean	Median	Max.	Min.
MARKET EXC. RET.	3.615	2.814	15.949	0.329
ILLIQU.	1.092	0.797	9.435	0.032

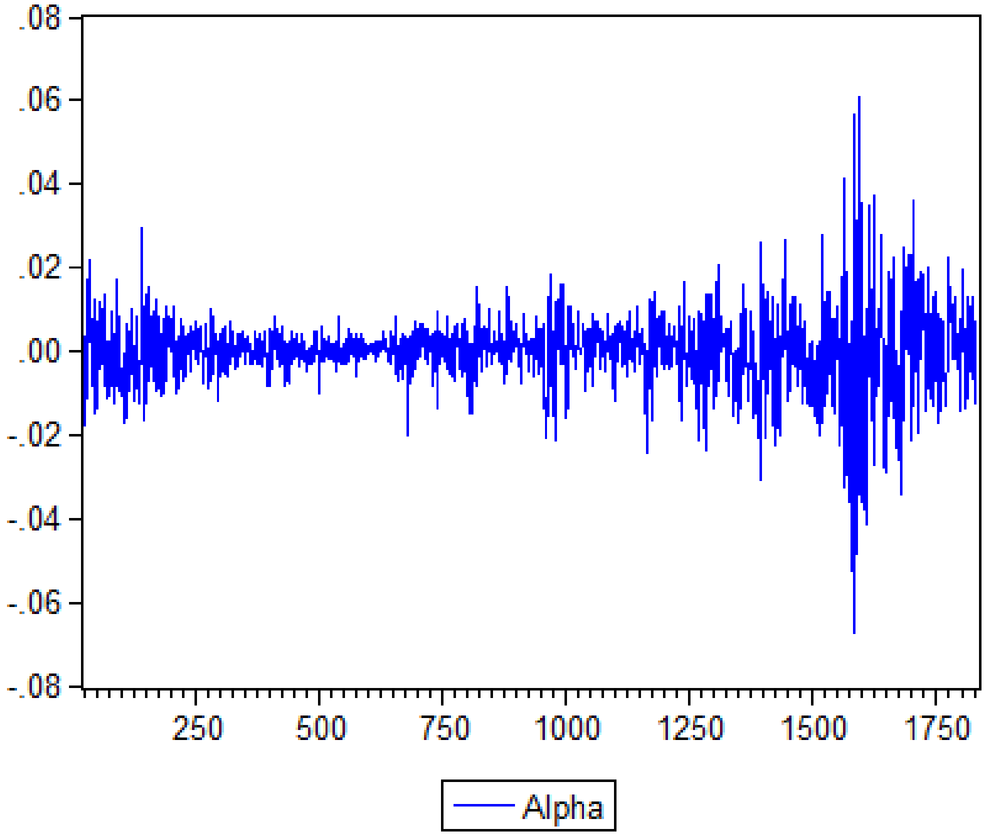

Figure A.2: Time-varying alpha for the equal-weighted mutual fund portfolio

This graph shows the time-varying alpha in the liquidity augmented CAPM for the equal-weighted mutual fund portfolio which has been estimated by the Kalman filter. The Kalman filter specification follows Equations 6.18 and 6.19, where alpha is additionally considered to follow a random walk model, see Equation 6.21. Sample period: 1808 daily observations from October 1, 2002 to September 30, 2009.

Table A.45: Timing and time-varying alpha: Equal-weighted mutual fund portfolio

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the equal-weighted mutual fund portfolio have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19, where alpha is additionally considered to follow a random walk model, see Equation 6.21. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 1, 2002 to September 30, 2009.

E.-w. mut. fund portf.	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Liquidity augmented CAPM												
MARKET EXC. RET.: Coeff.	-0.029	1.095	0.859	0.843	0.866	1.014	0.873	1.060	1.152	1.034	0.997	0.949
T-stat.	-1.214	1.759*	1.412	1.296	1.440	1.684*	1.501	1.697*	1.750*	1.664*	1.644	1.638
Adj. R^2	0.005	F-stat.	1.865**									
ILLIQU.: Coeff.	0.059	1.319	-0.281	-1.503	-2.021	-1.989	-1.778	-0.489	-0.080	0.258	-1.304	-2.025
T-stat.	3.074***	0.433	-0.108	-0.636	-0.928	-1.006	-1.066	-0.170	-0.029	0.093	-0.530	-1.103
Adj. R^2	-0.001	F-stat.	0.917									

A.8 Dynamic hedge fund results: Robustness tests

Table A.46: Summary statistics: Hedge fund indices

All statistics are calculated using monthly returns derived from hedge fund index values. Means and standard deviations are annualized. The excess kurtosis is the kurtosis minus the kurtosis of a normally distributed variable. Sample period: October 2002 to September 2009.

Name of hedge fund index	Hedge Fund Index	Arbitrage	CTA / Managed Futures	Distressed Debt	Event Driven	Fixed Income	Long / Short Equities	Macro	Multi-Strategy	Relative Value
Mean p.a.	8.33%	-2.04%	5.90%	8.36%	6.51%	6.41%	8.75%	24.34%	11.37%	3.55%
Median	1.01%	0.02%	0.62%	0.82%	0.68%	0.93%	1.04%	1.82%	1.58%	0.41%
Max.	0.043	0.065	0.045	0.103	0.061	0.033	0.046	0.290	0.063	0.025
Min.	-0.067	-0.073	-0.031	-0.151	-0.054	-0.098	-0.071	-0.410	-0.127	-0.051
Std. dev. p.a.	6.77%	5.75%	5.08%	10.95%	6.04%	6.57%	7.22%	29.59%	9.84%	3.86%
Skewness	-1.317	-0.563	-0.061	-1.449	-0.686	-2.421	-1.090	-1.009	-1.822	-1.870
Exc. kurt.	3.073	6.964	0.138	8.332	2.392	9.860	2.095	7.171	6.093	7.709

Table A.47: Monthly timing results: European hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

European hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.292	-0.303	0.423	0.691	0.903	0.452	0.200	-0.502	0.052	0.467	0.194	0.708
T-stat.	8.171***	-0.854	1.394	2.019**	2.016**	1.300	0.542	-1.483	0.148	1.283	0.612	2.149**
Adj. R^2	0.114	F-stat.	1.855*									
ILLIQU.: Coeff.	0.299	0.294	0.120	0.151	-0.168	0.081	0.284	-0.018	-0.108	0.235	0.125	-0.208
T-stat.	25.484***	0.673	0.310	0.498	-0.586	0.335	1.103	-0.049	-0.322	0.681	0.410	-0.590
Adj. R^2	-0.128	F-stat.	0.247									

Table A.48: Monthly timing results: Arbitrage hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the arbitrage hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Arbitrage hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.034	-0.076	-0.110	-0.131	-0.116	-0.114	-0.162	-0.019	0.014	0.059	0.078	0.078
T-stat.	12.950***	-1.997*	-4.180***	-3.743***	-3.676***	-3.278***	-4.078***	-0.706	0.636	2.350**	3.293***	2.848***
Adj. R^2	0.710	F-stat.	17.264***									
ILLIQU.: Coeff.	0.053	0.693	0.637	0.960	1.081	0.887	1.219	1.391	1.822	0.571	0.977	1.601
T-stat.	1.333	0.985	0.684	1.298	1.449	0.910	1.111	1.870*	2.307**	0.796	1.195	2.416**
Adj. R^2	0.107	F-stat.	1.796*									

Table A.49: Monthly timing results: CTA / managed futures hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the CTA / managed futures hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

CTA / managed futures hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.032	0.046	0.037	0.051	0.098	0.032	0.040	-0.042	0.030	0.012	0.002	0.007
T-stat.	13.259***	1.517	1.453	1.553	1.960*	0.882	0.773	-0.739	1.060	0.390	0.084	0.233
Adj. R^2	0.191	F-stat.	2.571***									
ILLIQU.: Coeff.	0.197	-1.169	-1.310	-0.837	-0.859	-0.618	-0.563	-1.107	-0.296	-0.545	-0.465	-0.107
T-stat.	8.447***	-1.887	-1.795*	-1.141	-1.125	-0.792	-0.719	-1.745*	-0.457	-0.808	-0.680	-0.158
Adj. R^2	-0.006	F-stat.	0.963									

Table A.50: Monthly timing results: Distressed debt hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the distressed debt hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Distressed debt hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.249	-1.611	1.678	2.077	0.087	0.675	-0.305	-2.420	-0.071	-0.486	-0.209	2.680
T-stat.	5.748***	-1.649	2.015**	2.566**	0.126	0.589	-0.497	-4.831***	-0.123	-0.760	-0.364	3.944***
Adj. R^2	0.315	F-stat.	4.053***									
ILLIQU.: Coeff.	0.096	2.843	0.724	-0.854	0.074	6.709	5.158	6.169	4.749	6.157	4.069	3.970
T-stat.	0.424	0.519	0.163	-0.238	0.014	0.917	0.696	1.082	1.052	1.533	0.899	0.758
Adj. R^2	-0.028	F-stat.	0.822									

Table A.51: Monthly timing results: Event driven hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the event driven hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Event driven hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.219	-0.195	0.214	0.461	0.678	0.270	0.023	-0.577	-0.478	0.086	-0.158	0.108
T-stat.	8.156***	-0.717	0.820	1.460	1.849*	0.845	0.061	-2.258**	-1.825*	0.292	-0.587	0.493
Adj. R^2	0.077	F-stat.	1.553									
ILLIQU.: Coeff.	0.095	-0.054	-0.042	-0.095	-0.298	-0.110	-0.109	-0.616	-1.198	-0.483	-0.759	-1.156
T-stat.	2.489**	-0.050	-0.037	-0.094	-0.319	-0.122	-0.126	-0.611	-1.191	-0.491	-0.961	-1.626
Adj. R^2	-0.090	F-stat.	0.454									

Table A.52: Monthly timing results: Fixed income hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the fixed income hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Fixed income hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.116	0.006	-0.174	0.129	-0.136	-0.844	-0.783	-0.739	-0.629	-0.638	-1.166	-0.661
T-stat.	6.195***	0.016	-0.700	0.353	-0.413	-2.879***	-2.202**	-2.010**	-2.141**	-2.222**	-2.824***	-2.589**
Adj. R^2	0.552	F-stat.	9.170***									
ILLIQU.: Coeff.	0.075	1.878	1.420	1.000	0.262	-0.040	-0.163	2.055	2.760	1.883	2.028	1.972
T-stat.	1.553	1.818*	1.224	0.954	0.232	-0.034	-0.135	1.675*	2.157**	1.359	1.625	1.748*
Adj. R^2	0.085	F-stat.	1.617									

Table A.53: Monthly timing results: Long / short equities hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the long / short equities hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Long / short equities hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.331	-0.255	0.490	0.775	1.003	0.601	0.363	-0.472	0.103	0.587	0.295	0.783
T-stat.	8.625***	-0.724	1.484	2.139**	2.137**	1.616	0.888	-1.319	0.282	1.615	0.960	2.293**
Adj. R^2	0.175	F-stat.	2.407**									
ILLIQU.: Coeff.	0.331	-0.001	-0.172	0.140	-0.033	0.412	0.818	0.049	-0.093	0.108	-0.160	-0.194
T-stat.	11.847***	-0.001	-0.212	0.243	-0.084	0.784	1.185	0.066	-0.142	0.169	-0.271	-0.315
Adj. R^2	-0.129	F-stat.	0.244									

Table A.54: Monthly timing results: Macro hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the macro hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Macro hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.469	-0.358	-0.120	-0.303	-0.105	-0.226	-0.633	-0.491	-0.021	0.270	0.033	0.350
T-stat.	20.986***	-1.368	-0.590	-1.102	-0.409	-1.170	-2.189**	-1.825*	-0.094	1.284	0.161	1.711*
Adj. R^2	0.126	F-stat.	1.959**									
ILLIQU.: Coeff.	0.849	2.008	1.521	-1.051	-4.444	-2.849	-2.164	0.302	-0.333	3.648	3.568	-1.581
T-stat.	6.961***	0.532	0.442	-0.354	-1.622	-1.060	-0.881	0.088	-0.093	0.972	1.013	-0.462
Adj. R^2	-0.089	F-stat.	0.459									

Table A.55: Monthly timing results: Multi-strategy hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the multi-strategy hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Multi-strategy hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.304	-0.619	0.446	0.485	0.774	0.155	-0.151	-0.716	0.480	0.352	0.228	1.041
T-stat.	5.366***	-1.175	1.055	1.070	1.290	0.271	-0.298	-1.212	0.801	0.650	0.427	1.915*
Adj. R^2	-0.043	F-stat.	0.725									
ILLIQU.: Coeff.	0.429	0.719	0.419	0.357	-0.296	0.150	0.578	0.297	0.186	0.662	0.695	0.050
T-stat.	18.294***	1.027	0.691	0.544	-0.370	0.202	0.793	0.414	0.281	1.051	0.950	0.069
Adj. R^2	-0.106	F-stat.	0.361									

Table A.56: Monthly timing results: Relative value hedge fund index

This table gives the timing coefficients $b_{i,k,t-j}$ and the respective t-statistics in Equation 6.16 for each risk factor k in the liquidity augmented CAPM as well as the adj. R^2 and F-statistics. The time-varying risk factor exposures for the relative value hedge fund index have been estimated by the Kalman filter and are then the dependent variables in Equation 6.16 with different lags and leads of each risk factor being the explanatory variables. For example, lag 2 corresponds to $b_{i,k,t-2}$ and lead 5 to $b_{i,k,t+5}$. Const. equals the constant a in Equation 6.16. The Kalman filter specification follows Equations 6.18 and 6.19. The monthly data sample comprises 84 monthly observations. Significance of the timing coefficients at the 1%-, 5%-, 10%-level is denoted by ***, **, and *, respectively. Sample period: October 2002 to September 2009.

Relative value hedge fund index	Const.	Current	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
MARKET EXC. RET.: Coeff.	0.154	-0.133	0.128	0.729	0.470	0.253	0.264	-0.458	0.068	0.099	-0.060	0.428
T-stat.	5.615***	-0.479	0.513	2.290**	1.457	0.968	1.008	-1.591	0.273	0.321	-0.202	1.616
Adj. R^2	0.055	F-stat.	1.383									
ILLIQU.: Coeff.	0.093	-0.806	-0.848	-0.686	-0.528	-0.452	-0.555	-0.774	-0.906	-0.706	-0.914	-0.808
T-stat.	4.103***	-1.487	-1.472	-1.268	-1.050	-0.962	-1.274	-1.497	-1.793*	-1.472	-2.250**	-2.470**
Adj. R^2	0.217	F-stat.	2.843***									

A.9 Hedge fund strategy classification by Eurekahedge

The following description of the hedge fund strategies used to classify hedge funds into the different Eurekahedge strategy subindices is obtained from Eurekahedge at www.eurekahedge.com. Hedge funds are self-classified into the different strategies by the hedge fund management companies. Overlaps between different strategies are inevitable as some strategies are not only specific to certain asset classes or styles, but are broader in scope. This is also the case for indices of other hedge fund index providers.

Arbitrage: Involves the purchase of an asset followed by immediate resale, exploiting pricing inefficiencies in a variety of situations in similar or different markets. It is usually regarded to have low risk, but this may differ depending on the circumstances. The most basic form of arbitrage is triangle arbitrage, where an asset is being sold at two different prices at different markets. Such gaps are often closed off almost instantly. Merger arbitrage takes place following M&A announcements as funds may purchase stocks of the target company and short the stocks of the acquiring company. Capital structure arbitrage involves taking advantage of pricing anomalies among different securities issued by the same or related firm. For example, a fund might go long on a high yield bond and short the stock of the company. Given the nature of opportunities pursued, returns tend to be market neutral.

CTA / Managed Futures: Invests in commodity futures, options and forex contracts either directly or through a Commodity Trading Advisor (CTA) who is registered with the Commodities Futures Trading Commission.

Distressed Debt: Invests in the debt of companies that are sick, bankrupt or in the course of a turnaround at deep discounts. Given the nature of these securities, there is selling pressure in the market as many of the institutional investors cannot own below investment grade securities. This results in lower demand, coupled with the negative publicity of a bankruptcy filing, leading to an undervaluation which this strategy is trying to capitalize on.

Event Driven: Exploits opportunities in specific situations, such as mergers, public offerings, leveraged buyouts or hostile takeovers, and is generally unaffected by the movements in the market or trends. They need not necessarily be limited to any particular investment style or asset class. One example of an event driven arbitrage strategy is merger arbitrage, distressed debt, or more generally speaking, distressed securities.

Fixed Income: Invests in fixed income securities (long, short or both) and / or fixed income arbitrage (exploiting pricing anomalies in similar fixed income securities) opportunities, usually along with the use of leverage. For this strategy, they may focus on interest rate swaps, forward yield curves or mortgage-backed securities.

Long / Short Equity: Attempts to hedge out market risk by investing on the long (buy then sell as prices rise) as well as short (borrow, sell and buy as prices go down, and settle the loan) side of the equity markets. The fund's net exposure to the markets is reduced if not completely hedged out, owing to the short-selling. Managers shift from stocks of small values to that of large ones, resulting in a tilt in the net long or short position to gain returns. Absolute returns are accentuated by such use of leverage and may also make use of options and futures. Note that this strategy is different from a true equity market neutral strategy. The key difference lies in the fact that the manager is betting that one stock will do better than the other relatively, regardless of the general market movement.

Macro Funds: A top-down strategy that tracks and profits from global macro-economic directional shifts or changes in government policies. This, in turn, affects foreign currencies / economies, interest rates and commodities. Managers using this strategy are usually involved in all kinds of markets, such as equities, bonds, etc. The use of leverage (and derivatives, in particular) accentuates the impact of market movements on fund performance.

Multi-Strategy: Adds a further layer of diversification to asset allocations (as opposed to merely diversifying across asset classes) by investing in more than one of the strategies described here. To loosely analogize, a multi-strategy fund would be the single-manager fund equivalent of a fund of hedge funds. The volatility for this strategy is considered to be variable.

Relative Value: This is an overarching classification and encompasses all strategies that use pair-trading, leverage in a variety of securities and aim to hedge out market risk. For instance, fixed income arbitrage, capital structure arbitrage and long/short equities are all technically relative value strategies.