

On The Stability Of Portfolio Risk -

An Analysis Of The Impact Of Portfolio Size And Risk Based Fund Classification



Martin Ewen

Department of Business and Economics

University of Trier

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54295 Trier

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Abstract

This dissertation is dedicated to the analysis of the stability of portfolio risk and the impact of European regulation introducing risk based classifications for investment funds.

The first paper examines the relationship between portfolio size and the stability of mutual fund risk measures, presenting evidence for economies of scale in risk management. In a unique sample of 338 fund portfolios we find that the volatility of risk numbers decreases for larger funds. This finding holds for dispersion as well as tail risk measures. Further analyses across asset classes provide evidence for the robustness of the effect for balanced and fixed income portfolios. However, a size effect did not emerge for equity funds, suggesting that equity fund managers simply scale their strategy up as they grow. Analyses conducted on the differences in risk stability between tail risk measures and volatilities reveal that smaller funds show higher discrepancies in that respect. In contrast to the majority of prior studies on the basis of ex-post time series risk numbers, this study contributes to the literature by using ex-ante risk numbers based on the actual assets and de facto portfolio data.

The second paper examines the influence of European legislation regarding risk classification of mutual funds. We conduct analyses on a set of worldwide equity indices and find that a strategy based on the long term volatility as it is imposed by the Synthetic Risk Reward Indicator (SRRI) would lead to substantial variations in exposures ranging from short phases of very high leverage to long periods of under investments that would be required to keep the risk classes. In some cases, funds will be forced to migrate to higher risk classes due to limited means to reduce volatilities after crises events. In other cases they might have to migrate to lower risk classes or increase their leverage to ridiculous amounts. Overall, we find if the SRRI creates a binding mechanism for fund managers, it will create substantial interference with the core investment strategy and may incur substantial deviations from it. Furthermore due to the forced migrations the SRRI degenerates to a passive indicator.

The third paper examines the impact of this volatility based fund classification on portfolio performance. Using historical data on equity indices we find

initially that a strategy based on long term portfolio volatility, as it is imposed by the Synthetic Risk Reward Indicator (SRRI), yields better Sharpe Ratios (SRs) and Buy and Hold Returns (BHRs) for the investment strategies matching the risk classes. Accounting for the Fama-French factors reveals no significant alphas for the vast majority of the strategies. In our simulation study where volatility was modelled through a GJR(1,1) - model we find no significant difference in mean returns, but significantly lower SRs for the volatility based strategies. These results were confirmed in robustness checks using alternative models and timeframes. Overall we present evidence which suggests that neither the higher leverage induced by the SRRI nor the potential protection in downside markets does pay off on a risk adjusted basis.

Keywords: portfolio risk, volatility, portfolio size, tail risk, SRRI, regulation

JEL: G11,G23, G32

Zusammenfassung

Die vorliegende Dissertation umfasst drei Forschungsarbeiten zu dem Thema Portfoliorisiko von Investmentfonds in Finanzaktiva, sowie die Effekte der regulatorischen Einbeziehung von Risikokennzahlen in deren Veröffentlichungspflichten. In der ersten Arbeit wird der Einfluss der Portfoliogröße auf die Stabilität der Risikokennzahlen untersucht. Dies erfolgt anhand einer Stichprobe von täglichen Risikokennzahlen, die von einem Unternehmen für Risikodienstleistungen aus der Praxis erhalten wurden. Eine Besonderheit der Daten ist, dass es sich um so genannte ex-ante Kennzahlen handelt. Diese werden, im Gegensatz zu auf den realisierten Renditen basierenden Kennzahlen, auf Basis der Portfoliowerte geschätzt, spiegeln somit die Anlageentscheidungen des Portfoliomanagers unmittelbar wider. Die Ergebnisse der Untersuchungen zeigen, dass Portfolios mit größerem Volumen signifikant geringere Schwankungen der Risikokennzahlen aufweisen als kleinere Portfolios. Für die Gesamtstichprobe konnte der Effekt für Streuungs-, sowie Tail Risk - Kennzahlen nachgewiesen werden und ist robust im Hinblick auf Variationen des Regressionsmodells bzgl. der Einbeziehung des Anlageuniversums und der Portfoliowährung. Bei der individuellen Analyse der Teilstichprobe nach Anlageuniversum wurde der Effekt für Anleihe- und Mischfonds nachgewiesen. Für Aktienfonds konnte er hingegen nicht bestätigt werden. Dieses Ergebnis ist kohärent mit bisherigen Forschungsergebnissen zu dem Verhalten von Fondsmanagern von Aktienfonds, die zeigen, dass die vorhandene Strategie lediglich hochskaliert wird wenn das Fondsvolumen steigt. Schließlich wird in diesem Aufsatz für die verwendete Stichprobe gezeigt, dass größere Fonds weniger Abweichungen aufweisen zwischen den Streuungs- und den Tail Risk - Risikomaßen. Insgesamt konnte dargelegt werden, dass das Volumen der Assets eines Investmentportfolios ein wichtiger Einflussfaktor auf die Stabilität der Risikokennzahlen ist.

Die Stabilität der Risikokennzahlen hat in den letzten Jahren ebenfalls Einzug in die europäische Regelsetzung gefunden. So sind bestimmte Investmentfonds verpflichtet den so genannten Synthetic Risk Reward Indicator (SRRI) zu veröffentlichen und regelmäßig zu überwachen. Dieser Indikator basiert im

Wesentlichen auf der realisierten Volatilität und dient als Maßstab zur Fondsklassifizierung in eine von 7 Risikoklassen nach vorgegebenen Risikobandbreiten. Änderungen der Risikoklassen, die auftreten, wenn die realisierte Volatilität länger als 16 Wochen außerhalb der definierten Risikobandbreite liegt, können Mittelabflüsse nach sich ziehen, da das neue Chance-Risiko Profil nicht mit dem von den Investoren ausgewählten übereinstimmt. Dies impliziert eine die Kern-Investmentstrategie des Fonds überlagernde zweite Anlageregel basierend auf den Volatilitätsbändern des SRRI.

Der zweite Aufsatz untersucht, wie Aktienfondsmanager die Exposures ihrer Portfolios verändern müssten, wenn die Risikoklassen eingehalten werden sollen. Die Untersuchungen zeigen, dass Fondsmanager im Zeitablauf erhebliche Variationen der Exposures vornehmen müssten und in gewissen Szenarien keine Möglichkeiten haben die Risikoklassen zu halten. Höhere Risikoklassen sind mitunter nur unter erheblichem Einsatz von Derivaten zu halten und Fonds mit begrenzten Hebelmöglichkeiten sind in vielen Fällen nicht in der Lage diese zu halten. Diese Fonds haben also keine Möglichkeit eine andere Risikoklasse auszuweisen. Was die Migration von niedrigeren in höhere Risikoklassen betrifft, so sind diese nur mit extremen Kürzungen des Exposures ebenfalls unter Umständen sogar überhaupt nicht möglich. Letzteres ist z.B. der Fall, wenn starke Schocks wie z.B. das Lehman - Event an den Märkten auftreten und die realisierte Volatilität eines Portfolios (ggf. mit einer einzigen neuen Beobachtung) in eine höhere Risikoklasse katapultiert. Die Möglichkeiten die Volatilität zu senken sind definitionsgemäß beschränkt, was i.V.m. den starren Riskobändern erneut zu unvermeidbaren Migrationen führt. Zusammenfassend kann man festhalten, dass der SRRI enormen Einfluss auf die Anlageentscheidungen des Portfoliomanagers und damit die Anlagestrategie haben kann, wenn er eine bindende Anlagerestriktion darstellt. Darüber hinaus ist die Aussagekraft durch die erzwungenen Migrationen, bzw. die Unmöglichkeit der Einhaltung der Risikoklassen deutlich eingeschränkt. Die regulatorisch erzwungene veränderte Portfolioallokation hat ebenfalls zur Folge, dass die Performancemessung und - attribution erheblich erschwert wird.

Der dritte Aufsatz analysiert den Einfluss der durch den SRRI induzierten veränderten Portfolioallokation auf die Portfolioerträge. In der Analyse der historischen Daten für 10 weltweite Aktienindizes zeichnet sich zunächst ein positives Bild mit höheren Sharpe Ratios und besseren Buy and Hold Returns für die Volatilitätsstrategien. Dieser positive Eindruck kann jedoch nicht bestätigt werden in Fama - French (1992) Regressionen, in denen, bis auf eine

Ausnahme, keine signifikant positiven Alphas nachgewiesen werden können. Ferner untermauert ein Paired T-Test, der auf einer Monte Carlo - Simulation basiert, bei der die Renditen durch ein GJR(1,1) - Modell erzeugt werden, dieses Ergebnis. Es konnten keine Unterschiede in den Durchschnittsrenditen, jedoch signifikant geringere Sharpe Ratios festgestellt werden. Die Ergebnisse der Monte Carlo Simulation wurde in verschiedenen Spezifikationen auf Robustheit untersucht und bestätigt. Es bleibt also festzuhalten, dass die durch den SRRI induzierten Effekte, geprägt durch mitunter sehr hohe Schwankungen, sich also nicht auf risikoadjustierter Basis nicht auszahlen.

Stichwörter: Volatilität, Value at Risk, Portfoliogröße, SRRI, Performance, Fondsaufsicht, Regulatorik

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Chapter 1

Introduction

A considerable amount of research has been devoted to the risks associated with investments in financial assets and how it affects investors. In that context it has mostly focused on how to correctly account for the risks taken by fund managers when assessing their performance. Various models have been developed to account for the risk factors a portfolio is exposed to when assessing the fund managers performance. The stability of risk numbers, or more generally speaking for the risk profile of a portfolio have been much less examined.

The first chapter of this dissertation examines how fund size affects the stability of risk numbers. Portfolio size and its impact on performance is a well known parameter in the context of research on mutual funds. However its effects on risk numbers, notably the stability of risk numbers is much less examined. Using a set of ex-ante risk numbers, i.e. risk numbers that are estimated based on the actual portfolio holdings as opposed to timeseries data when find for our sample that bigger portfolios have more stable risk numbers. This finding holds for dispersion as well as tail risk measures. Breaking our sample down into asset universes the size effect was confirmed for fixed income and balanced funds, but not for equity funds, the latter being in line with former research on equity funds.

European Regulators have recently not only put into focus the risk levels of portfolios, but also the stability of the risk numbers when signaling the riskiness of a portfolio to investors. The Synthetic Risk Reward Indicator (SRRI) classifies mutual funds on the basis of volatility bands. This classification aims to create more transparency when comparing investment alternatives and needs to be updated if the current volatility of the portfolio falls outside the current bucket. This implicitly overlays the core strategy of the portfolios with a volatility strategy. This raises two questions: what do fund managers

have to do to maintain the risk classes prescribed by regulators and what is the impact on the returns for investors?

The second chapter presented in this dissertation focusses on the first question and finds that huge and long lasting variations of exposures would be required to maintain the risk classes. Notably high levels of leverage would be required to keep realized volatility up in times of low market volatilities. Even more striking is the finding that one particular subgroup of the funds concerned would, because of leverage constraints, not be able to maintain the risk classes. Even for the funds with no leverage constraints certain risk classes would not be maintainable in case of severe shocks in the market such as the Lehman event. So for equity portfolio the choice for a risk class effectively boils down to risk classes 6 and 7, that is to say the most two risky ones.

Chapter 3 is devoted to the impact of the SRRI regulation on fund performance. Historical backtesting of the volatility based strategies reveals indeed indications for a positive impact on fund performance, without providing a clear-cut picture. However, the results were not confirmed running Fama - French three factor regressions. Furthermore, our simulation study based on a GJR (1,1) - model does not find any significant difference mean returns and even shows significantly lower Sharpe Ratios for the volatility based strategies. The results were confirmed in several robustness checks. We therefore conclude that there is no positive impact on portfolio performance induced by the SRRI.

Chapter 2

Fund Size and the Stability of Portfolio Risk

2.1 Introduction

Portfolio risk is a core field of research in Financial Economics. An overwhelming amount of this research is devoted to mutual fund performance and mostly indicates that, in the long run, fund managers are not able to deliver higher risk adjusted net returns against passive or simple strategies (e.g. Carhart (1997), Blake and Timmerman (1998), Barras et al. (2010)). As a matter of fact, active fund management is still a popular concept; particularly large funds still exist and the asset management industry continues to grow (see e.g. Otten and Schweitzer (2002), EFAMA (2013)). This study examines the relationship between portfolio size and risk stability (or the adherence to a risk profile) to identify another dimension that adds value for investors and serves as a distinguishing feature of actively managed portfolios from passive strategies. This attribute might be a driving factor that leads to the growth of the mutual fund industry and the existence of large portfolios that are actively managed by a fund manager despite the growing competition through Exchange Traded Funds (ETFs).

The size of a managed portfolio is a popular variable in the research on fund performance. It has been argued that the size of a portfolio leads to lower returns due to manager turnover, market impact and decreasing returns to scale in fund management or information acquisition. However, despite the widespread lack of outperformance or persistence, large funds still emerge and exist. One explanation might be that larger

funds offer investors less variations in wealth, hence less uncertainty, which makes them willing to pay a premium in terms of lower returns.

Against this background, this study examines fund size and its impact on the stability of the risk patterns of portfolios. Basic reasoning intuitively leads to the assumption that the risk of bigger funds is more stable than the risk of smaller funds because they can diversify more extensively, can handle cash flows better and are more likely to effectively leverage managerial resources (analysts, star managers). However, literature still lacks a detailed analysis of these hypotheses. Furthermore, funds may well profit from economies of scale as they grow but, several aspects have to be taken into account, which will show that the stability of risk numbers is not a clearcut consequence in this context. These are described below.

Another aspect that has to be taken into account is that the risk profiles of portfolios have to be seen in the light of the agency structure in the industry. A continuously growing stream of research is devoted to the risk taking behaviour of mutual fund managers, particularly considering the agency implications that arise from the two layer delegation in the asset management industry (e.g. Chevalier and Ellison (1997), Kempf and Ruenzi (2008)). Results indicate that fund managers may be substantially engaged in gaming behaviour themselves or be exposed to such within their corporate structure. As the fund grows, the agency problems will change due to changes in the oversight structure organization. This will have an effect on the stability of the risk measures.

This shows that it is somewhat unclear whether the stability of the risk numbers (as opposed to the levels of risk) is actually part of the fund manager's objectives. However, European legislation is trying to enforce this through the introduction of the Synthetic Risk Reward Indicator (SRRI). The SRRI is a metric that funds have to disclose to investors through the selling documents which aims at describing the riskiness of the fund by putting it into risk classes based on volatility bands ranging from 1 (low risk) to 7 (high risk). If the risk pattern changes, the SRRI has to be adapted accordingly. The exact determination depends on the fund type, but in most cases it is based on the realized volatility of the fund (ESMA 10-673).

Some of the fund managers are tied to a benchmark which will not allow them to diverge too much from a predefined asset allocation. Funds that are tightly bound to a benchmark will not be able to diversify more as they grow due to limited investment opportunities constrained by the assets in the benchmark. They will just have to scale their current investment selection up. This is backed by the results of Pollet and Willson (2008). The impact of the benchmark depends on the asset universe of the fund. Fixed income funds and balanced funds will be less exposed to the issue resulting from a benchmark as fixed income fund managers have a lot more investment opportunities with

similar risk patterns than e.g. an equity fund benchmarked against the EuroStoxx50.¹

The asset universe is another parameter that will affect the stability of the risk patterns as the fund grows. The range of risk numbers differs considerably as one would expect between equity and fixed income markets, so potentially the variations in portfolio risk show different behaviours. By definition, balanced funds have more flexibility regarding their asset allocation and investment selection as they may shift investments from risky asset classes to less risky ones in times of crisis. Further they may park large subscriptions in safer asset classes before investing them, so they have the possibility for better market timing of the investments of new money. Hence it makes sense to consider the investment universe when examining the stability of risk numbers of portfolios.

Overall, the risk pattern displayed by mutual funds is influenced by various factors. However, these factors have not been examined in depth. This study focuses on portfolio size in the context of mutual fund risk stability, i.e. it analyzes the volatility of the risk numbers as opposed to the levels only. The risk levels will be the choice of the investors when they select a fund (through its realized volatility) and the asset universe of the fund. The volatility of the risk measures will give an indication of the uncertainty of the adherence to the selected risk profile and finally to the variations of wealth of the investors.

The study aims at analyzing the dynamics of portfolio risk patterns. If performance is not a distinguishing factor between funds and passive strategies, it is somewhat intuitive to examine the second dimension of mutual fund performance with respect to its driving factors and distinguishing features in order to identify a potential field of value added to investors. Active risk management leading to more stable risk numbers could in particular be a distinguishing factor against the recently growing competition coming from ETFs. We focus on the impact of portfolio size on the stability of risk numbers to shed some light on the driver of the growth, the existence of large portfolios and the benefits of active portfolio management.

The rest of the chapter is organized as follows: The next section provides an overview of the relevant literature. Section 2.3 describes the sample examined. Section 2.4 analyses portfolio size and asset classes regarding the stability of risk metrics, whereas section 2.5 concentrates on the differences in the volatilities of dispersion and tail risk measures. Section 2.6 concludes this chapter.

¹Benchmarks of fixed income portfolios are typically large, often containing several thousands of bonds.

2.2 Review of Literature

2.2.1 Size and Portfolio Risk

A considerable amount of financial research has been devoted to examining the influence of portfolio size on mutual fund performance, but very few exist dealing with the relation of size and the volatility of risk. It has been shown that portfolio size has a mostly negative impact on the performance of mutual funds (Indro et al. (1999), Chen et al. (2004)). Indro et al. (1999) find that mutual funds have to reach a critical size to justify their costs, but that after a certain optimal size the marginal returns to information activities diminish. Decreasing returns to scale in information acquisition and manager turnover have been proposed as reasons for this by e.g. Berk and Green (2004). Another reason for this as presented by e.g. Chen et al. (2004) is asset liquidity, as the trading activities of larger funds have a higher market impact.

Regarding portfolio risk, classical financial theory suggests that with increasing portfolio size the risk levels of the portfolios should go down, as the portfolio can profit more from diversification effects (Markowitz (1952)). An analytical solution for this has been proposed by Elton and Gruber (1977). In their model of portfolio variance, risk goes down at decreasing rates as the number of assets is raised. However, this implies that the portfolio manager invests the new money in new assets and does not simply scale his current investment strategy up. It should be noted as well that this model relates to the levels of risk and not to the volatility of risk. Although one can assume that more diversification generally yields more stable risk numbers, there are obviously decreasing returns to scale regarding diversification. For large portfolios each asset added within the current investment universe will only very marginally reduce the risk levels after a certain critical number of assets is attained, so that at a certain level of diversification, the level of portfolio volatility will converge to a maximum diversified level in the asset universe the portfolio is invested in. Larger funds will be able to maintain this level more easily, they can hold bigger positions in their bets and they may vary exposures more easily. This will help them to keep the volatility of the risk numbers more stable. Passive strategies or ETFs will typically expose investors to a constant diversification level of volatility which will only vary with market volatility and not vary as the fund grows. Pollet and Willson (2008) find empirical evidence that equity mutual fund managers do not tend to diversify as the assets under management grow. Extending this stream of research, it is intuitive to examine size as well in a dynamic context as a factor regarding the stability of mutual fund risk. Portfolios that can allocate their investments between asset classes can obviously reach a higher degree of diversification.

To the best of our knowledge very few studies exist on variations of the risk numbers. Busse (1999) examines the variations of fund volatility based on time series

data and finds that fund managers are able to successfully time market volatility. He provides evidence that they vary their exposures as a response to changes in market volatility. He also finds that this is a distinguishing feature between surviving and non surviving funds. His findings show that portfolio managers can provide insurance against variations in the wealth of their investors.

Another stream of research on the agency problems induced by the two layers of delegation in the asset management industry shows that risk-taking behaviour and the role of portfolio size has to be seen in the light of agency problems as well. Tournaments between mutual fund managers were first empirically examined by Brown et al. (1996), who show that portfolio managers with a poorer performance alter their risk in a different manner than winning fund managers. Chevalier and Ellison (1997) also find evidence that fund managers alter the risk profile of their portfolios as a response to their realized performance. Kempf and Ruenzi (2008) extend this aspect to mutual fund families and show that mutual funds change their risk-taking behaviour depending on their rank within the family they belong to. Chevalier and Ellison (1999b) find that younger fund managers hold less systematic risk than older fund managers. Ding and Wermers (2009) find that independent directors impact the performance of mutual funds positively. Overall, one can state that the risk-taking behaviour of fund managers will be influenced by the agency and governance structure of the fund. Larger funds are more likely to be monitored more closely as they belong to bigger companies, where the oversight of the fund managers activities is organized in a more formal or rigorous framework, or they have predominantly institutional investors which monitor the fund manager's activities more closely due to legal obligations. Given these considerations one would expect them to be more disciplined with respect to risk profile than managers of small portfolios.

It should be noted that most of the studies focus on the level of risk numbers as opposed to the variations of risk, whereas for the context described above the dynamics of the risk numbers are even more important. To examine whether larger portfolios do indeed profit from economies of scale it is more adequate to look at the volatilities of risk numbers. As larger funds are likely to be able to handle cash flows induced by redemptions better and due to the fact that usually more resources are dedicated to large funds, one would expect that high total net assets funds are able to keep the volatility of risk measures more stable than small funds.²

This study aims at extending the body of literature initiated by Busse (1999) to provide more insights into which factors drive the funds' ability to supply a "hedge against volatility". For investors, the risk levels are primarily determined by the targeted asset class they choose to invest in. When this choice has been made, the stability of the risk numbers mirrored by the volatility of the risk measures becomes the key differentiating

²Large funds are more likely to be managed by teams instead of single managers or attract higher skilled fund managers due to better remuneration.

criterion (further to the return) for funds within the same asset class. After portfolio selection, i.e. the choice of the risk levels, the adherence to the selected risk profile is the most important aspect apart from the return delivered.

2.2.2 Risk Measures

Some practitioners argue that measuring the risk of portfolios that contain financial assets is more an art than a science as there is a plethora of risk metrics all based on different assumptions and methods, which in turn makes it harder to interpret and compare these numbers. Volatility is probably the most prominent measure in risk management. As a measure of dispersion over typically one year it describes the variation around the mean over that period. As such it contains substantial pitfalls e.g. the fact that it treats positive and negative returns equally.

Another wide spread risk number that overcomes this problem is the Value at Risk (VaR), which, as opposed to volatility, describes the worst loss for a given time horizon at a given confidence interval. As both numbers are different with respect to their interpretation, it is interesting to examine the impact of size on these two measures and whether fund managers manage the volatilities of these differently. A discussion of the risk measures themselves is beyond the scope of this text. An overview of estimation models for VaR and volatility can be found in Jorion (2006) or Andersen et al. (2006). A theoretical framework for coherent risk measures is provided by Artzner et al. (1999).

In this study we also examine whether there are differences regarding the stability of the risk measures presented above, i.e. if fund managers manage dispersion risk measures and tail risk measures differently. Further we examine if portfolio size has an impact on the differences, to extend the results presented above.

If a group of portfolios does indeed show higher variations in the VaR numbers, this would indicate that fund managers expose investors to more changes in tail risk (i.e. bigger variations of investors wealth) than to changes in portfolio volatility. This would mean that selecting a portfolio based on the volatility (or the stability of volatility) can lead to higher exposures to extreme risks. On the other hand, the opposite result might indicate that fund managers actually do care about extreme risks and provide security in times of highly volatile markets, which is typically where the tail risk losses occur.

2.3 Data

Our sample consists of daily data for 338 portfolios for the period between August 1, 2007 and May 5, 2011. The portfolios belong to mutual funds or insurance companies.

The data has been obtained from the database of ARKUS Financial Services.³ To avoid bias due to portfolio construction etc. we only include funds with a minimum record of 250 days. The sample has further been cleaned for some extreme outliers or inconsistent values, which will be due to data errors or set up errors in the risk system. The volatility (annualized standard deviation) as a measure of dispersion and two downside risk measures (Value at Risk and expected shortfall, both on a time horizon of 20 days and with a confidence interval of 0.99) are available to us. The numbers examined are ex-ante measures, that is to say they are estimates based on the portfolio holdings of the very day they have been calculated. The downside risk numbers are the result of Monte Carlo simulations whereas the volatilities are estimated through a linear factor model. The factor models used are statistical factor models from industry standard suppliers (such as Sungard APT or EM Applications). Survivorship bias does not seem to be an issue in our set-up as there is no evidence for correlation between survivorship and the risk stability - size relationship examined below.

As the estimation is based on the assets in the portfolio of that day, the estimates immediately reflect the fund manager's actions. In this way we have daily risk numbers that immediately reflect trades as opposed to purely return based time series data, which would only show the cumulated effect of all positions and reflect only trades if they have considerable impact on the returns. Another problem with return based risk measures is the smoothing induced by the choice of the time horizon that is used for the calculation of an historically realized volatility. Trades will have very little impact if a long time horizon is chosen. To illustrate this point, consider for example an equity portfolio closely replicating a major stock index. If the fund manager decides to hedge the long only portfolio with a short future for a day or two (which is not uncommon in current market conditions), the ex-ante risk estimates used in this study will immediately reflect this and yield lower risk estimates as they are directly based on the portfolio holdings. An estimate based on a time series model would only gradually come into effect with the latest observations dropping in. If the position is only maintained for a short period, it may, depending on the number of observations taken into account, have only very little effect on the final risk number. Return based time series estimates of portfolio volatility are as such not always adequate for the analysis of variation of portfolio risk. Using ex-ante risk numbers is quite distinguishing for the analysis presented below, as time series data is predominantly used in the research regarding portfolio risk. Further to the risk numbers the total net assets (TNA), the fund currency and the portfolio type (i.e. the asset class the fund invests in) are used.

The descriptive statistics of the sample are shown in tables 2.1 and 2.2. The values for the risk numbers lie in the expected ranges usually associated with the fund

³ARKUS Financial Services is a company which provides risk metrics and risk consultancy services to the financial industry.

types. The average volatility for an equity fund in our sample is 16.11% and has a standard deviation of 3.81%. For a balanced fund and fixed income fund the average risk levels and their standard deviations are, as to be expected, much lower with 6.57% and 4.67% respectively (standard deviation: 2.31%/1.44%). The average levels of volatility of balanced funds and fixed income funds are quite close which suggests that the subgroup of balanced funds is mainly composed of fixed income dominated funds. Looking at the tail risk measures, a similar picture evolves with the equities unsurprisingly being the riskiest class with an average VaR 20d 0.99 of 9.93% as opposed to 4.14 % (balanced) and 3.02% (fixed income). For the expected shortfall the picture is very similar with the exception that the standard deviations are higher compared to the VaR for all subgroups, which indicates that the behaviour at the extreme end of the tail of the returns shows more variation than the VaR. The average TNA is 863,6 million EUR. The biggest sub-group are balanced funds which is, with an average size of 1393,5 million EUR, also the biggest group in terms of TNA. Putting the numbers into perspective with respect to the SRRI (described in section 4.1) one finds that the equity portfolios range from risk class 4-7,⁴ whereas balanced funds would range from 3 to 5.⁵ These results are as expected and reflect the riskiness generally associated with these fund types.

⁴The maximum average volatility value is actually 24.52%, but taking into account the standard deviation of 3.81% it is save to include risk class 7 as well.

⁵Again quite close to the upper limit of 15%.

Descriptive Statistics Sample							
Subgroup	Min.	Mean Vola	Max.	Std Vola	Min.	VaRMean	Max.
Equity (n=50)	8.97	16.11	24.52	3.81	5.50	9.93	16.50
Balanced (n=164)	2.89	6.57	14.07	2.31	1.79	4.15	9.04
Fixed Income(n=94))	2.53	4.67	9.07	1.44	1.59	3.02	6.96
Fund of Funds (n= 28)	3.60	9.16	16.39	3.42	2.24	5.84	11.53
EUR (n=306)	3.41	7.01	13.78	2.25	2.11	4.43	9.45
Non-EUR(n=32)	6.95	14.14	23.33	4.05	4.33	8.87	15.62
Sample (n=338)	3.75	7.69	14.50	2.40	2.32	4.85	9.91

Table 2.1: Descriptive statistics I for the whole sample, fund types and Euro vs. Non Euro Funds.

Descriptive Statistics Sample								
Subgroup	Std VaR	Min.	Mean ES	Max.	Std ES	TNA		Nobs (Av)
Equity (n=50)	2.42	6.26	11.30	18.81	2.75	255	522 611.73	551.80
Balanced (n=164)	1.48	2.05	4.74	10.34	1.69	1 393	483 599.78	505.16
Fixed Income(n=94))	0.98	1.83	3.46	8.17	1.13	521	134 594.39	496.52
Fund of Funds (n= 28)	2.19	2.56	6.65	13.20	2.50	56	828 521.29	681.89
EUR (n=306)	1.46	2.41	5.05	10.87	1.68	903	265 766.72	518.84
Non-EUR(n=32)	2.58	4.93	10.12	17.84	2.94	457	936 564.52	581.19
Sample (n=338)	1.56	2.65	5.53	11.39	1.78	863	618 057.12	525.28

Table 2.2: Descriptive statistics II for the whole sample, fund types and Euro vs. Non Euro Funds.

2.4 Portfolio Size and the Volatilities of Risk Numbers

2.4.1 Cross Sectional Evidence

To examine the effect of TNA (i.e. fund size) on the stability of the risk numbers, we conduct cross-sectional regressions on the standard deviations of the risk numbers across the funds.

First we calculate the standard deviation of the daily risk numbers for each portfolio in our sample for all observation dates available. This yields 338 daily volatilities of the estimated portfolio volatility, the VaR and the expected shortfall. To measure size we use the average TNA of each fund for the sample period available. As the regression variables (precisely the TNA and the volatilities of risk numbers) are extremely skewed to the right across the sample we use the log values of those variables in the regression.

In a first step we estimate the following model for the whole sample:

$$\log(\sigma_{rm_i}) = \beta_0 + \beta_1 * \log(TNA_i) + \beta_2 * DEQ + \beta_3 * DBAL + \beta_4 * DFI + \beta_5 * DNONEUR + \epsilon_i \quad (2.1)$$

where:

σ_{rm_i} = The standard deviation of the daily estimated risk measure for each portfolio (volatility, VaR, expected shortfall)

TNA_i = The average total net assets of the portfolio

DEQ = Dummy variable for equity funds

$DBAL$ = Dummy variable for balanced funds

DFI = Dummy variable for fixed income funds

$DNONEUR$ = Currency Dummy (Variable that takes the value 1 if the portfolio Currency is not EUR and 0 otherwise.)

ϵ_i = IID error term

We include a constant to model a general level of market variation in the risk numbers that e.g. might be induced by changes in general market conditions or external shocks. It could further account for other parameters that influence risk in a structural way, such as estimation error by the fund manager or systematic changes in risk patterns due to agency problems. The Dummy variables are included to reflect the fact that the risk levels and their variations will differ considerably across asset universes. To avoid redundancy in the model we do not include Dummy variables for the fund of funds and hedge funds in our sample. Further we control for currency effects through the inclusion of the currency dummy. The differences between EUR and Non-EUR funds can clearly be seen from the sample overview in tables 2.1 and 2.2. To further check the results for robustness we re-estimate the model varying the set-up regarding the Dummy variables as presented in table 2.3.

The results of the regression for the volatilities of the volatility (vovo) of the portfolios are presented in table 2.3. The beta is significantly negative for the size factor (TNA) in all models estimated. So even when controlling for fund type and a constant to reflect general market conditions, the first results support the hypothesis that bigger funds have more stable risk measures i.e. expose investors to less variations regarding the risk profile of the portfolio. This indicates that bigger funds are able to profit from economies of scale in risk management as they manage risk more efficiently and keep their risk numbers more stable.

The estimated coefficients for the balanced and fixed income sector are significantly negative in the most comprehensive set-ups. These results regarding the Dummy variables for the fund types are not surprising, as they indicate that the variations in risk are lower for balanced and fixed income funds than for equity funds where the Dummy variable does not have a significant effect. This is in line with expectations, particularly for fixed income and balanced funds, as these subgroups are associated with lower risk levels in general. However, it should be noted that these results are sensitive to the inclusion of the full set of control variables. Further the inclusion of a constant proves to yield a significant estimate in all models estimated, so there is a structural element in the variations of portfolio risk.

To check the results for robustness we run the same regression as above on the tail risk measures available in our sample. So we regress the same explanatory variables against the volatility of the VaR (VoVaR) and the volatility of the expected shortfall. The results are presented in tables 2.4 and 2.5.⁶

⁶Analysis of the residuals carried out for all three models does not reveal any particular problems

Regression Results Volatilities						
Intercept	$\log(TNA_i)$	DEQ	DFI	DBAL	DNONEUR	R^2
3.9243*** (9.2256)	-0.1277*** (-6.0435)	-0.2353 (-1.2016)	-0.4744*** (-2.8807)	-0.9285*** (-5.3555)	0.6995*** (-4.2733)	0.2737
3.1270*** (7.976)	-0.1219*** (-5.635)	0.0144 (0.075)	-0.4632*** (-2.743)	-0.8708*** (-4.912)		0.2245
2.8355*** (7.0758)	-0.1425*** (-6.4916)	0.6571*** (4.5358)	0.2077** (2.0225)			0.1782
2.8626*** (7.1146)	-0.1374*** (-6.2749)	0.5445*** (4.0526)				0.1681
3.2433*** (8.106)	-0.1541*** (-7.002)					0.1273

Table 2.3: Regression results volatility of volatility for the whole sample (n= 338). Here and in the following tables: t-values in parantheses, *** = significance level of 99%, ** = significance level of 95%, * = significance level of 90%. The results indicate that bigger funds show significantly more stable risk numbers. This finding holds for all set-ups examined.

The effect of portfolio size remains significantly negative across all models estimated and is robust across the risk numbers. It persists for dispersion as well as tail risk measures. The sensitivity to size is in the same range across the risk measures, though a little less in magnitude. Overall the results confirm the hypothesis that bigger funds are more stable in their risk numbers. Size matters for the stability of risk numbers. As to be expected the most negative coefficient is observed for the fixed income sector. The general tendency of results regarding significance and the direction of the effect is very similar across the different risk numbers, indicating that the explanatory variables influence tail risk and dispersion risk measures in a similar fashion. Overall the results regarding the size effect are robust to variations in the set-up of the model.

with autocorrelation or non-normality. (Durbin - Watson Statistic: 1.91 (Vol)/1.85 (VaR)/1.84 (ES) and Jarque - Bera Statistic: 2.67 (Vol)/3.06 (VaR)/3.34 (ES)).

Regression Results Value at Risk						
Intercept	$\log(TNA_i)$	DEQ	DFI	DBAL	DNONEUR	R^2
2.4759*** (6.3437)	-0.1091*** (-5.0653)	-0.2524 (-1.2646)	-0.5056*** (-3.0125)	-0.9032*** (-5.1121)	0.661*** (3.9624)	0.2344
2.3836*** (5.987)	-0.1036*** (-4.716)	-0.0164 (-0.084)	-0.4950*** (-2.887)	-0.8487*** (-4.715)		0.1982
2.0997*** (5.1732)	-0.1236*** (-5.5631)	0.61*** (4.158)	0.1589 (1.5278)			0.1447
2.1202*** (5.2169)	-0.1198*** (-5.4147)	0.5239*** (3.8602)				0.1387
2.4864*** (6.1655)	-0.1358*** (-6.1227)					0.1004

Table 2.4: Regression results volatility of VaR for the whole sample (n= 338). It is visible from this table that the negative effect of portfolio size on the stability of risk numbers could be confirmed also the VaR.

Regression Results Expected Shortfall						
Intercept	$\log(TNA_i)$	DEQ	DFI	DBAL	DNONEUR	R^2
2.5806*** (6.5992)	-0.1074*** (-4.9781)	-0.2552 (-1.2762)	-0.5066*** (-3.0126)	-0.8994*** (-5.0804)	0.6559*** (3.9241)	0.2302
2.4891*** (6.243)	-0.102*** (-4.635)	-0.021 (-0.108)	-0.4961*** (-2.889)	-0.8453*** (-4.689)		0.1944
2.2061*** (5.4296)	-0.1219*** (-5.4799)	0.6028*** (4.1043)	0.1552 (1.4903)			0.1413
2.2263*** (5.4725)	-0.1182*** (-5.3362)	0.5188*** (3.8183)				0.1355
2.5889*** (6.4163)	-0.134*** (-6.0394)					0.0979

Table 2.5: Regression results volatility of expected shortfall for the whole sample (n= 338). As per this table the size effect can also be found for our sample using the Expected Shortfall as a tail risk measure.

2.4.2 Risk Stability and Asset Universes

2.4.2.1 Design of the Analysis

The analysis so far is carried out on the sample as a whole. To gain further insights into the effect, we examine the relation of portfolio size and risk stability by the investment universe. To do so we split the sample into subgroups by asset type (equity, balanced, fixed income) and conduct the following cross sectional regressions for each subgroup individually.

The regression formula is as follows:

$$\log(\sigma_{rm_i}) = \beta_0 + \beta_1 * \log(TNA_i) + \beta_2 * DNONEUR + \epsilon_i \quad (2.2)$$

All variables are defined as in the previous section. The constant is also used to minimize the potential effect of omitted variables.

2.4.2.2 Fixed Income

As visible from table 2.6, the negative relation between the stability of the risk numbers and the size of TNA can be confirmed for the fixed income subgroup. The estimated coefficients are significantly negative in the model estimated for this subgroup with the effect being more pronounced in magnitude for this subgroup than for the whole sample in the first set-up. The effect remains significant for the tail risk measures, albeit at a slightly lower level. The portfolio currency does not have a significant impact on the volatility of the tail risk numbers (see table 2.6). It is significant for the vovo though, which might hint a different pattern in that respect for positive and negative returns. Although the explanatory power is substantially lower than in the set-up of the previous section, it is still at an acceptable level for cross sectional regressions.

Regression Results Fixed Income Funds				
Risk Measure	Intercept	$\log(TNA_i)$	DNONEUR	R^2
Volatility	2.3845*** (3.0710)	-0.1316*** (-3.1130)	0.5198** (1.8930)	0.1204
VaR	1.8494*** (2.3300)	-0.1232*** (-2.8500)	0.4570 (1.6280)	0.1001
ES	1.9696*** (2.4640)	-0.1221*** (-2.8050)	0.4486 (1.5870)	0.0969

Table 2.6: Regression results for the standard deviations of the risk measures for the fixed income subgroup (n= 94). The size effect is confirmed for this subgroup across the model estimated.

2.4.2.3 Balanced

The subgroup containing the balanced portfolios yields the most significant estimates of all subsamples. The negative relation between portfolio size and the volatilities of the risk numbers can be confirmed for the dispersion and the tail risk measures. The size effect regarding the stability of risk numbers is most pronounced for balanced funds. The currency Dummy shows a significantly positive coefficient at the 5%-level, which is more pronounced in magnitude than the beta estimated for the size factor as can be seen in table 2.7. This shows that the portfolios with a base currency other than Euro show considerably higher variations in risk. Once again the inclusion of the constant yields a significant coefficient. The balanced subgroup is the asset universe where the highest R-Squared can be observed in this set-up.

Regression Results Balanced Funds				
Risk Measure	Intercept	$\log(TNA_i)$	DNONEUR	R^2
Volatility	3.4046*** (6.4490)	-0.1636*** (-5.7700)	0.9148*** (2.3820)	0.2025
VaR	2.5465*** (4.7220)	-0.1407*** (-4.8580)	0.8486** (2.1630)	0.1559
ES	2.6477*** (4.9000)	-0.1388*** (-4.7860)	0.8457** (2.1520)	0.1524

Table 2.7: Regression results for the standard deviations of the risk measures for the Balanced subgroup (n= 164). This subgroup also displays significantly more stable risk numbers for bigger funds throughout the models examined.

Regression Results Equity Funds				
Risk Measure	Intercept	$\log(TNA_i)$	DNONEUR	R^2
Volatility	0.5114 (0.5020)	0.0203 (0.0605)	0.5648** (2.319)	0.1192
VaR	-0.1879 (-0.1820)	0.03415 (0.5570)	0.5654** (2.2900)	0.1253
ES	-0.1879 (-0.0850)	0.0359 (0.5900)	0.5619** (2.2980)	0.1272

Table 2.8: Regression results for the standard deviations of the risk measures for the equity subgroup (n= 50). The size effect could not be found for this subgroup.

2.4.2.4 Equity

No evidence for the size effect in the equity sector could be found in the sample as can be seen in table 2.8. The pattern remains the same for the dispersion and tail risk measures.⁷ This is in line with what we expect given the results of Pollet and Willson (2008) as it indicates that equity fund manager simply scale their existing strategy up as the fund grows. The constant is insignificant in this set-up for all risk numbers examined. The estimated beta for the currency Dummy is positive and significant at the 5%-level for this subgroup. As for balanced funds the effect seems to be higher than that of the size effect in terms of magnitude, but overall it ranges on lower levels of significance. This finding holds for dispersion as well as tail risk measures.

2.4.3 The Impact of Portfolio Size on the Stability of Portfolio Risk

The evidence presented above suggests that bigger funds keep their risk numbers less volatile than small funds, so they expose investors to less uncertainty about the adherence to a risk profile of the fund they selected. As they have more resources available (better fund managers/analysts) and as they can react better to changes in cash flows, this is generally an expected result. However, looking at the investment universe yields a more diverse picture.

Balanced funds and fixed income funds do indeed show economies of scale in risk management with respect to portfolio size. Such an effect could not be found for equity funds, however. Balanced funds seem to profit most from size which is not surprising

⁷Subdividing the equity subgroup yields negative betas for some subgroups with lower marginal probabilities, but still no significant effect.

since these funds may invest across asset type and can thus use diversification effects more intensively. If their portfolio grows in size, they have more flexibility in risk management to keep the risk stable in times of highly volatile markets (flexible asset allocation between riskier and safer asset classes). Furthermore they can handle new cash inflows better as they may park them in safer asset classes. This finding shows that flexibility for fund managers regarding the asset universes they invest in may yield less variations in the risk profile of the fund as it grows compared to funds that invest only in a single asset class.

Regarding fixed income funds, the fact that larger funds can manage the risk numbers more easily in this group might be linked to certain properties of the fixed income market. As the fund grows, it almost inevitably has to diversify across bonds, as new debt is permanently issued and the positions in the portfolio cannot be simply scaled up due to constraints in the issued amount or illiquidity on the secondary market. Further, each new investment (which might be induced by new inflows as well as bonds that matured, both obviously coming more into play for large funds) will be done in the light of the current estimate of the yield curve development so the investment and risk strategy is bound to be updated regularly. This is obviously more often the case for bigger funds that have to diversify across many debt issues.

For the equity subgroup no significant effect related to size could be found. This is in line with the evidence presented by Pollet and Willson (2008) who show that equity funds just scale their existing portfolio strategy as the assets under their management grow. It is quite intuitive that equity funds after having attained a certain size do not find any further attractive investment opportunities in their investment universe and consequently keep on playing their current bets, if they receive new money inflow. This holds even more true for equity funds that are closely tied to a benchmark so their diversification potential is limited. These funds have very little possibilities to profit further from diversification as they grow, so their only means to manage risk stability is derivatives (if they may invest in these after all). However, the use of derivatives for hedging purposes will not be significantly affected by the size of the portfolio.

Further this study presents evidence that the Non-EUR funds show higher variations in risk in some asset universes. The effect is most pronounced and significant for the subsample containing the balanced funds, but it is also significant at the 5% level for the equity subgroup. As the sample is dominated by Europe-based portfolios this is a somewhat intuitive result. Overall the effect of a Non-EUR base currency seems to have a higher impact on the stability of risk numbers than the size effect, though at overall lower levels of significance.⁸ As the sample (or the management companies of the portfolios in our sample) is EUR dominated, potentially the fund managers have less experience and expertise in Non-EUR markets consequently their skills in managing risk in these regions

⁸It should be mentioned that the subgroup of NON-EUR funds is rather small with $n = 32$.

are less good than for investments in their home currency. This might be an indication for a home bias of fund managers regarding their managing skills in foreign currencies.⁹

2.5 Variations in Tail Risk and Dispersion Measures

2.5.1 Motivation

As mentioned above volatility, although used predominantly in practice, suffers from substantial pitfalls in the context of risk measurement. The most striking problem comes from the fact that it treats positive and negative deviations from the mean equally, whereas in the context of asset management positive returns are obviously desirable. This is the reason why loss-based measures such as VaR and Expected Shortfall were advocated for risk measurement purposes. So despite the latest regulatory emphasis on volatilities, tail risk measures are more suited as they capture "real" losses which, particularly in times of crisis, is what matters for investors in terms of risk. Regarding the stability of the risk measures, it is interesting to verify if there are differences in the volatilities of these risk numbers and if the size of the portfolio has an impact on these differences. Differences will be induced by non-linear products such as options and certificates. It is interesting to examine the investment universes regarding differences between the two types of measures as the availability of such products will typically be different across asset classes.

2.5.2 Aligning Tail Risk Measures and Volatilities

Different risk metrics such as VaR and volatility are somewhat difficult to compare as they are conceptionally different (as mentioned above). The volatilities of the risk metrics used in the analyses above, which are based on the original numbers, differ regarding the time horizon and as such are difficult to compare. To derive a meaningful comparison of the variations of both risk numbers we take the following approach. First, we derive a VaR number from volatility that matches the time horizon and confidence interval (20d, 0.99 CI) to convert the volatility estimate into the equivalent tail risk measure, in this case the VaR.

This is done using the following formula:

$$VaR(20d, 0.99)_{i,t} = \frac{\sigma_{i,t}}{\sqrt{12}} * f_{0.99} \quad (2.3)$$

⁹Please note that when referring to currencies here we relate to the base currency of the fund as opposed to the currencies of the investments of the fund.

$\sigma_{i,t}$ = The estimated portfolio volatility (annualized) per portfolio and trading day.

$f_{0.99}$ = The 99% percentile of the standard normal distribution.

ϵ_i = IID error term

So for each daily volatility of each portfolio we derive a linear VaR at the 99% confidence interval with a time horizon of 20 days. The scaling rule with the square root of time assumes the iid property of the underlying returns. The multiplication with the corresponding percentile of the normal distribution obviously implies the normality assumption. This approach gives us two sets of VaR numbers on the same VaR set-up for all datapoints available per portfolio. They differ with respect to the methodology used (linear VaR vs MC VaR) but are based on the same underlying factor model. Next we calculate the standard deviations of these linear VaR numbers for each portfolio to obtain the variations of the newly calculated risk numbers.

Following this step, we calculate the difference between the volatilities of the Monte Carlo VaR and the linear VaR, now on the same time horizon.

$$\Delta_{\sigma_{VaR,i}} = \sigma_{VaRMC_i} - \sigma_{VaRLinear_i} \quad (2.4)$$

In this way we obtain a series of the differences between the volatilities in linear and Monte Carlo VaR across the portfolios. If the difference is positive, it means that the observed volatility of the simulated VaR was higher than that of the equivalent derived in a linear framework assuming a Gaussian. In this case the portfolio would have exposed investors to more variations in tail risk than measured through volatility.

2.5.3 Portfolio Size and Differences in Tail Risk Measures

The mean of the difference is -0.0554% and its standard deviation of 0.2623% indicates that it is spread around zero. However, a t-test reveals that the mean is significantly smaller than zero (t-stat= -3.89). This gives evidence that the tail risk measures show more stability than the equivalent figure derived from the dispersion measure volatility. When turning to the subgroups of funds, we find that it is significantly different at the 99%-level for the equity and balanced funds (t-stats= -2.96 and -3.90) but not so for fixed income funds (t-stat= 0.42). This might stem from the fact that there are far fewer non-linear investment products available for the fixed income market than for the equity market. These products will typically cause differences in the tail of the simulated distribution between the linear and Monte Carlo VaR numbers, as the latter will account

for non-linearities. So based on our sample we find that overall investors were relatively less exposed to volatilities of tail risk measures than to the volatilities of the volatility. That is to say that extreme risks were contained more stable than the overall dispersion of the returns.

To further examine the role of portfolio size in this context we conduct regression on the differences between the risk measures with models of the form:

$$\Delta_{\sigma_{VaR},i} = \beta_0 + \beta_1 * \log(TNA_i) + \beta_2 * DEQ + \beta_3 * DBAL + \beta_4 * DFI + \beta_5 * DNONEUR + \epsilon_i \quad (2.5)$$

All variables are defined as above. We include a constant to account for possible structural differences between the methodologies that might affect the variations in risk numbers (Normality assumption vs MC). The results are presented in table 2.9. The significant coefficient for the constant suggests that there are indeed structural differences in the variations. As the estimated coefficient for the constant is significantly negative, we see that the variations in tail risk measures are less pronounced than for the dispersion measures in our sample.

Accounting for the investment universe and fund currency, the coefficient for portfolio size is significantly positive, which indicates that size has a positive impact on the difference in volatilities. The effect persists for all models estimated. So for larger funds the difference moves closer to zero. This means that for larger portfolios the volatilities of dispersion and tail risk measure become more aligned.

Further the results indicate that the differences in the stability of the risk numbers are not significantly influenced by the investment universe. This can be seen by the fact that the coefficients estimated for the fund type Dummy variables are all not significant in almost all set-ups estimated. The effect of the fund currency seems to be higher in magnitude, but it is only significant at the 10% level.

2.5.4 Implications for Risk Managers and Investors

Overall it has been shown for our sample that the original tail risk measures are less volatile than the equivalent derived from the volatility. So the tail risk measures are contained more stable than the dispersion measures. Tail risk stability seems to matter to fund managers more than volatility, which seems natural given the shortcomings of the concept described above. At first glance there seem to be differences between the subgroups with their different investment universes, but when accounting for an overall structural difference between the two methodologies through a constant and for portfolio

Regression Results Delta VaR						
Intercept	$\log(TNA_i)$	DEQ	DFI	DBAL	DNONEUR	R^2
-0.4958*** (-4.1317)	0.026*** (3.9194)	-0.0514 (-0.8380)	-0.0493 (-0.9555)	0.0407 (0.7497)	-0.0846* (-1.6488)	0.0811
-0.4840*** (-4.030)	0.0253*** (3.8110)	-0.0816 (-1.3900)	-0.0507 (-0.9790)	-0.0337 (0.6220)		0.0736
-0.4727*** (-3.9856)	0.026*** (4.0107)	-0.1065*** (-2.4846)	-0.0767*** (-2.5223)			0.0725
-0.4827*** (3.7206)	0.0242*** (3.7206)	-0.065* (-1.6287)				0.0549
-0.5281*** (-4.5347)	0.0262*** (4.088)					0.0474

Table 2.9: Regression results Delta VaR for the whole sample (n= 338). The results indicate that volatilities of risk numbers are more aligned for larger funds.

size, no significant difference persists between the subgroups. From a risk manager's perspective it certainly makes more sense to look at the tail risk measures as these try to capture "real" losses, as opposed to the dispersion of positive and negative returns. However, considering that volatility is still predominately used in performance evaluation of fund managers in practice, this finding is a little astonishing.

The differences in volatilities are less pronounced for bigger funds, which indicates that smaller funds provide more relative stability of tail risks. Putting this into perspective with the results from section 3 reveals an interesting aspect. The previous section shows that bigger funds contain their risk numbers more stably compared to smaller funds, however the results presented here show that bigger funds provide fewer differences in the variations between extreme risks and dispersion risk. That is to say small funds display lower relative volatilities in the loss-based risk measures. This needs of course to be seen in the light that the overall variations for small funds tend to be at higher levels. So portfolio size seems to have an impact not only on the volatility of the risk numbers, but also on the differences between tail risk and dispersion risk measures. The reasons for this might be associated with higher level of diversification or more resources dedicated to risk management. This would be an interesting subject for future research. Another potential reason for this might be more extended usage of non-linear products in small portfolios (or a higher impact of these in small portfolios).

When accounting for the structural difference and TNA, no significant difference could be found between the asset universes of the portfolios. This indicates that the asset universes do not seem to cause differences in the management of tail risk.

So overall this study presents evidence that small funds expose their investors to higher volatilities of the risk numbers in general, albeit at relatively lower variations of extreme risks. Portfolio size matters for both the volatilities of the risk numbers and

the differences between loss-based measures and variation-based measures. As the assets under management grow, the variations between the two classes of risk numbers become more aligned.

2.6 Conclusion

This study finds that the volatility of risk numbers is significantly negatively related to portfolio size measured by the TNA. Even when controlling for fund type, a constant to reflect general market conditions and fund currency, evidence was presented that bigger funds have more stable risk measures. The effect of size remains significantly negative across all the models estimated so it persists for dispersion as well as tail risk measures. The sensitivity to size is in the same range across the risk measures, though a little less in magnitude. Further analysis conducted on the sample divided by subgroups shows that the effect remains robust for fixed income and balanced funds, but not for equity portfolios. The latter is in line with former research on equity portfolio risk and indicates that equity funds do not diversify more as they grow (Pollet and Willson 2004). This might be the case because they are tightly linked to a benchmark and as such may not profit from economies of scale in risk management when the assets under management grow. In contrast, balanced funds and fixed income funds may well profit from such economies of scale if the fund size grows.

So larger funds expose investors less to variations in the risk patterns of the portfolio they have selected. However, this effect depends on the investment universe of the portfolio. Further we find indications that Non-EUR funds show higher variations in risk numbers for both dispersion and tail risk numbers. The impact seems to be higher in magnitude than the size effect, but overall at a lower level of significance, being most significant for equity and balanced funds. Further to that, evidence was found that the volatilities of tail risk measures and dispersion risk measures show different patterns. The volatilities for the dispersion risk measures are higher, which can be interpreted as a sign that fund managers manage tail risk differently than overall volatility. The difference seems to be less pronounced for larger funds than for small funds. So smaller funds (measured by the TNA) expose investors to less variations in tail risk compared to variations in volatilities, whereas high TNA funds show more alignment in that respect. This, however, has to be seen in light of the fact that the variations of bigger funds are generally at lower levels for the risk numbers (if you look at them in isolation). Initially the results indicate that there are differences between the asset universes of the funds regarding the differences between tail risk and dispersion measures, but these do not persist when one accounts for structural differences and portfolio size. Overall it can be stated that portfolio size impacts the stability of risk numbers as well as the differences between loss-based measures and dispersion-based measures.

Larger fixed income and balanced funds profit from economies of scale and offer as such a non negligible alternative to passive investments. Further, small funds seem to offer different risk patterns regarding tail risk and dispersion risk. This is one aspect that may lead to the growth of large funds despite the widespread longterm underperformance of

mutual fund managers. The findings of this study further extend the argument raised by Busse (1999) that actively managed funds may provide a hedge against volatility.

Future research might focus on the origin of differences of the diversification between the asset universes, e.g. the verification of whether there is a critical level of equity investments that leads to the loss of the economies of scale. Further the impact of recent legislation (such as the ESMA guidelines), which classifies mutual funds into risk classes based on the realized volatility, should be examined in the light of these results. Another interesting topic for future research would be to examine whether risk stability is costing investors a premium in terms of lower returns.

Chapter 3

Systemic Impact of the SRRI and Implications for Fund Management

3.1 Introduction

Recently introduced European regulation implicitly overlays the core strategy of a mutual fund under the regime for undertakings for collective investments in transferable securities (UCITS) with a long term target volatility strategy, if investors are unwilling to accept a change in the risk class of their fund. In this context we would like to examine two questions. Firstly, what is an effective way to keep the volatility in the desired risk class and secondly, how far this will alter the investment strategy of a portfolio and what will be the systemic effects.

To maintain a predetermined volatility band we use strategies that are structured along the investment constraints for UCITS funds, i.e. we examine two risk on - risk off strategies that cut all exposures to the market, if the upper limit is exceeded and raise the exposures, if the realized volatility falls below the lower limit. We find that huge variations in exposures would be required to maintain the risk bands and that in some cases funds would not be able to keep the risk class. The impact on the investment strategy can at times be quite substantial and potentially induce style drift. We further find that the SRRI may cause systemic effects at an aggregate level. As they may lead to herding behaviour and considering the well documented phenomenon of volatility spillovers between equity markets, there is a danger of a potential amplification of extreme events.

The rest of the chapter is organised as follows. Section 3.2 outlines in detail the regulatory framework and the impact on fund management to finally outline the

investment strategies used in section 3.3 for historical backtesting of said investment strategies outlining the problems associated with the SRRI. Section 3.4 examines potential herding effects induced by the SRRI and section 3.5 concludes this chapter.

3.2 Fund Classification and Impact on Portfolio Management

3.2.1 Regulatory Background

Investment funds in Europe are required to publish a document that contains principle information about the strategy, costs, risk and return characteristics of the fund (Key Investor Information Document - KIID). One element of this document is the so called Synthetic Risk Reward Indicator (SRRI) which classifies funds according to their riskiness (ESMA 10-673). The aim is to improve comparability and investor awareness of the risks associated with their investments. The classification is based on the volatility of the portfolio and is performed according to table 3.1.

SRRI Risk Classes		
Risk class	Volatility \geq	Volatility $<$
1	0%	0.5%
2	0.5%	2%
3	2%	5%
4	5%	10%
5	10%	15%
6	15%	25%
7	25%	

Table 3.1: SRRI risk classes on corresponding volatility buckets as defined in the ESMA 10-673 guidelines.

Initially one has to determine to which fund type the strategy belongs. The process for the determination of the fund types is outlined in the decision tree in figure 3.1. As you can see the distinction is made between investments across asset classes, the constraint through a risk limit, the change of the asset allocation and pay-off structures. In the case of a market fund¹⁰ the historical annual volatility of its weekly return time series or of

¹⁰According to ESMA 10-673 market funds are portfolios whose investment objective is to reflect risk and return characteristics of specific predetermined market segments.

a representative asset mix (resp. Benchmark) are used to calculate the SRRI. In other cases the volatility reverse engineered from the VaR limit or the maximum of all three are used to read the risk class from table 3.1. This approach applies for absolute return or total return funds. Regarding structured funds a simulation study is required to obtain a VaR number that may be transferred into a volatility number. Most of the standard funds that follow an index for retail investors will fall into the category of market funds.

Should the volatility obtained by one of the approaches above not lie within the current range for more than 16 weeks, the SRRI will change into the new risk class and consequently the KIID needs to be updated. This may be undesirable from a fund's point of view for two reasons. Firstly, of course, the administrative burden is cumbersome and costly. Secondly, the change of the risk class may incline investors to reallocate their funds, if the new risk and reward structure does not suit their investment objectives. This may be the case for migrations to riskier classes as well as to less risky classes as both signal deviations from the risk and reward profile initially subscribed by investors. To avoid outflows and supplementary costs the fund manager needs to keep the risk classes stable. This overlays the core strategy of the fund with a longterm volatility strategy.

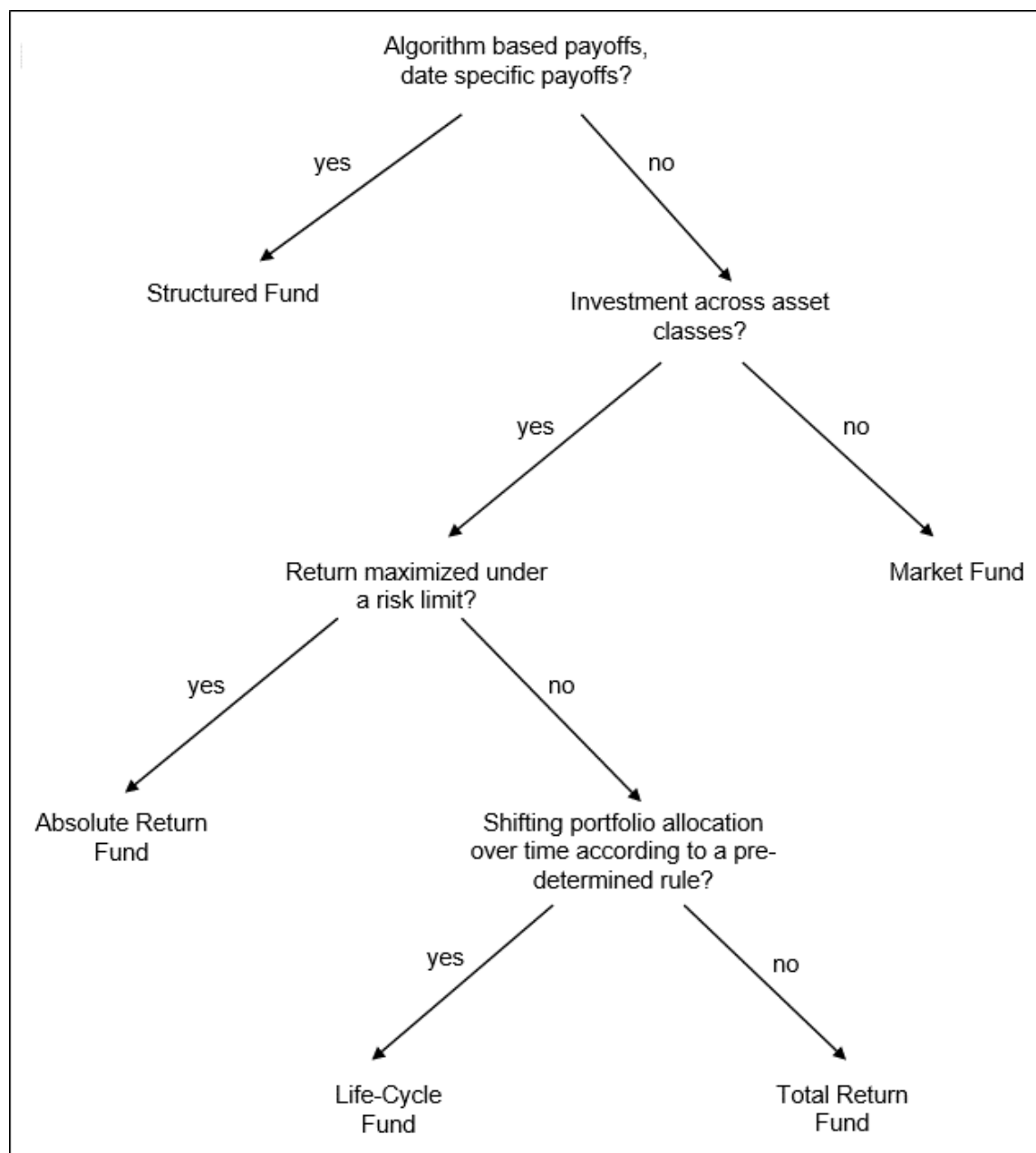


Figure 3.1: This figure shows the decision tree that is applicable as per the ESMA 10-673 Guidelines to determine the fund type for SRRI purposes.

3.2.2 Critical Review of the SRRI

3.2.2.1 General Remarks

Although volatility plays a predominant role in asset and risk management, its drawbacks are well known and have been discussed extensively in literature. Being a measure of dispersion volatility treats positive and negative returns equally, which is not quite intuitive since positive returns are generally beneficial for investors. Overall, Arztnner et al. (1999) conclude that volatility is not a coherent measure of risk. However, the regulatory background described above paves the way to foster its role even further. Regulators attempt to force fund managers to take a more dynamic perspective in their assessment of portfolio risk rather than looking at the levels of risk measures only. For the SRRI it is the stability of the risk measure (or more generally the risk profile) of the fund that has been added to the objective function of the fund managers. Besides the particularities of the measure chosen to describe the riskiness of a portfolio, it is quite surprising that the level of the returns does not come into play at all. It is standard in the asset management industry (by researchers and practitioners) to consider the risk and return dimension when measuring the performance of mutual funds. As the name SRRI suggests, regulators have been aware of this as well. However the SRRI is only based on the risk dimension, in that sense the term is somewhat misleading.

3.2.2.2 Implications for Fund Management

The implications of the SRRI will depend on the fund type chosen. However, for market funds and in certain cases for absolute and total return funds, realized volatility is the decisive metric for the SRRI and as such needs to be monitored and controlled. So it is worth having a closer look at this metric with respect to its implications.

The concept of the SRRI effectively overlays the core investment strategy with a secondary investment principle based on the long term ex post volatility of the fund's returns. This overlaying strategy will only be applied if investors are unwilling to accept the new risk class and exercise their power accordingly.

To avoid changes in the risk class the portfolio manager either needs to reduce the risk in the portfolio, if the portfolio migrates to a riskier class, or increase the risk in case of a transition to a less risky class. In the first case the fund manager needs to deliver the realized mean of weekly returns in the upcoming weeks to add as few dispersion as possible and bring portfolio volatility back to lower levels. This is of course only a theoretical alternative for mainly two reasons. Firstly it would require perfect information by the fund manager, particularly perfect prediction capacities and secondly,

from a more practical angle, if the realized mean was close to zero or even negative, it would certainly not be in the interest of neither fund manager nor investors to repeat this outcome to maintain the risk band. In practice achieving lower realized volatility will go along with a reduction of exposures to either the entire market or high risk stocks.

In order to bring realized volatility up, fund managers need to add as much variation to realized returns (ideally to the positive side) as possible by raising the exposure e.g. through derivatives. An alternative would of course be to raise the concentration in the portfolio (i.e. reduce the number of positions by taking out less risky assets), but this would of course also need to be seen in the light of return expectations the fund manager has. It should be noted that the SRRI is based on longterm data (250 datapoints of weekly data) so it will show a rather smooth pattern in most of the cases and fund managers are given a 16 weeks grandfathering period. However, depending on the distance between the current volatility and the critical limit of the binding risk class the strategy will take some time to bring volatility back down (or up) as new observations only have a limited impact. The indirect effect of high contributing observations dropping out may be much more pronounced.

The course of the metric chosen to be relevant for the determination of the risk class can be characterized by two patterns. The first is a trendlike movement within its current regime which may lead to a smooth migration to other classes. In this case the fund manager can react gradually and will have time to re-allocate the portfolio if the trend proves to be persistent. On the other side volatility is exposed to shocks induced by systemic events (see e.g. Engle (2001) or Engle and Patton (2001)). This pattern, also known as regime switches, in conjunction with the fact that fixed boundaries are prescribed by regulators, will create pressure on fund managers to reduce their exposures drastically in a very timely manner in an attempt to maintain the current risk class, if such shocks (or more generally volatility regime shifts) put their realized volatility into a higher risk class.

On the other side, the opposite is true in times of lower volatilities where fund managers are inclined to raise the exposure by e.g. leveraging the portfolio up to keep higher volatilities. This second aspect may also occur in an ad hoc way when e.g. highly contributing observations drop out of the observation period. In this case fund managers would generally be able to anticipate the effect, though. Another potentially problematic phenomenon around volatility is that it tends to cause spillovers between equity markets. This may lead to herding behaviour consequently creating the danger of an amplification of extreme events and contagion of market slides across equity markets.

There will be limits as to how much variation a UCITS fund can add to the portfolio, as they are constrained through either VaR or leverage limits. Most portfolios classified as market funds can not use derivatives extensively and have a legal maximum limit of 100% on the leverage, so the maximum exposure to the market is 200%.

This would be the case for portfolios that monitor their global exposure through the commitment approach as per ESMA Guidelines 10-766. This restriction would not apply for funds measuring their global exposure through the Value at Risk approach.¹¹ It should finally be noted that any trading activity taken as response to the SRRI will incur supplementary trading costs that will be borne by investors. Further to this, potential migrations will evoke additional administrative burden for the management company of the funds as the investor and marketing documents will have to be changed.

3.2.3 Investment Strategies Based on the SRRI

As mentioned above, if the SRRI creates a binding mechanism for fund managers, it basically introduces a longterm volatility trading strategy that overlays the core strategy of the portfolio. That is to say it creates a trading signal to either reduce the amount of risk in the portfolio in times of high volatility (compared to the current volatility band) or to add more risk to the portfolio in times of lower volatility. To investigate in how far fund managers are able to maintain the defined risk classes and what the impact would be, we carry out an historical backtesting which uses the SRRI as a trading signal using two trading strategies that are structured around the legal constraints fund managers concerned by this regulation face. First, we consider an investment strategy that follows an equity index and only alters the exposure according to the following rule:

$$E(\sigma) = \begin{cases} 0, & \text{if } \sigma_{t-1} > ub \\ 2, & \text{if } \sigma_{t-1} < lb \\ 1, & \text{else} \end{cases}$$

where:

E = The Exposure to the index

σ = Annual volatility of weekly returns calculated for the purposes of the Synthetic Risk Reward Indicator (ESMA 10-673)

ub = upper bound of the selected risk class

lb = lower bound of the selected risk class

So basically the portfolio follows a risk on - risk off strategy if the SRRI of the previous period falls outside the current band. If the upper bound is breached the exposure is reduced to zero (in practice this could be done by e.g. hedging the portfolio completely through derivatives). To add as few dispersion as possible the fund manager

¹¹These funds do also have restrictions such as 20% VaR on 20 days (CI 0.99) or two times the benchmark VaR, we abstract from these for the time being.

would theoretically need to deliver the realized mean over the observation period. This would require perfect information and would not be senseful in cases of negative mean returns. If the previous volatility falls below the lower bound, the exposure to the index is raised to 200%. This is the most a fund manager of a UCITS structure measuring the global exposure according to the commitment approach can do to maintain the portfolio in a defined risk class. When the portfolio is not invested in the index we assume an investment in the risk free rate. If realized volatility lies within the current band, the fund is just 100% invested in the index. Using passive indices isolates the impact of the SRRI implied trading rule from that of active investment decisions by the fund managers. To account for the greater possibilities to add exposure that VaR portfolios may dispose of the second trading strategy we examine follows the same approach as above, but doubles the exposure in case the lower bound is not reached within 4 weeks. This pattern is repeated until the desired risk class is reached.

$$E(\sigma, n) = \begin{cases} 0, & \text{if } \sigma_{t-1} > ub \\ 2^{\lfloor \frac{n}{4} + 1 \rfloor}, & \text{if } \sigma_{t-1 \dots t-s} < lb, n \in \mathbb{N}^+ \\ 1, & \text{else} \end{cases}$$

where:

E = The Exposure to the index

σ = Annual volatility of weekly returns calculated for the purposes of the Synthetic Risk Reward Indicator (ESMA 10-673)

n = Number of weeks where where σ has been consecutively below lb , and $\lfloor x \rfloor$ denotes the interger part of x

ub = Upper bound of the selected risk class

lb = Lower bound of the selected risk class

This strategy has more means to add exposure to the portfolio to bring risk levels back up if a lower bound is undercut. As our focus is on equity markets we concentrate the analysis on risk classes 5-7, because the lower risk classes would rather match with the risk levels associated with balanced or fixed income funds, where the asset allocation would obviously be managed differently. Furthermore historically, equity indices mostly displayed volatilities calculated as per the SRRI that were in the ranges of with these risk classes.

3.3 Backtesting on Historical Data for Equity Indices

We apply the trading rules to ten equity indices from economies around the world. The price indices are obtained from the Thomson Reuters database and the risk free rates are obtained from Kenneth French's webpage. Weekly return data are available for the period 13-09-1991 to 27-02-2015. The descriptive statistics of the indices are presented in table 3.2. As mentioned above the analysis is only conducted on risk classes 5-7, so the strategies we examine have a minimum target volatility of 10% per annum.

3.3.1 Effectiveness of the Strategies

3.3.1.1 Commitment Portfolios

We start by examining the results for the portfolios with limited possibilities to raise exposures.¹² First, one notices that the volatilities of the strategies show the expected run up times in case the initial risk class differs from the intended strategy. These may be substantial depending on how far the actual volatility is away from the binding boundary. This is true for migrations to the upside e.g. risk class 7 for the S&P500 or to lower volatility bands such as risk class 5 for the HangSeng Index (please refer to figures 3.2 and 3.3). Both patterns are not surprising given the limited possibilities in both directions coming from the investment restrictions (200% leverage) to the upside and to downside migrations from the limited means to reduce volatility. It should be noted that this situation is similar to occasions where the volatility is changing in a sudden disruptive way putting the fund into another risk class. This can be seen e.g. at the beginning of the Lehman crisis throughout the indices examined. The limited firepower in times of lower volatilities is more problematic for risk class 7 of course, we can see migrations for most of the indices in the years preceding the Lehman Event. To a lesser extent this effect can also be observed for risk class 6, with a notably lower number of weeks outside the current band and fewer overall migrations (e.g. S&P500).

Risk classes 5 and 6 are highly impacted by crises events such as the Technology Bubble or the Lehman Event. The strategies where risk class 5 is applied are notoriously close to the upper boundary with some exceptions in the years preceding the Lehmann event (e.g. Dow Jones, MSCI World displayed in figures 3.4 and 3.5). This indicates that risk class 5 might not be suited for pure equity portfolios but rather for balanced portfolios. The results also illustrate that the categories will highly depend and datapoint

¹²For reasons of brevity we only show selected figures. All results are available on demand.

Metric/Index	S&P 500	EuroStoxx50	DAX	FTSE	CAC40	IBEX 35	Hang Seng	Dow Jones	MSCI World	NASDAQ
Volatility	0.1671	0.1870	0.2219	0.1684	0.2116	0.2207	0.2461	0.1623	0.1602	0.2548
Mean	0.0016	0.0013	0.0021	0.0011	0.0012	0.0016	0.0021	0.0017	0.0013	0.0029
Min	-0.1820	-0.2318	-0.2161	-0.2105	-0.2216	-0.2120	-0.1806	-0.1815	-0.2007	-0.2530
Max	0.1203	0.1455	0.1612	0.1341	0.1324	0.1455	0.1493	0.1129	0.1237	0.2109
VaR	0.0603	0.0669	0.0742	0.0632	0.0751	0.0732	0.0979	0.0577	0.0553	0.0926
SR	0.0712	0.0505	0.0669	0.0453	0.0421	0.0526	0.0610	0.0765	0.0569	0.0817

Table 3.2: This table shows the descriptive statistics of the equity indices used in our analysis. Volatility is calculated as per the ESMA 10-788 guidelines. The set-up for the Value at Risk (VaR) is 0.99 5 days (weekly returns).

effects induced by either market events or subsequent actions taken to raise the exposure. The reversal will be observed 260 weeks later when the highly contributing observations drop out.

It should be noted that unless a disruptive event catapults volatility into another band, the volatility based strategies managed to avoid clear penetrations in adjacent risk classes. We observe that the strategies' volatilities hover around the respective binding boundaries occasionally, only in some cases slightly surpassing the allowed number of 16 weeks outside the current bands.

The maximum number of weeks outside the respective risk class and the overall number of migrations per strategy are given in table 3.3. Overall, however, we can state that in only one case, the HangSeng Index for risk class 6, the strategy was able to maintain the risk class for the entire period under review without breaking the rule of 16 weeks as defined by ESMA. This leads to the conclusion that the effectiveness of the strategies in maintaining the risk classes based on the commitment approach is very limited. Although our strategies are indeed quite extreme, a less drastic reaction would have even more problems to maintain the risk class.

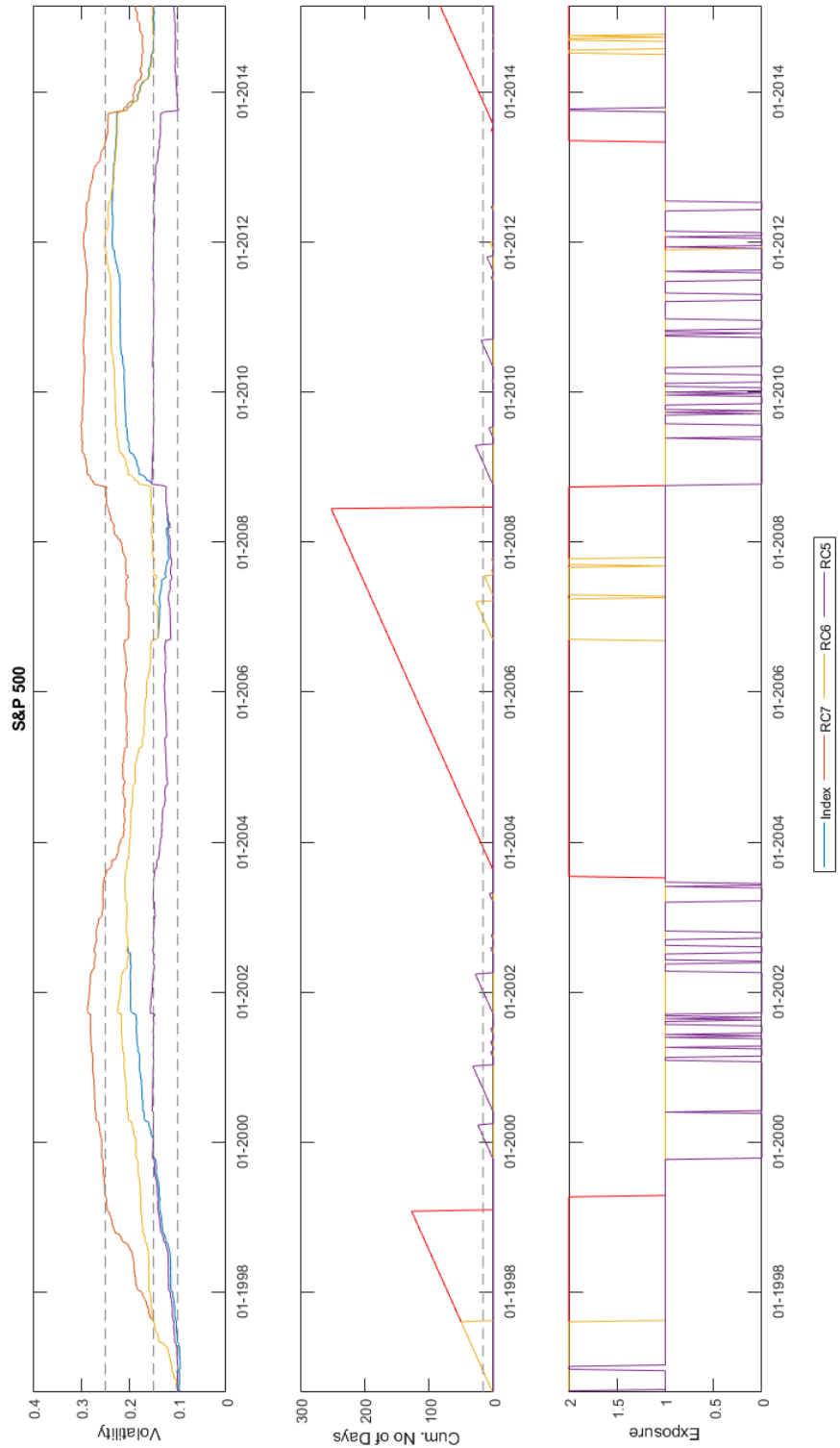


Figure 3.2: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the commitment approach. It is calculated as per the ESMA 10-673 guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

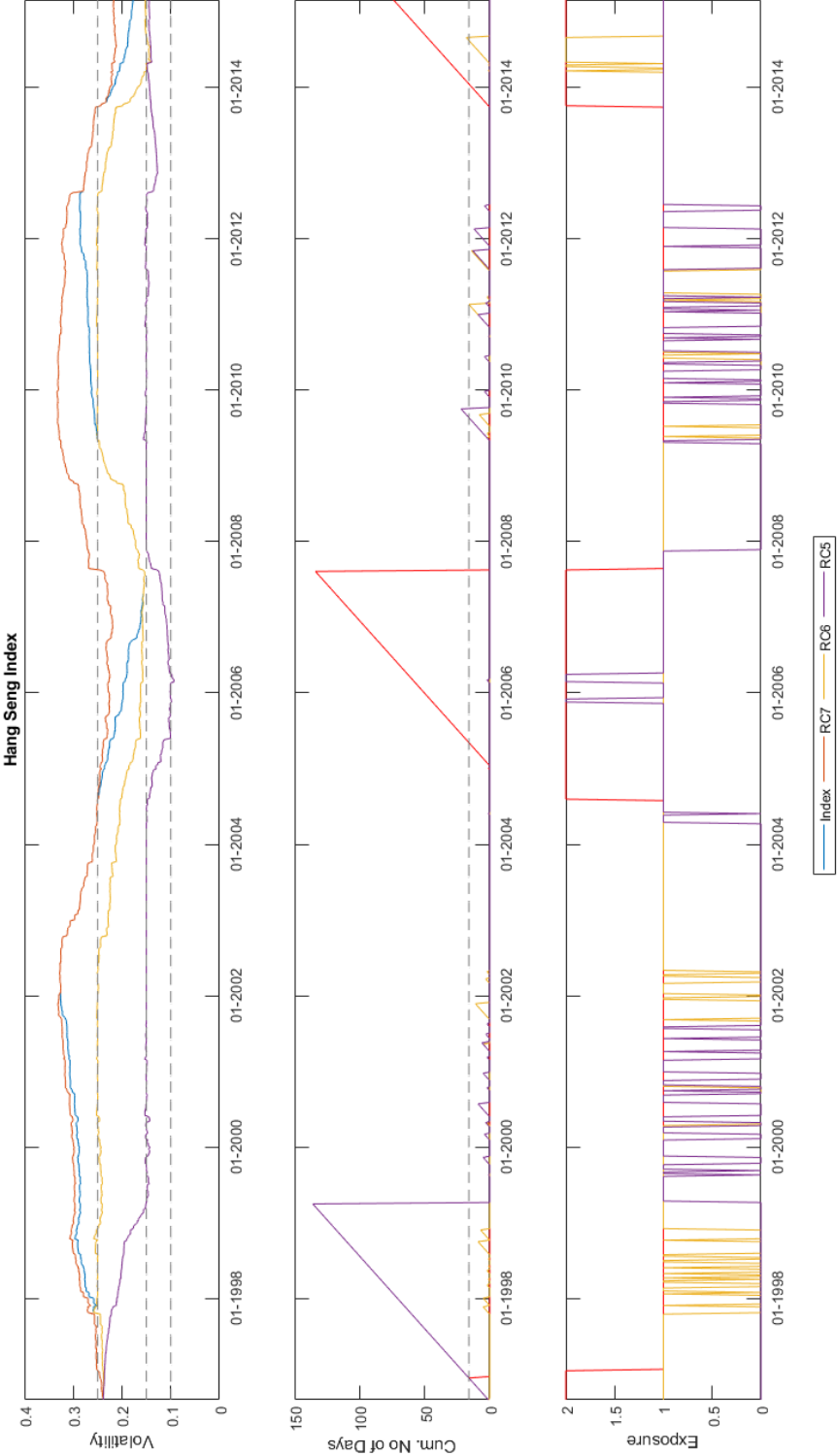


Figure 3.3: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the commitment approach. It is calculated as per the ESMA 10-673 guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

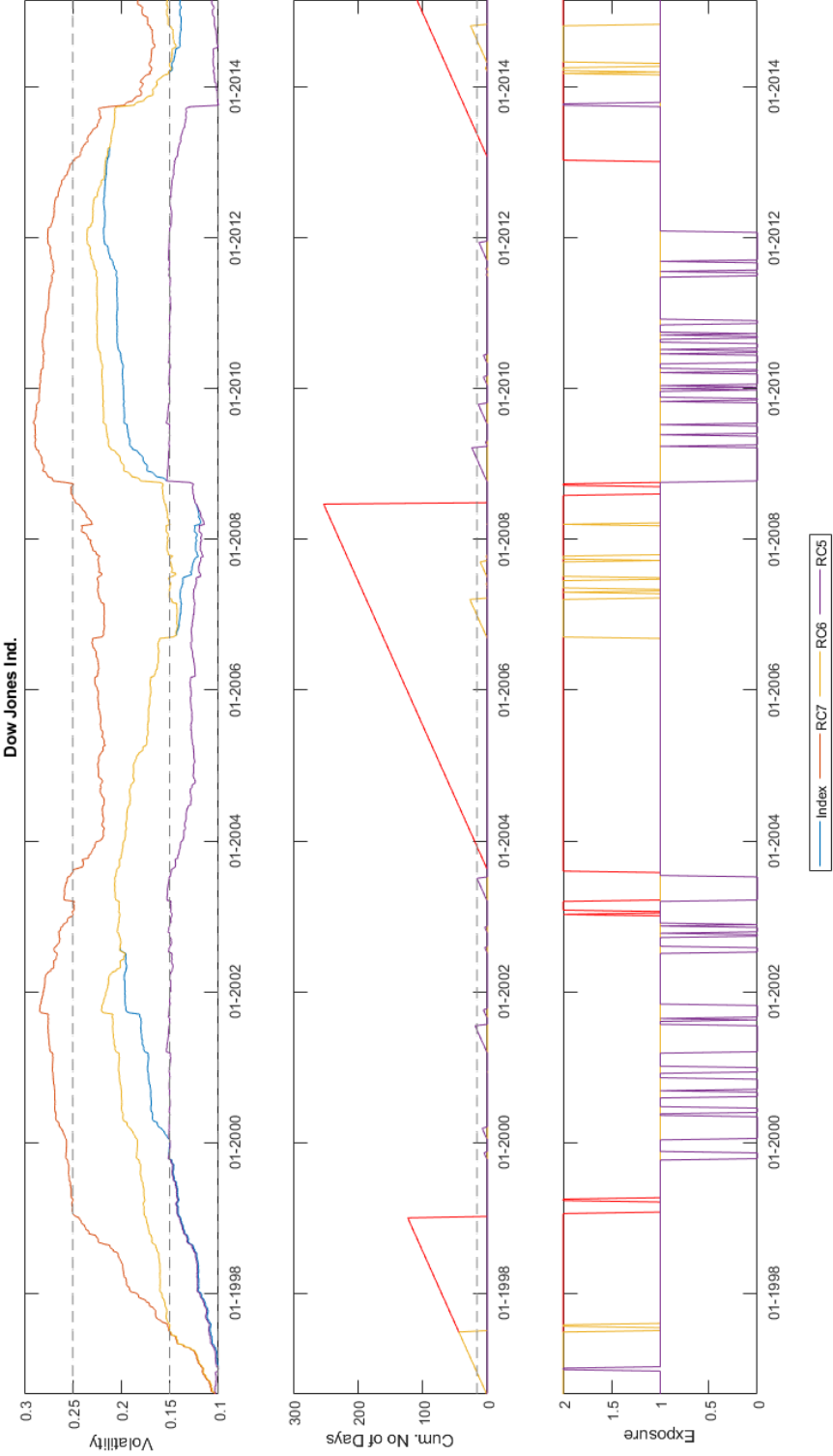


Figure 3.4: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the commitment approach. It is calculated as per the ESMA 10-673 guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

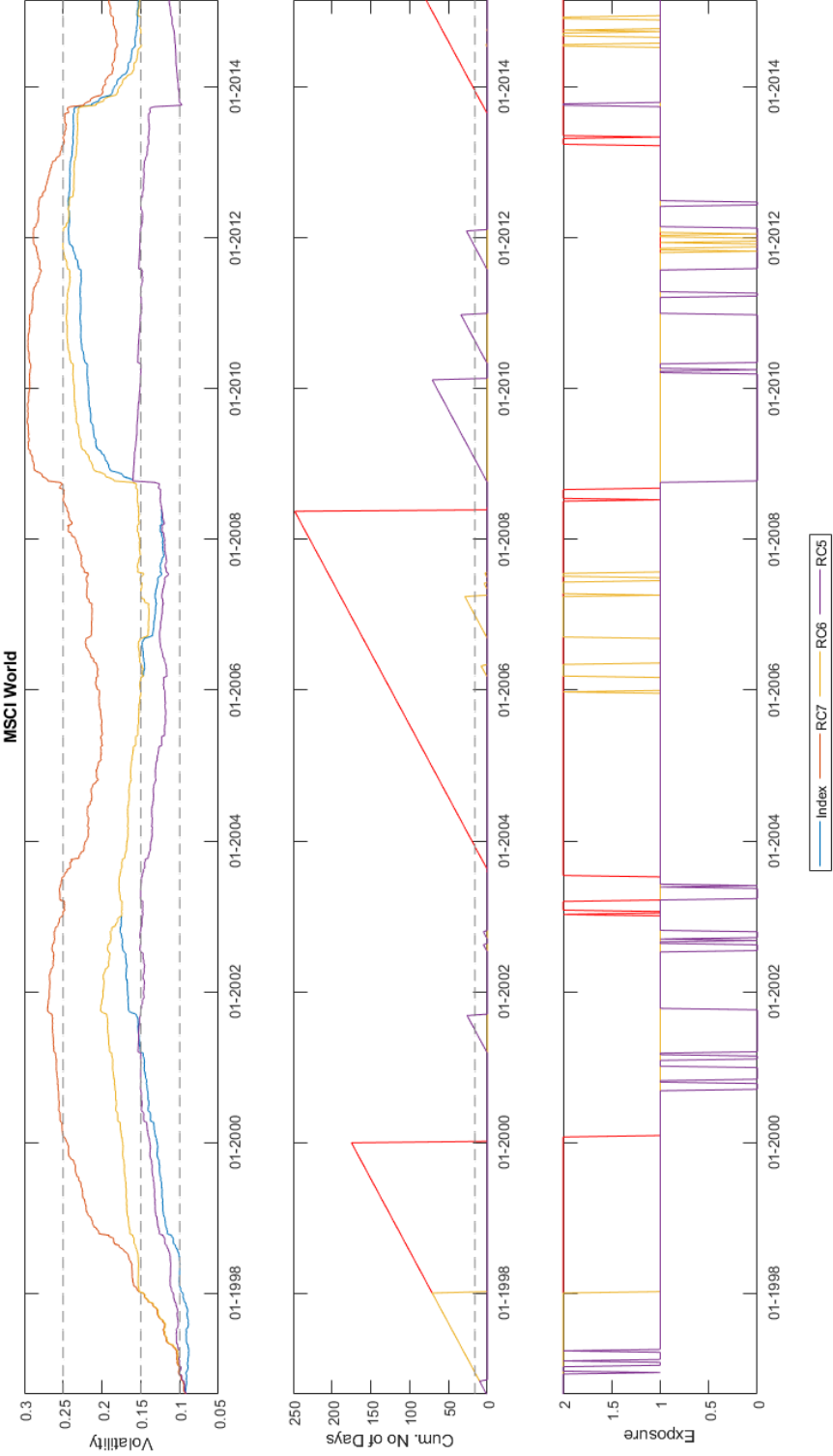


Figure 3.5: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the commitment approach. It is calculated as per the ESMA 10-673 guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

3.3.1.2 VaR Portfolios

We now turn to the results for the portfolios with unlimited firepower in times of lower market volatilities. As expected the run-up times are notably lower as for the strategies with limited leverage possibilities. This result comes, however, at the cost of a larger swing back when the high contributing observations drop out. This effect is visible for risk class 6, but most pronounced on the graphs for risk class 7. It can lead to severe distortions in form of regular swings, which are either introduced by market shocks or stem from the fact that the initial risk class has not been properly chosen. The unlimited firepower unsurprisingly helps to maintain the highest risk class for most of the indices during the period studied, albeit at the cost of very high levels of leverage (levels greater than 15) and huge swings in volatility induced by observations dropping out. Two indices (S&P500/ Dow Jones) still show one migration each with 16 weeks outside the current bucket, but these are due to datapoint effects as the high levels of exposures due to the run up times are dropping out. Further to this they could have been avoided by just raising the exposure more drastically, but for the purposes of this study the results are satisfactory, as it may be interpreted as the minimum level of leverage required to keep the risk band. It should also be mentioned of course that the high level of leverage also exposes the portfolios to large swings in case of huge market movements as can be seen in figure 3.6 for risk class 7 applied e.g. on the CAC 40 in July 2016.

Turning to risk class 6 we also find that the portfolios with no leverage constraints perform notably better in maintaining this risk class than the strategies based on the commitment approach. The number of migrations and the maximum number of weeks outside the bucket is greatly reduced. As expected, the higher leverage levels help to avoid migrations from risk class 6 to risk class 5 in markets of lower volatilities before the Lehman event. This can e.g. be seen for the MSCI World in figure 3.7. In contrast to the previous set-up risk class 6 is maintained for the S&P500, FTSE, Dow Jones and the MSCI World (please refer to table 3.3). For the rest of the strategies it should also be noted that no clear penetration in the adjacent risk class is observable as the respective volatility hovers around the boundary in each case. Further to this all migrations would be to the upper risk class. As mentioned above, there would not be much more a fund manager could do in this case as his means to reduce volatility are limited, consequently these portfolios would be forced to change risk classes. For risk class 5 we did not expect major differences in the results as most of the migrations for this risk class are to the upside, so more capacity to raise exposures is not helpful here. Indeed this is confirmed as we find a very similar picture as for the commitment portfolios with most of the strategies being close to the upper boundary, with few exceptions e.g. MSCI World or S&P500 towards the end of the observation period (figures 3.7 and 3.8). As in the set-up above none of the strategies managed according to risk class 5 would have avoided a

migration to risk class 6. This once again links to the fact that the means to reduce volatility after a shock or even a drift that proves to be persistent are limited and once again shows the limited possibilities of fund managers to avoid migrations for lower risk classes in such market environments.

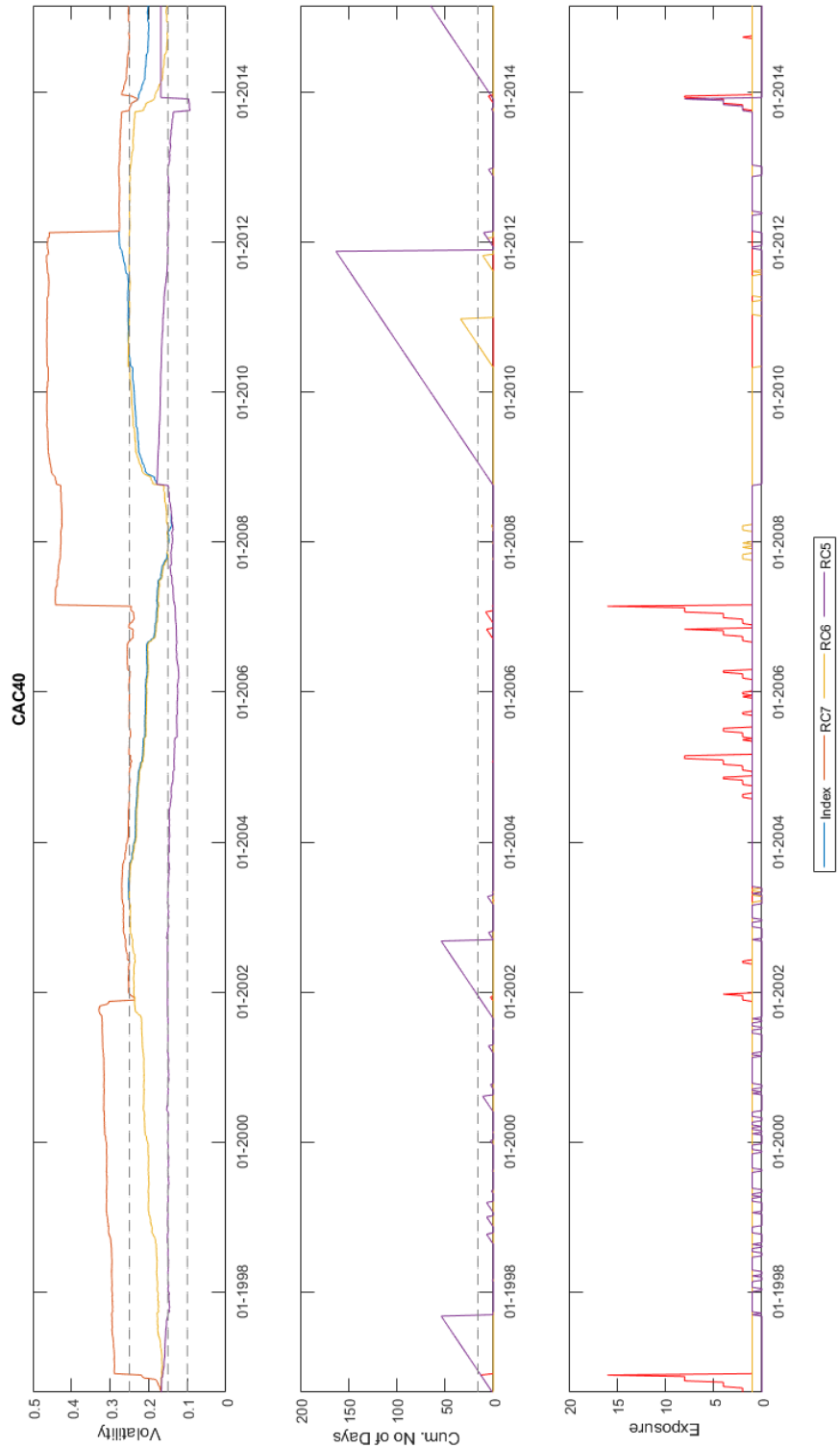


Figure 3.6: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the Value at Risk approach. It is calculated as per the ESMA 10-673 Guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

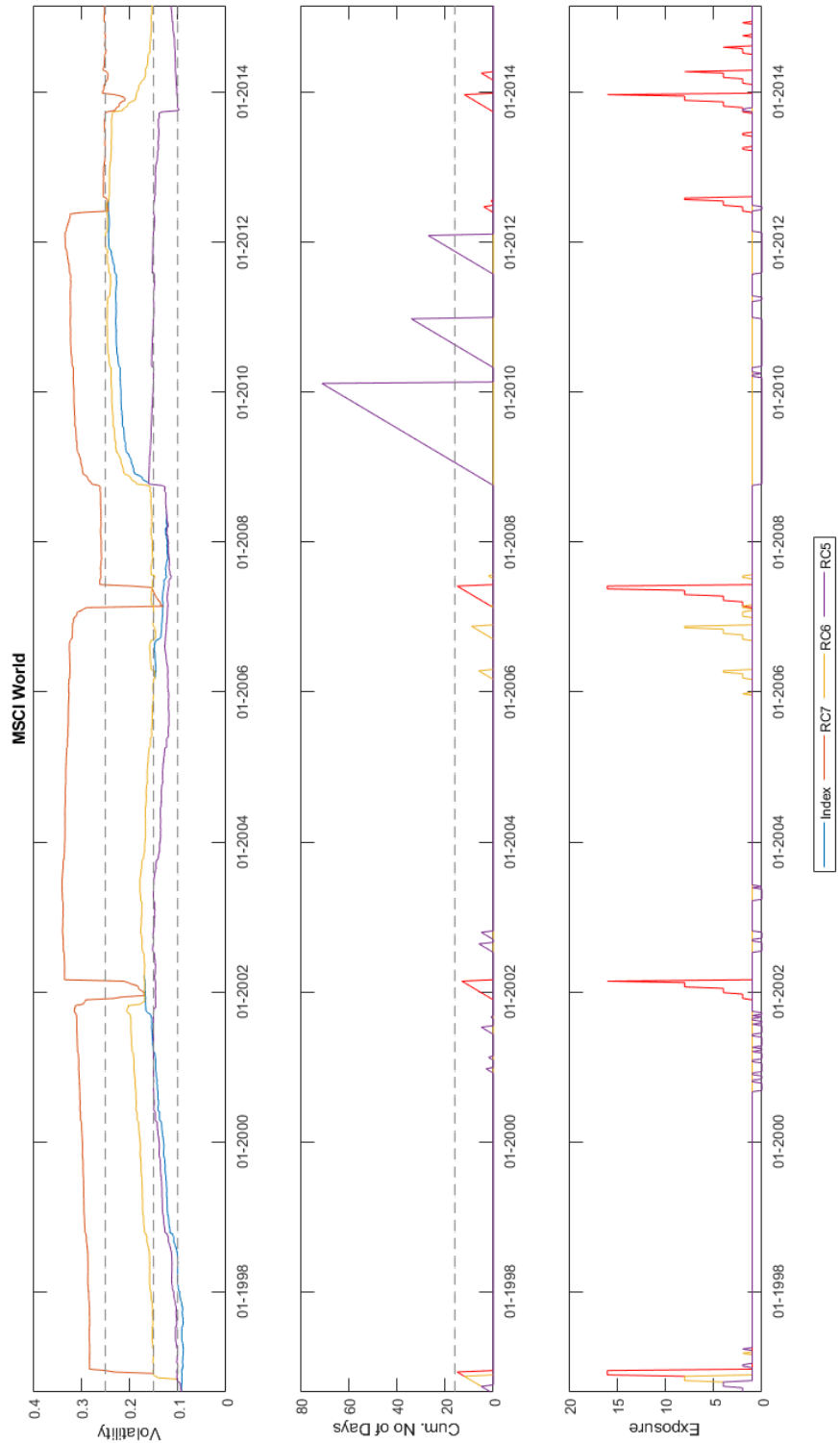


Figure 3.7: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the Value at Risk approach. It is calculated as per the ESMA 10-673 Guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

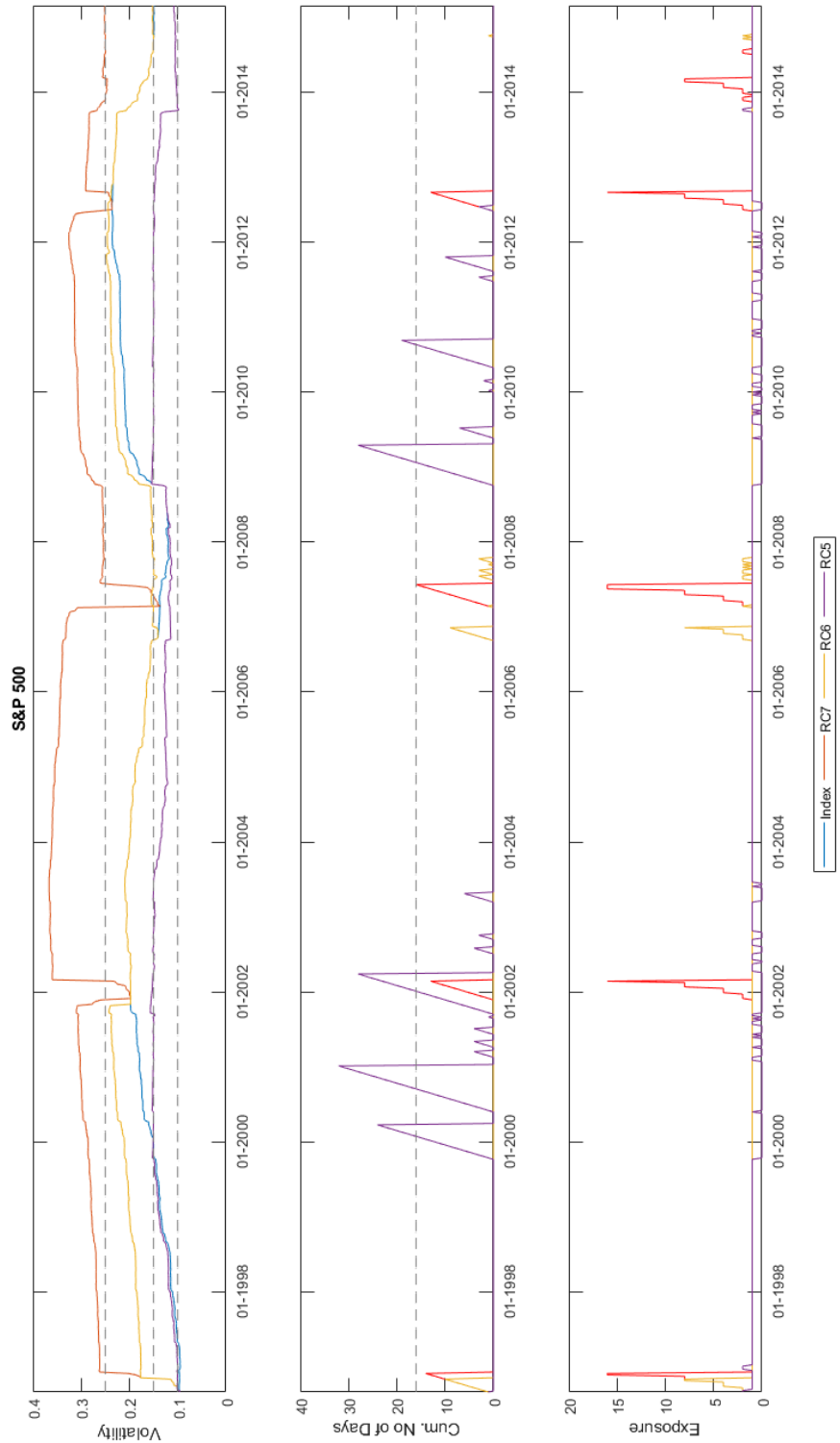


Figure 3.8: The upper graph shows the annual volatility of weekly returns of the portfolios managed according to the Value at Risk approach. It is calculated as per the ESMA 10-673 Guidelines. The horizontal lines indicate the upper or lower boundaries for the risk classes defined by European regulators. Below we show the cumulated number of days outside the bucket of the respective risk class and the related exposures that the strategies take according to the trading rules based on the realized volatility.

3.3.1.3 Robustness Checks

For robustness checks we rerun the analyses with alternative set-ups. First we rerun the VaR strategies using a theoretical alternative where the current realized mean at the time of computation is delivered instead of the risk free rate during times where realized volatility is breaching the upper band. In this set-up we examine the hypothetical scenario where the fund manager would dispose of perfect information and was able to perfectly anticipate future returns.

The results are presented in table 3.3, which shows the number of migrations per strategy and the maximum number of weeks outside the current bucket for the strategies.¹³ Of course, for risk class 7, no changes are observable as only migrations to the downside may occur in this risk class. For risk class 6 we find, however, that no migrations would have occurred for any index, so migrations to both directions would have been avoided. It can be seen that in this set-up that the strategies manage to keep risk classes 6 and 7 for the entire period examined, so the four migrations to the upside we still observed for the VaR Portfolios in risk class 6 would have been avoided in the theoretical set-up. The biggest improvements can be seen for risk class 6 (e.g. CAC40, Ibex) and occur due to the avoidance of drifts into risk class 7 after the Lehman crisis.

The situation only changes marginally for risk class 5 without any real improvement regarding the effectiveness in keeping the desired volatility range. An exception to this is the DAX, where the number of weeks outside the relevant bucket almost doubles during the Lehmann crisis using the realized mean. This, maybe surprising result, stems from the fact that the strategy applying the realized mean was re-invested on the week ending on October 10th, 2008 during which the DAX experienced a loss of -21.61% whereas the strategies using the risk free rate were not invested as they required more time to bring volatilities down again. More precisely the latter was only invested one day later which is the reason why the strategy is less exposed to the shocks markets experienced during this period. Actually, this was beneficial for the risk free rate strategy not only in terms of avoided losses, but the strategy could also profit from the rebounds in markets, which of course also lead to higher volatilities hence no further investments in the following weeks. This illustrates quite glaringly how exposed the concept of the SRRI is to datapoint effects. In this set-up we examine the hypothetical scenario where the fund manager would dispose of an investment alternative that would bring volatility down as fast as possible in case of breaches to the upside. As we have shown above even in this thought experiment risk class 5 would not have been maintained.

Another alternative to our set-up aiming to maintain the risk classes would be to use lower warning limits as a trading signal to avoid migrations, so we rerun our analyses using different warning limits below and above the actual limit. We proceed by narrowing

¹³The unreported details of the robustness checks are available upon request.

the buckets for the remaining risk classes with migrations for the VaR portfolios where the realized mean is used gradually without material effects just up to the scenario presented in the last section of table 3.3. This is the case where the warning limits are set to a band from 11% to 12% for risk class 5 and at 28% for risk class 7. As you can see the situation would improve, but of course such set-up would not be practically relevant as it would literally not allow for active fund management. So within the realms of practicability warning limits based on the risk classes would not help much to maintain risk classes 5 or 7 for equity portfolios.

3.3.2 Problematic Aspects Induced by the SRRI

3.3.2.1 Limitations for UCITS Funds

We find that none of the commitment portfolios manages to keep risk class 6 during the period under review and only four of the VaR portfolios. The results are similar for risk class 7 where the commitment portfolios are clearly not able to maintain the risk classes in times of low market volatilities. For the VaR portfolios we see that the strategies work well to keep volatility up, being exposed to large swings in the results due to observations dropping out. Turning to risk class 5, we find that both strategies have difficulties in managing to keep the realized volatility in the required risk bands, more particularly this risk class is much more exposed to volatility shocks. These lead for some indices to clear migrations to risk class 6. Risk class 5 has historically not really been an option for equity only funds. The required band was not maintained in any set-up chosen and the strategies were for most of the time hovering over the upper limit of risk class 5. Robustness checks using the realized mean (as an hypothetical alternative) show that migrations to the upside could be avoided for our sample indices managed to maintain risk class 6, but not for risk class 5.

We find that fund managers are exposed to two problems with the boundaries imposed by the risk classes according to the SRRI regulation. To generate an upside movement to volatility some of them have limited firepower in terms of leverage and to the downside they can only gradually reduce the contributions to volatility. This first problem is alleviated for VaR portfolios at the cost of swing backs when high contributing observations drop out and at the systemic cost of considerably higher leverage which further exposes investors to supplementary swings. The second problem is linked to the fact that means to reduce volatility are limited. Delivering the realized mean is the most efficient, albeit theoretical alternative which may more importantly not even be desirable in cases of negative returns. We find that portfolios which are managed according to the commitment approach would not be able to avoid migrations to the

CA RF	S&P 500	EuroStoxx50	DAX	FTSE	CAC40	IBEX 35	Hang Seng	Dow Jones	MSCI World	NASDAQ
RC7	3 (252)	3 (236)	3 (104)	4 (223)	5 (62)	3 (149)	3 (134)	3 (253)	3 (248)	3 (101)
RC6	2 (50)	3 (34)	3 (29)	2 (44)	1 (34)	1 (51)	2 (18)	3 (44)	2 (71)	2 (42)
RC5	5 (32)	5 (134)	4 (65)	5 (79)	3 (163)	3 (141)	2 (136)	3 (24)	4 (71)	4 (161)
VaR RF										
RC7	1 (16)	0 (14)	0 (13)	0 (14)	0 (13)	0 (13)	0 (10)	1 (16)	0 (15)	0 (10)
RC6	0 (10)	1 (20)	2 (29)	0 (11)	1 (34)	1 (49)	1 (16)	0 (10)	0 (12)	2 (42)
RC5	5 (32)	5 (134)	4 (65)	5 (79)	4 (163)	3 (141)	3 (136)	3 (24)	3 (71)	4 (161)
VaR Mean										
RC7	1 (16)	0 (14)	0 (13)	0 (14)	0 (13)	0 (13)	0 (10)	1 (16)	0 (15)	0 (10)
RC6	0 (10)	0 (11)	0 (9)	0 (11)	0 (2)	0 (5)	0 (9)	0 (10)	0 (12)	0 (4)
RC5	5 (31)	5 (131)	4 (127)	5 (78)	4 (163)	4 (141)	5 (137)	2 (24)	3 (71)	4 (161)
VaR WL										
RC7	0 (14)	0 (14)	0 (13)	0 (14)	0 (13)	0 (13)	0 (6)	0 (14)	0 (15)	0 (10)
RC6	0 (10)	0 (11)	0 (9)	0 (10)	0 (1)	0 (1)	0 (1)	0 (10)	0 (12)	0 (1)
RC5	0 (1)	0 (1)	0 (9)	0 (1)	1 (54)	2 (74)	1 (137)	0 (1)	1 (231)	2 (80)

Table 3.3: This table displays the number of migrations to adjacent risk classes and, in brackets, the maximum number of weeks that the realised volatility has fallen outside the defined range for the respective risk class, either to the upside or the downside. The first three rows show the results for the commitment approach portfolios that have limited possibilities to add variation due to leverage constraints. The following two VaR set-ups differ in the way the non-investment returns are captured in that one uses the risk free rate, whereas the other used the realized mean as the theoretically optimal alternative to reduce volatility. The last VaR set-up is one where the trading signal is set at levels narrower than the prescribed ones to avoid migrations, the limits in the case presented are 11% to 12% for risk class 5 and at 28% for risk class 7. It should be noted that for lack of clear prescriptions in the legal texts and in order to avoid overly conservative results, the hits for the counter are based on rounded values e.g. a volatility coming down to 14.5 would still be counted to risk class 6.

upside in most of the cases. For the portfolios with unlimited firepower to bring volatility up, migrations to lower risk classes can be avoided at the cost of high leverage and swing backs displayed in the volatility patterns. The results from above suggest that in certain market environments fund managers will not be able to avoid migrations. This also means that the spectrum of risk classes for equity portfolios boils down to 6 and 7 which raises the question whether the SRRI is actually a reasonable indicator for the equity space, giving only really two options, i.e the most risky and the second risky category. These forced migrations may lead to investor outflows unrelated to any actions taken by the portfolio manager. This finding joins some of the aspects discussed by Doehrer et al. (2012) who conclude that flexible boundaries would be more beneficial. Due to the static boundaries the SRRI bears the risk of degenerating to a passive indicator which is only mirroring changes in market conditions and does not relate to the investment strategy initially chosen by investors. Furthermore it should be noted that pure data point effects may distort the judgement based on the SRRI.

3.3.2.2 Interference with the Investment Strategy

As shown above high variations in exposures in either direction are required to maintain the risk bands of the SRRI. Furthermore, in cases where the realized volatility of the strategies hovers around one of the boundaries this leads to phases of risk on - risk off patterns. These may be periods of non-investments, or only sporadic investments in the case of an upper bound or those alternating between higher leverage and just regular exposure to the index if a lower boundary is undercut. This would prevent the fund manager from applying a consistent strategy.

Periods of higher exposure may either be induced by periods of low market volatility, as observed e.g. in the late 1990s or prior to the Lehman event, or, simply by high contributing data points dropping out. For the sake of completeness it should also be mentioned that selecting the wrong risk class may lead to long run up times with extensive periods of higher exposures. These interventions may evoke some cyclical pattern with recurring periods of high and low exposures. We abstract from the question whether a migration to a lower risk class is a positive event for investors and should as such not create a binding investment restriction for the fund manager. Required adjustments to the upside are only temporary in nature, which is due to the design of the SRRI providing a 16 week grandfathering period to redirect a deviating strategy. They induce high contributing observations, hence themselves expose the strategies to datapoints effects. Overall, substantially higher levels of leverage are required to keep risk classes 6 and 7 in times of low volatility, these levels would usually be associated with hedge funds. This leads to a drift in the investment style which may not be intended by the investor.

Interventions to the upside may be induced by Macro events that have a massive impact on realized volatility such as the Lehman Event or the European debt crisis. While the mechanism may generally be desirable, i.e. reducing exposures in times of high market volatility and vice versa, it will effectively prevent fund managers from delivering the strategy promised to investors for extended periods as the high contributing observations will have an impact for the next five years before they drop out and reverse the effect they caused initially. It should be noted that this second round effect may of course be anticipated by fund managers as its occurrence is well known beforehand. Being exposed to datapoint effects does nevertheless create an additional (unnecessary) factor to take into account when managing a portfolio. A smoothing mechanism, such as a weighting scheme of to limit the impact of single observations, would be helpful to avoid these complications.

The interventions range from substantially higher levels of leverage to extended periods of no investments, consequently the fund manager would not be able to do his job and deliver the strategy promised to investors during these periods. Regulation would hence impose fund managers to deviate from the expected investment strategy and interfere in the delegation relationship between fund managers and investors. This style drift obviously dilutes responsibilities when attributing performance. It would be an interesting topic for future research to examine how the volatility strategy imposed by the SRRI impacts fund performance.

3.4 Herding and Spillovers

3.4.1 Review of Literature

Spillovers between equity markets is a documented phenomenon in financial literature. Hamao et al. (1990) present evidence for price volatility spillover effects mainly originating from US markets. Liu and Pan (1997) find a similar pattern from US markets to Asian markets. Furthermore Baele (2005) documents volatility spill overs with increasing intensities between US and European equity markets. He further documents contagion from the US to local European markets in times of high volatility regimes. Diebold and Yilmaz (2009) find for nineteen global equity markets that volatility spillovers display no trend but clear bursts that occur with an associated crisis event. Looking at the volatilities calculated for the indices in our sample as shown in graph 3.9, one clearly sees that volatilities across markets move in very similar patterns and that they are impacted by shocks in a similar ways, the most significant being the Lehman event. As pointed out

above also regional shocks such as the European Debt crisis may occur that lead to the coupling of regional markets.

Putting this into context with the SRRI one clearly sees that, if the SRRI creates an investment restriction for fund managers, these volatility spillovers may lead to herding behaviour as they will evoke the same trading directions across markets. This bears the risk of amplifying crises or shocks worldwide induced by regulation, which initially aimed at helping investors to make an informed investment decision. Particularly the finding of Diebold and Yilmaz (2009) should be considered here, as volatility will display jumps in terms of crisis which may lead to immediate required action by the fund managers as it may catapult the SRRI into a riskier class, as opposed to a smooth gradual migration. The results so far indicate that fund managers would have to alter their exposures considerably during those periods, so the resulting sell-off or shorting by fund managers may lead to further market slides. This will amplify shocks in the markets and creates more systemic risk. As per the EFAMA Q2 2017 Statistical Release the assets under management in UCITS following an equity strategy amounts to EUR 3,474 billion representing 38% of the overall volume invested in UCITS. Given this number and the results from above, which indicate that either substantial leverage or shorting may be required to maintain a risk class, it is obvious that systemic impact may arise from the SRRI.

3.4.2 Aggregate Exposures

We first look at how the overall leverage levels potentially induced by the SRRI for strategies that want to maintain the risk class. To assess the impact on the exposures from a systemic perspective we aggregate the exposures from the VaR portfolios across markets for each week in our sample. The standard exposure in the passive scenario without the SRRI is 10, i.e. all market participants are fully invested to a 100% in their target equity market. Figure 3.9 shows the aggregate exposures across the markets examined. It should be noted that we subtract 10 from the overall aggregate across markets to isolate the effect induced by the SRRI. So the minimum value is -10 which means that none of the investors in the respective risk class would be invested at all in any of the indices. As we examine the portfolios with unlimited leverage opportunities, there is no limitation to the upside on the graph.

We abstract from the high peaks at the beginning as these are due to the run up times to attain the selected risk class. However, one can see that the potential leverage induced to the system by funds managed to maintain risk class seven is substantial, with levels exceeding 60 in peak times. This means that the indices in our sample (as a proxy financial system) would be leveraged 50 times only for risk class 7. The cyclical patterns are also visible at an aggregate level, so the higher levels of leverage that occur across

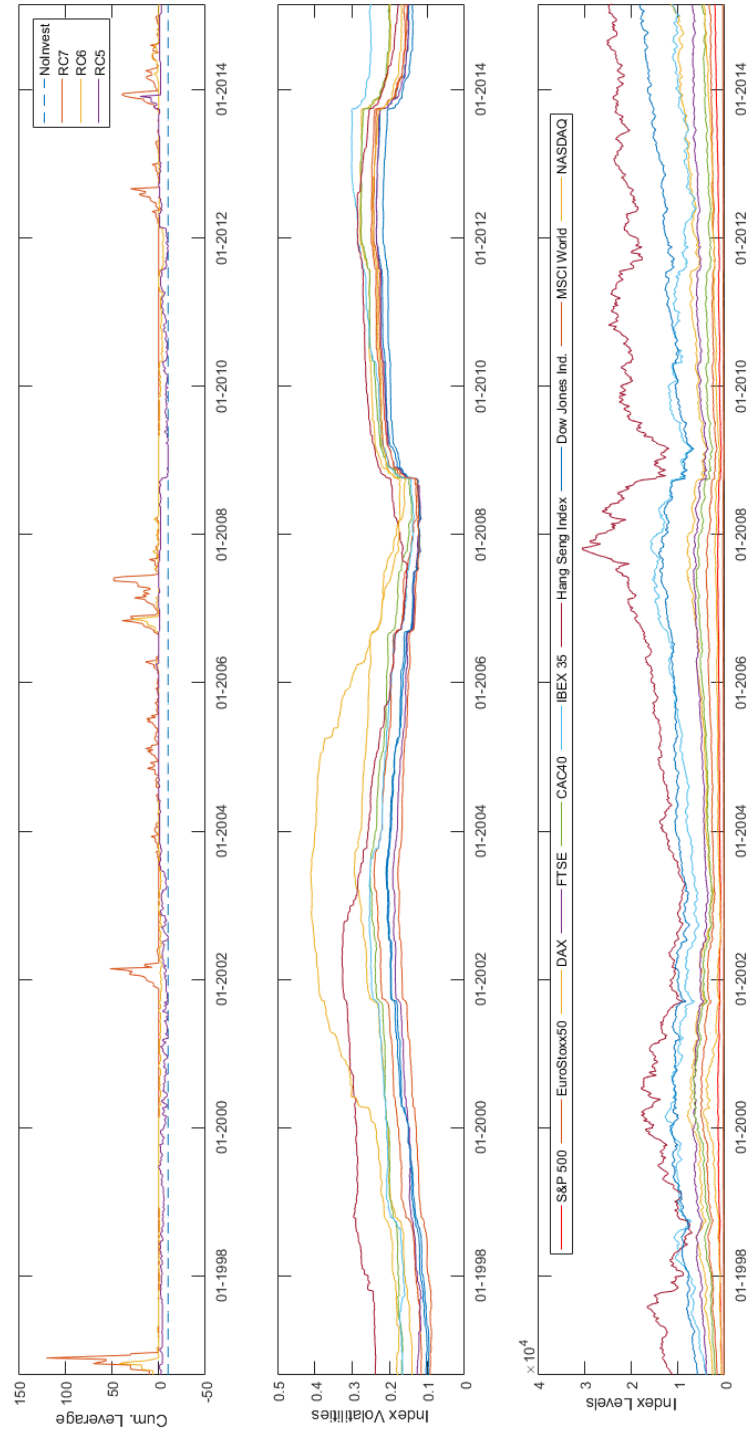


Figure 3.9: The first graph displays the aggregated exposures across the indices used in our analysis for each week. We subtract 10 from the results to isolate the effect from the SRRI. The red line indicates the non-investment border. The two graphs below show the annual volatilities and the index levels respectively.

markets due to crises events have an influence on an aggregate level. Some of the phases of higher leverage coincide with elevated levels of leverage also for risk class 6, e.g. August 2006, which further emphasises the importance of this phenomenon.

For risk class 5, we find that for substantial periods during our observation window funds would be underinvested, which mirrors our findings from above and supports the argumentation that the SRRI may lead to downside pressure in the markets if boundaries to higher risk classes are breached. The periods of underinvestments in the years 2010 and the following years coincide with those for risk class 6, so we see that risk class 6 tends to "team - up" with either risk class 7 for leverage in times of lower volatility or risk class 5 in times of higher volatilities. The latter would have led to further downside pressure in the markets following the years of the Lehman event and the European Debt crisis. Once again the effect of systemwide shocks that lead to high contributing observations are visible on the graph, which means that the swing backs observable at index level also have an impact on a global scale. From a systemic perspective it should also be noted that the potential sell-off due to the money withdrawn from funds migrating to a higher risk class, may lead to further pressure in the market due to the portfolio re-allocation. The situation will be similar for balanced funds who will have to reduce their equity allocation as well during these periods.

To summarize there are two potential systemic dangers induced by the SRRI which may occur within specific markets or across markets due to correlation and spillover effects. The first danger is a higher level of leverage in the financial system that stems from fund managers trying to keep volatilities up to maintain a certain risk band in times of low risk levels, whereas the second is an amplification of shocks to the downside by the reduction of exposures (sell-off of assets or shorting as hedging arrangement) when volatilities spike in the wake of a crisis event. It should be noted that in both cases the corrective actions taken by fund managers to maintain the risk class may lead to herding among them. This will be the case for managers that follow the same index as they will all have to perform similar trades as their peers to keep the current risk class, but also across equity markets due to spillover effects.

3.5 Conclusion

European Regulation imposes volatility based fund classification and overlays the core investment strategy of a UCITS fund with a longterm volatility strategy. However, adherent to a constant grid of boundaries on a metric that may be characterised by gradual patterns as well as sudden disruptive changes entails several challenges for fund managers and further poses problems from a systemic perspective. If the SRRI creates a binding investment constraint, it will cause additional variations due to higher exposures

in times of low market volatility and also due to effects induced by singular events that lead to huge swings in the market as e.g. the Lehman crisis.

Migrations to the downside require short, but intensive action by raising the exposures drastically, whereas migrations to the upside result in either long periods of underinvestments or potentially to risk on - risk off patterns. We further find that maintaining certain risk classes as defined through the SRRI is not possible for funds with limited leverage possibilities due to limited means to add variations. Furthermore any fund will have troubles reducing volatility, if its volatility is shot up to far into a higher risk class as means to reduce volatility are limited. A further problematic aspect of the concept is that the set-up chosen is highly exposed to datapoint effects that have a huge impact twice, when they occur and drop out, thus creating a cyclical pattern.

The interventions induced by regulation would result in a substantial change of the investment strategy and would lead to phases that would not allow for active management. This leads to the question whether a change in the risk class is actually acceptable to investors, or in other words whether investors have to accept higher volatilities if they want to stick to the strategy they initially chose. This joins an aspect discussed by Döhrer et al. (2012) whether flexible boundaries might not be better suited to help investors follow the risk patterns of their investments. Another problematic aspect with the current set-up is that for equity portfolios our analyses provides evidence that the choice of the risk class boils down to either 6 and 7 which raises the question whether the SRRI is actually a reasonable indicator for the equity space, giving only really two options one already being the most risky one. In fact, it wouldn't even differentiate between some equity indices or leveraged investments, as both would fall into category 7.

Further analyses revealed indications that the interventions for individual indices would also be mirrored at an aggregate level across equity markets, thus creating further systemic effects. This combined with potential herding among fund managers bears the risk of an amplification of movements in stock markets, or higher volatilities.

Potential future research could focus on aspects regarding flexible boundaries also considering potential alternatives that might limit the effect of datapoints. Furthermore the impact of the SRRI on the return distribution of portfolios would be an interesting field of research.

Chapter 4

Where is the Risk Reward? - The Impact of Volatility Based Fund Classification on Performance

4.1 Introduction

European regulation implicitly overlays the core strategy of a mutual fund under the UCITS regime with a longterm target volatility strategy, if investors are unwilling to accept a change in the risk class of their fund. Besides the implications for the risk profile of the fund stemming from the revised asset allocation and the potential systemic impact this raises the question in how far it affects the returns that are delivered to investors. As the name Synthetic Risk Reward Indicator (SRRI) suggests, regulators have been aware that both dimensions have to be taken into account when assessing investment results. In the previous chapter we have shown that huge variations in exposures are required to maintain the risk classes prescribed. Notably very high levels of leverage are needed for higher risk classes to add variation in times of low volatilities. On the other hand exposures are reduced massively in times of high volatilities. This mechanism may provide protection in downside markets. In this chapter we examine whether this interference in the investment process actually pays off for investors. The rest of this chapter is organised in the following way. Section 4.2 outlines the regulatory background of the SRRI including a critical review with respect to its impact on performance, section

4.3 analyses the historical performance of SRRI based trading strategies on worldwide equity indices whereas section 4.5 deepens the analyses through a simulation study before section 4.6 concludes this chapter.

4.2 Risk Based Fund Classification

4.2.1 Regulatory Background

Since July 1st, 2012 European investment funds that are incepted according to UCITS regulation are obliged to publish a standard two page document called Key Investor Information Document (KIID) which aims to display general information and key figures of the fund to create more transparency and to enable investors to better compare investment alternatives. One key number to be displayed on this document is the SRRI which categorizes mutual funds with respect to their risk and return characteristics. As we will see below the element reward in the nomenclature is somewhat misleading as the categorization is actually only carried out using risk characteristics. Generally, the SRRI aims to be a stable and comparable indicator of the riskiness of an investment alternative. It is based on the volatility of the weekly returns time series of the fund of the last five years as funds are classified according to the schedule shown in table 3.1.

The first step is to classify the mutual fund (or rather the targeted portfolio strategy) in one of five fund types (market, absolute return, total return, life cycle or structured fund). Without providing a clearcut framework, European regulators (seem) to consider the following key determinants for the fund categorization:

- Investment across asset classes (if not and none of the others → market fund)
- Predefined risk limit (absolute return vs. total return)
- Change of the asset allocation over time (life cycle fund)
- Use of structured products (algorithm based payoffs, date specific payoffs etc. → structured fund)

Depending on the fund type and data availability, the historical volatility of the time series of the fund's returns or those of a representative asset mix (resp. benchmark) are considered to determine the SRRI. Further, in some cases the volatility reverse engineered from the VaR limit or from a VaR number obtained in a simulation study are used to determine the SRRI. In the case of an absolute return or total return fund the maximum of two or all three measures is taken respectively. As mentioned earlier, the distinction between fund types is not determined clearly in regulation. In any case, volatility

plays an important role and will for most plain vanilla strategies for retail investors be the decisive metric for the SRRI.

If the current volatility of the fund falls outside the current bucket for more than 16 consecutive weeks, the SRRI (and consequently the KIID) has to be revised accordingly and the portfolio migrates to the new risk class. Besides the administrative burden, this has further implications for the fund managers as the SRRI is intended to mirror the riskiness of the fund and give investors a signal if the risk profile changes. The intended logic is as follows: if a fund e.g. in risk class 4 migrates over time into risk class 6, this might not go along with a change in the risk appetite of its investors. So risk averse investors could feel inclined to redeem their shares to invest in a less risky fund. Consequently, fund managers will have an incentive to manage the volatility of their portfolio in a way to keep it in a risk class that has been promised to investors.

4.2.2 Critical Review of the SRRI

4.2.2.1 Implications for Fund Returns

The implications of the SRRI will depend on the fund type chosen. However, for market funds and in certain cases for absolute/total return funds the realized volatility is the decisive metric for the SRRI and as such needs to be monitored and controlled. So it is worth having a closer look at this metric with respect to its implications.

In the case of market funds, the concept of the SRRI effectively overlays the core investment strategy with a secondary investment principle based on the longterm ex-post volatility of the fund. This overlaying strategy will only be applied if investors are unwilling to accept the new risk class and exercise their power accordingly.

To avoid changes in the risk class the portfolio manager either needs to reduce the risk in the portfolio, if the portfolio migrates to a riskier class, or increase the risk in case of a transition to a less risky class. In the first case, the fund manager needs to deliver the realized mean of weekly returns in the upcoming weeks to add as few dispersion as possible and bring portfolio volatility back to the level he intends. In the second case, he needs to add as much variation (ideally to the positive side) as possible by raising the exposure e.g. through derivatives.

The revised investments will not only have an effect on the risk, but also on the return structure of the portfolio. Tail risk measures, such as the VaR, will indirectly be controlled by these volatility strategies as well due to the symmetrical nature of equity returns. This will of course only be the case if only linear assets are used to obtain market exposure.¹⁴

¹⁴Risk metrics may be gamed using non-linear products as shown in Cao and Rieger (2013).

However, regarding the performance of such strategy the situation is less clear cut. The potential scenarios for the overall impact on fund performance can be summarized in figure 4.1. The table describes the different scenarios which arise if a binding restriction is created by the SRRI, that is to say if the current realized volatility falls outside the current band and the fund manager wants to avoid a migration to an adjacent risk class. If the periods with lower risk levels outside the current SRRI coincide with mostly positive returns, the overinvestments will pay off and vice versa for the case where the current volatility is higher. In this case the portfolio can profit through avoided losses due to the underinvestments triggered by the trading strategy, if these go along with higher negative returns. These situations are marked by the green boxes on the figure, whereas the red areas show the negative scenarios where the opposite is true, i.e. higher exposures to avoid a migration to lower risk classes in times of downside markets or reduced exposures to avoid higher risk classes in times of positive market trends.

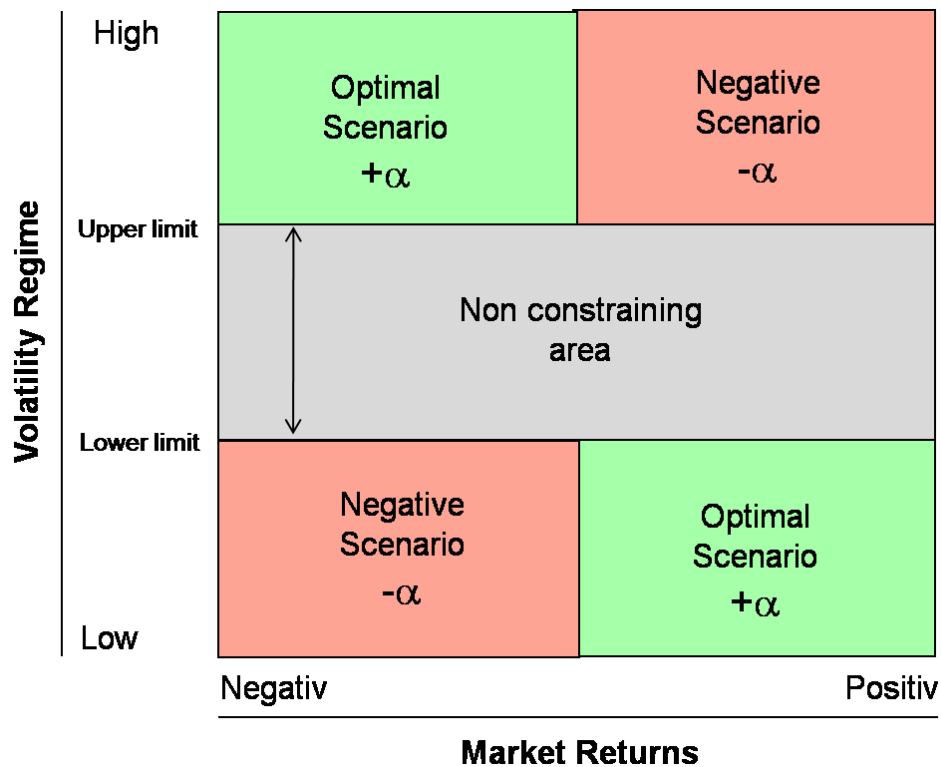


Figure 4.1: This figure shows the different scenarios of a volatility strategy and its implications for fund returns.

4.2.2.2 Review of Literature

Research on the intertemporal relation between risk and return does not provide a clear cut picture. An extensive overview is for example provided in Bali (2008). Bali et al. (2009) find, using daily returns and time horizons from 1-6 months, that realized volatility has no predictive power for future returns. Ang et al. (2009) find that stocks

with high idiosyncratic risk have low future returns. Harrison and Zhang (1999) find a positive relation between risk and return on horizons of 1 and 2 years. Further evidence for a positive relation is provided by Ghysels et al. (2005), Guo and Whitelaw (2006) and Bali (2008). Flemming et al. (2002) find that strategies based on volatilities outperform unconditionally efficient strategies. Goyal and Santa-Clara (2003) also find a significant positive relation between risk and return, when both the systematic and idiosyncratic components are included. Adrian and Rosenberg (2008) show that longterm volatility has a positive relation to returns, whereas the short term component is negatively related to the expected return. They suggest this as a potential reason for the mixed results.

Without providing conclusive evidence some studies suggest that volatility may be used as a trading signal to generate overall positive returns. However, none of the studies use a longterm horizon i.e. five year volatility as prescribed by the SRRI. Bali et al. (2009) present evidence for a positive relation between return and downside risk.

4.3 Investment Strategy based on the SRRI

If the SRRI creates a binding mechanism for fund managers, it overlays the core investment strategy of a portfolio with a longterm volatility trading strategy. The trading signal is given by the portfolio's realized volatility.

We have shown above that some portfolios that fall under the SRRI have limited possibilities to raise exposures in times of lower volatilities (please refer to section 3.3.2.1). These portfolios may not be able to maintain the risk classes. However, the analyses conducted revealed that those portfolios with unlimited leverage possibilities work quite well maintaining the risk classes avoiding migrations to the upside and within the realms of statistical possibilities also for migrations to lower risk classes. We are therefore of the opinion that the strategies with no leverage constraints are adequate to examine the impact of the SRRI on performance.

This leads to the following trading strategy:

$$E(\sigma, n) = \begin{cases} 0, & \text{if } \sigma_{t-1} > ub \\ 2^{\lfloor \frac{n}{4} + 1 \rfloor}, & \text{if } \sigma_{t-1 \dots t-s} < lb, n \in \mathbb{N}^+ \\ 1, & \text{else} \end{cases}$$

where:

E = The Exposure to the index

σ = Annual volatility of weekly returns calculated for the purposes of the Synthetic Risk Reward Indicator (ESMA 10-673)

n = Number of weeks where σ has been consecutively below lb , and $\lfloor x \rfloor$ denotes the integer part of x

ub = Upper bound of the selected risk class

lb = Lower bound of the selected risk class

As outlined in section 3.2.3 the portfolio follows a risk on - risk off strategy if the SRRI of the previous period falls outside the current band. If the upper bound is breached the exposure is reduced to zero, whereas the exposure is doubled for the next period if the previous SRRI falls below the lower bound.¹⁵ The exposure is doubled again in case the lower bound is not reached within 4 weeks. This pattern is repeated until the volatility is high enough to fall in the desired risk class again. If it lies within the current band, the fund is just invested a 100% in the index. When the portfolio is not invested in the index we assume an investment in the risk free rate.

Using passive indices has the advantage of isolating the effect of the SRRI implied trading rule on fund performance from any trading activity performed by fund managers. As in the previous chapter our focus is on equity markets so we focus on risk classes 5-7. Lower risk classes would obviously match with the risk levels associated with balanced or fixed income funds, requiring a different asset. Also these ranges for these risk classes have been closest historically to those of most equity indices. Furthermore, as we have shown in section 3.3.1 lower risk classes do not seem adequate for equity funds as they would not allow for fund management within the realms of practicability.

4.4 Backtesting on Historical Data for Equity Indices

We conduct our analysis on the same data set as presented in section 3.3. The descriptive statistics can be found in table 3.2.

¹⁵To add as few dispersion as possible the fund managers would theoretically need to deliver the realized mean over the observation period, but this would of course require perfect information and would not be senseful in case of negative mean returns.

4.4.1 Historical Performance Parameters of Volatility Based Strategies

The results are given in table 4.1. The realized volatilities of the strategies show the expected pattern as they decline with the lower risk classes and raise with higher risk classes. Apart from some exceptions for risk class 5 all average volatilities lie in the targeted ranges. Higher volatilities outside the prescribed band are observed for risk class 5 for the IBEX 35 and HangSeng. These are arguably high risk indices, so these results may not be surprising for risk class 5. Given the average volatilities for these two indices of 22.07% and 24.61% respectively risk class 5 may not be an adequate choice here.

Risk class 7 and for half of the indices in the sample also risk class 6 produce on average higher volatilities than the passive investment. The traditional strategy is aligned with risk class 5 when looking at the realized volatility. Looking at the VaR one finds that the VaR develops along with the risk classes in a similar way as volatility, that is to say it declines with lower risk classes and raises with higher risk classes. So controlling the volatility of portfolio investing in linear assets effectively also controls the tail risk of the portfolio in a similar way. This result is expected given the mostly symmetrical distribution of equity returns.

Looking at the return side the portfolios in risk class 7 show the highest mean returns, whereas on a (dispersion) risk adjusted basis the picture is more diverse. For 7 out of our 10 indices the volatility based strategies show the highest SRs without one of them clearly emerging. In three cases the traditional strategy yields the best results. Generally we can state that the volatility based strategies yield better SRs than passive investments in the index for our observation window.

Metric	Strategy	S&P 500	SX5E	DAX	FTSE	CAC40	IBEX 35	Hang Seng	DJ Ind	MSCI World	NASDAQ
Max	Index	0.1203	0.1455	0.1612	0.1341	0.1324	0.1455	0.1493	0.1129	0.1237	0.2109
	TR	0.0842	0.1021	0.1129	0.0939	0.0927	0.1021	0.1048	0.0791	0.0866	0.1480
	RC7	0.6157	0.3246	0.4585	0.4237	0.4270	0.4347	0.3093	0.6432	0.5780	0.4569
	RC6	0.3075	0.1689	0.1612	0.1341	0.1324	0.1455	0.1493	0.2629	0.2215	0.1243
	RC5	0.0758	0.1194	0.1612	0.0827	0.0888	0.0836	0.1687	0.0843	0.0814	0.0923
Mean	Index	0.0016	0.0013	0.0021	0.0011	0.0012	0.0016	0.0021	0.0017	0.0013	0.0029
	TR	0.0013	0.0011	0.0016	0.0009	0.0010	0.0013	0.0016	0.0014	0.0011	0.0022
	RC7	0.0029	0.0011	0.0027	0.0013	0.0022	0.0025	0.0029	0.0034	0.0022	0.0037
	RC6	0.0020	0.0014	0.0016	0.0011	0.0009	0.0015	0.0024	0.0022	0.0017	0.0035
	RC5	0.0013	0.0006	0.0022	0.0005	0.0003	0.0009	0.0020	0.0014	0.0010	0.0022
Min	Index	-0.1820	-0.2319	-0.2161	-0.2105	-0.2216	-0.2120	-0.1806	-0.1815	-0.2007	-0.2530
	TR	-0.1273	-0.1622	-0.1512	-0.1473	-0.1551	-0.1483	-0.1261	-0.1270	-0.1404	-0.1768
	RC7	-0.3682	-0.4127	-0.4263	-0.4418	-0.8164	-0.3350	-0.2365	-0.3429	-0.3901	-0.3244
	RC6	-0.1820	-0.2319	-0.2161	-0.2105	-0.2216	-0.2120	-0.1806	-0.1815	-0.2007	-0.1746
	RC5	-0.1820	-0.2319	-0.1289	-0.2105	-0.3089	-0.2120	-0.1200	-0.1815	-0.2007	-0.2530
SR	Index	0.0712	0.0505	0.0669	0.0453	0.0421	0.0526	0.0610	0.0765	0.0569	0.0817
	TR	0.0817	0.0599	0.0748	0.0557	0.0504	0.0605	0.0681	0.0873	0.0679	0.0886
	RC7	0.0746	0.0297	0.0701	0.0338	0.0505	0.0666	0.0733	0.0864	0.0557	0.0876
	RC6	0.0791	0.0505	0.0582	0.0448	0.0310	0.0511	0.0796	0.0882	0.0720	0.1208
	RC5	0.0727	0.0279	0.1059	0.0244	0.0122	0.0403	0.0876	0.0796	0.0536	0.1078
VaR	Index	0.0603	0.0669	0.0742	0.0632	0.0751	0.0732	0.0979	0.0577	0.0553	0.0926
	TR	0.0422	0.0469	0.0520	0.0443	0.0525	0.0514	0.0685	0.0406	0.0388	0.0649
	RC7	0.0905	0.0910	0.0936	0.0971	0.0990	0.0953	0.1065	0.1114	0.0872	0.1121
	RC6	0.0703	0.0777	0.0721	0.0721	0.0724	0.0696	0.0948	0.0690	0.0663	0.0744
	RC5	0.0464	0.0484	0.0543	0.0447	0.0538	0.0517	0.0762	0.0467	0.0408	0.0576
Vol	Index	0.1671	0.1870	0.2219	0.1685	0.2116	0.2207	0.2461	0.1623	0.1602	0.2548
	TR	0.1170	0.1309	0.1553	0.1179	0.1481	0.1545	0.1723	0.1136	0.1121	0.1784
	RC7	0.2808	0.2698	0.2769	0.2666	0.3121	0.2753	0.2805	0.2806	0.2791	0.3061
	RC6	0.1862	0.1972	0.2044	0.1801	0.2041	0.2071	0.2192	0.1809	0.1753	0.2063
	RC5	0.1295	0.1446	0.1485	0.1384	0.1586	0.1539	0.1650	0.1302	0.1290	0.1497

Table 4.1: Results of the SRRRI based trading strategy. If the realized volatility of the strategy falls outside the range defined by the risk class, the exposure altered by a trading rule based on volatility buckets. The table shows the mean values for the respective metric of the strategies applied to weekly returns for the period from 13/09/1991-27/02/2015. For reference purposes we also added the results for the index itself, representing a passive investment and a traditional 70/30 strategy. The highest mean returns are obtained for risk class 7, whereas a diverse pictures is shown regarding the SRs with no risk class clearly emerging.

4.4.2 Buy and Hold Returns

In order to gain a more dynamic perspective, we examine the Buy and Hold Returns (BHR) of the strategies. They are calculated over the whole sample period through the following formula:

$$BHR_{i,t} = \prod_{t=1}^n (1 + r_{i,t}) \quad (4.1)$$

We find that for all of the indices, one of the volatility based trading strategies is displaying higher BHRs than the passive index or the traditional strategies. For most of the indices risk classes 6 or 7 yield the highest BHRs for our observation window. We can, however, also state that these go along with notably higher variations for these risk classes compared to a passive investment. The outperformance of the strategies comes in most of the cases from higher participations during the upside markets e.g. during the 1990s or more recently in the years after the Lehman event (see e.g. S&P or CAC40 in figures 4.2 and 4.3).

It should be noted that risk class 6 and 7 (the latter even more so) provide a very low level of protection in downside markets which leads to more variations in the BHRs than e.g. the passive investments. A very striking example of this is shown in figure 4.3. We refer to risk class 7 for the CAC 40 which is invested with a leverage of 1600 % during a steep downside market in 2007 and consequently suffers a massive reduction in BHRs. Such protection would on the other side be expected with risk class 5. However, we observe that this mechanism only kicks in delayed also for risk class 5 in most of the cases. This pattern is particularly pronounced when disruptive events like the Lehman crisis happens.

On the other side, the signal to re-invest again is given too late in some cases when markets rebound, so particularly risk class 5 misses out to participate in upside markets in the second half of the 1990s or most recently after the Lehman event (e.g. refer to figures 4.6 or 4.7). In fact full protection to downside markets in risk classe 5 only proves to be valid for the DAX, where losses are avoided during both the Technology and the Lehman event. Consequently risk class 5 yields the best BHRs in this index.

So far we can state that from a return perspective our historical backtesting the volatility based strategies provides some evidence for better performance of these against indices. Regarding the BHRs the higher levels of returns are also associated with higher variations in BHRs. We find indications that the signal prescribed by the SRRI tends to be late in dynamic market environments.¹⁶

¹⁶For reasons of brevity, we only show selected graphs, the full results are available on demand.

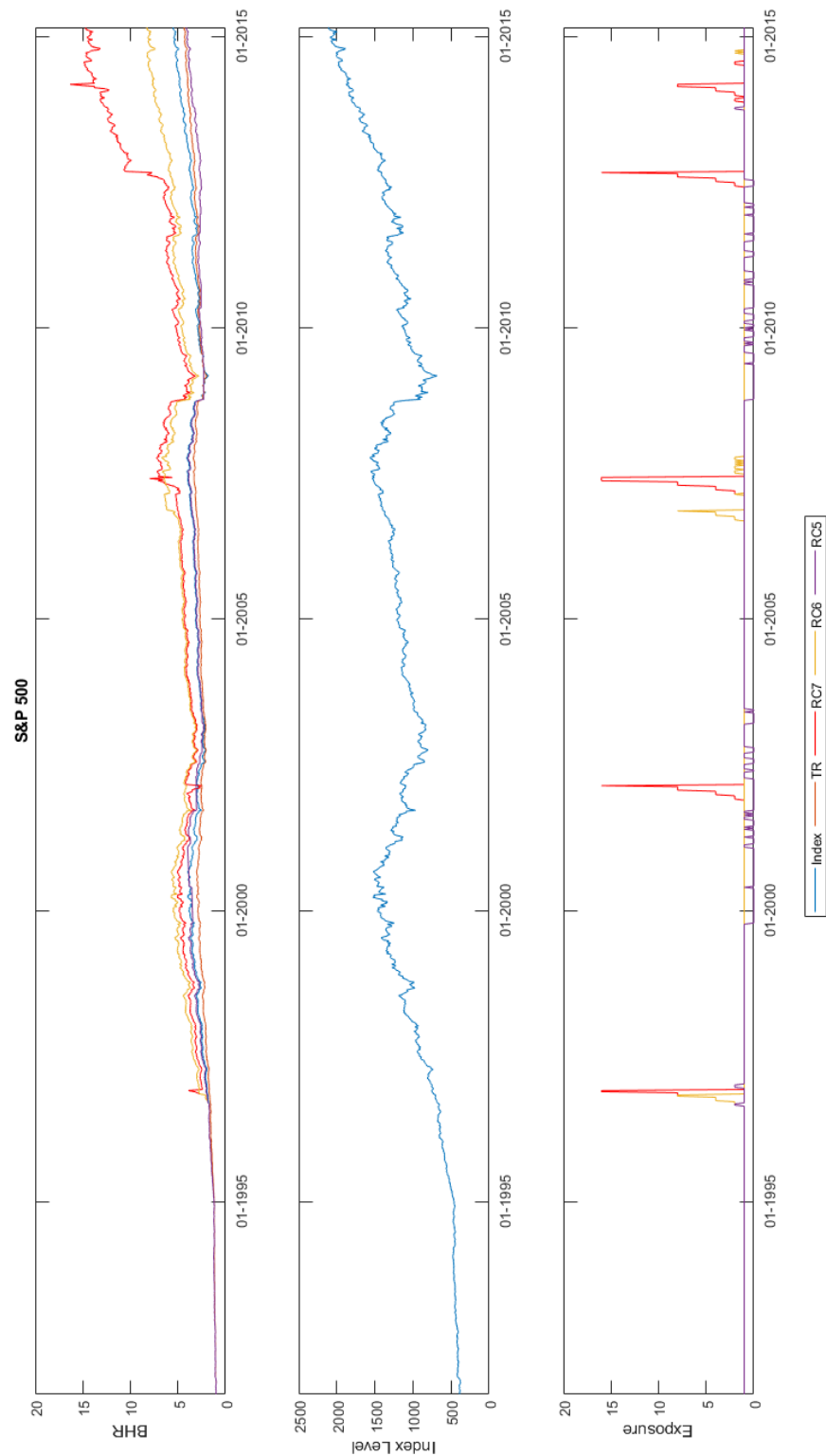


Figure 4.2: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

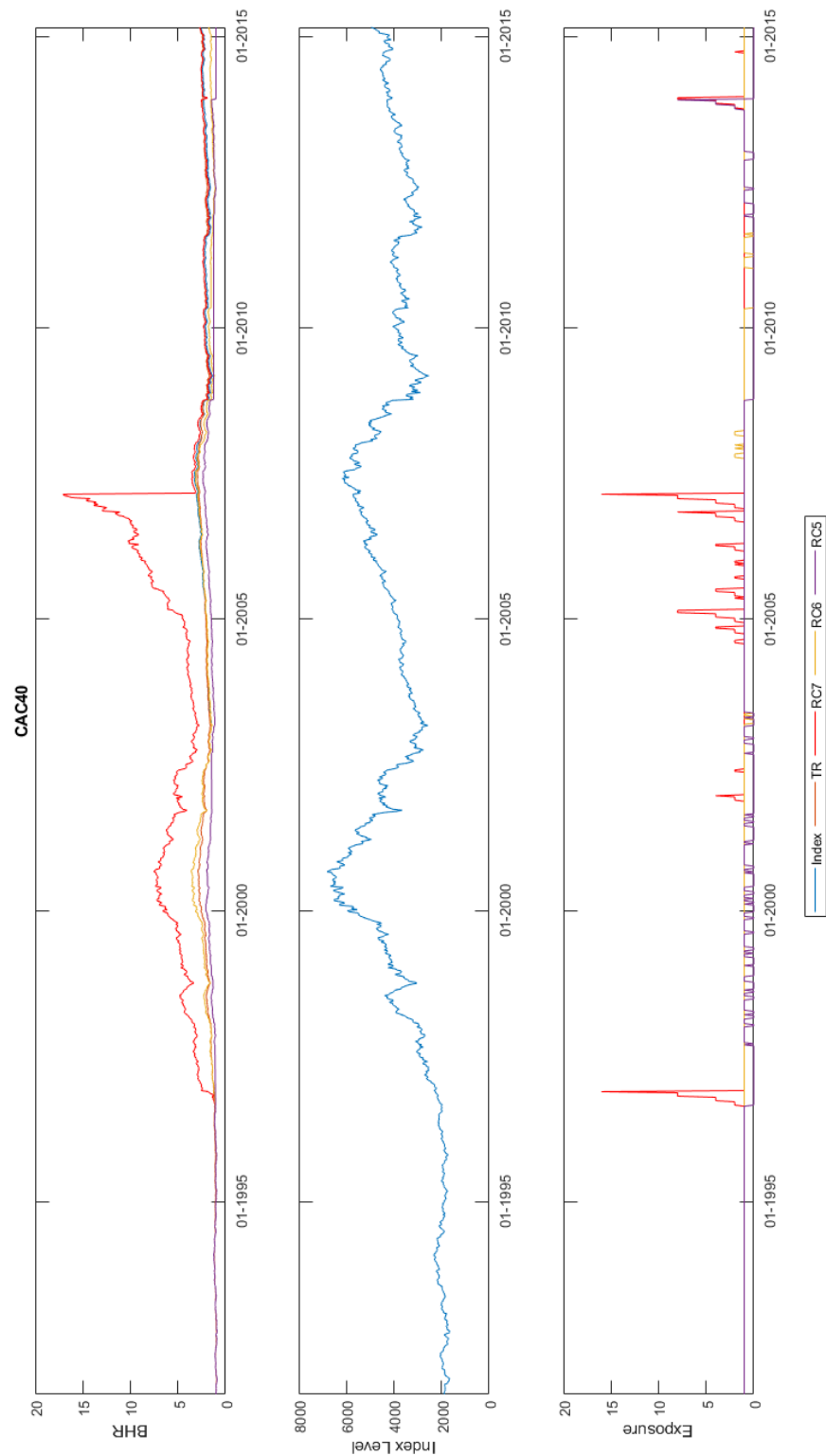


Figure 4.3: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

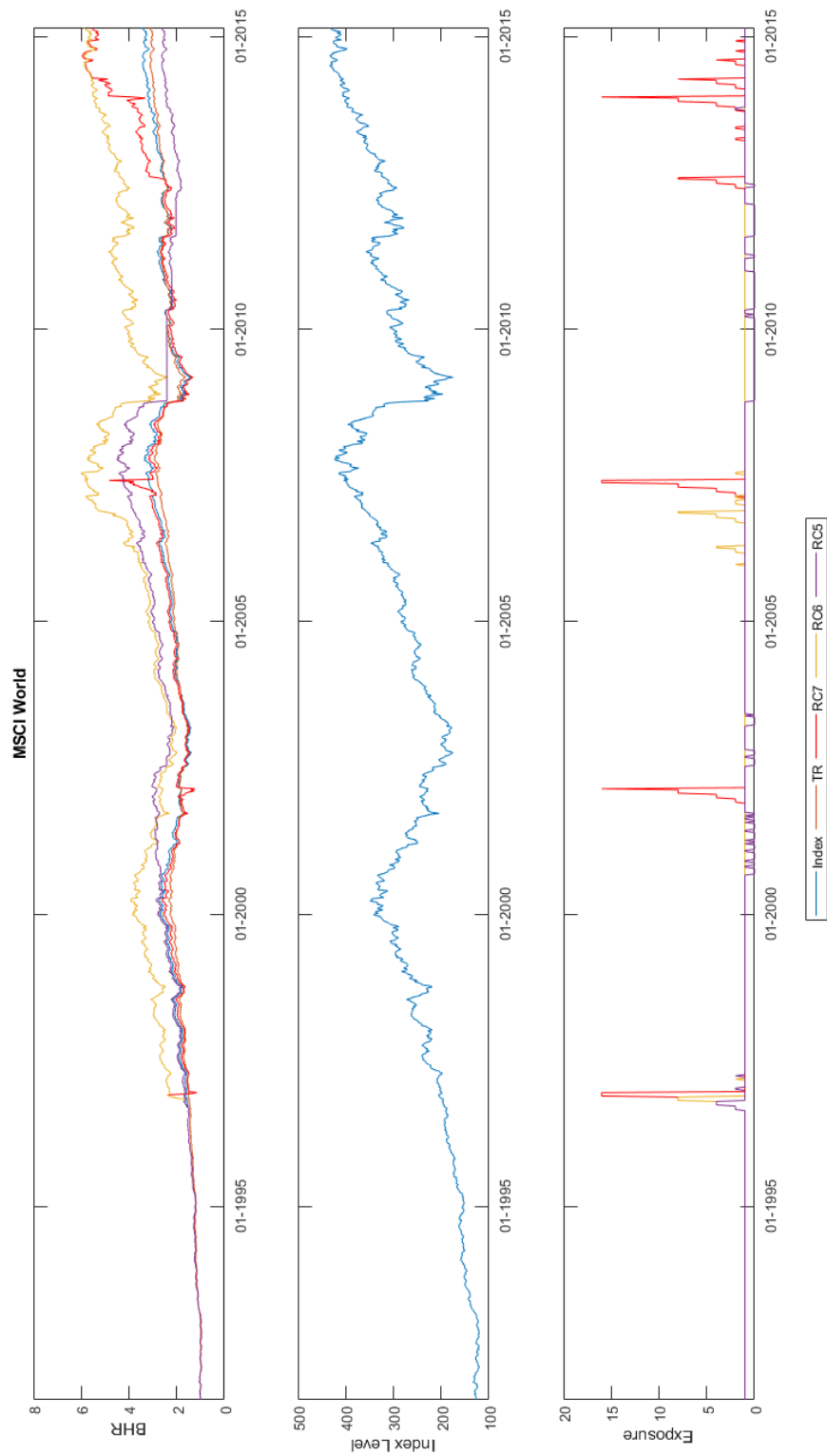


Figure 4.4: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

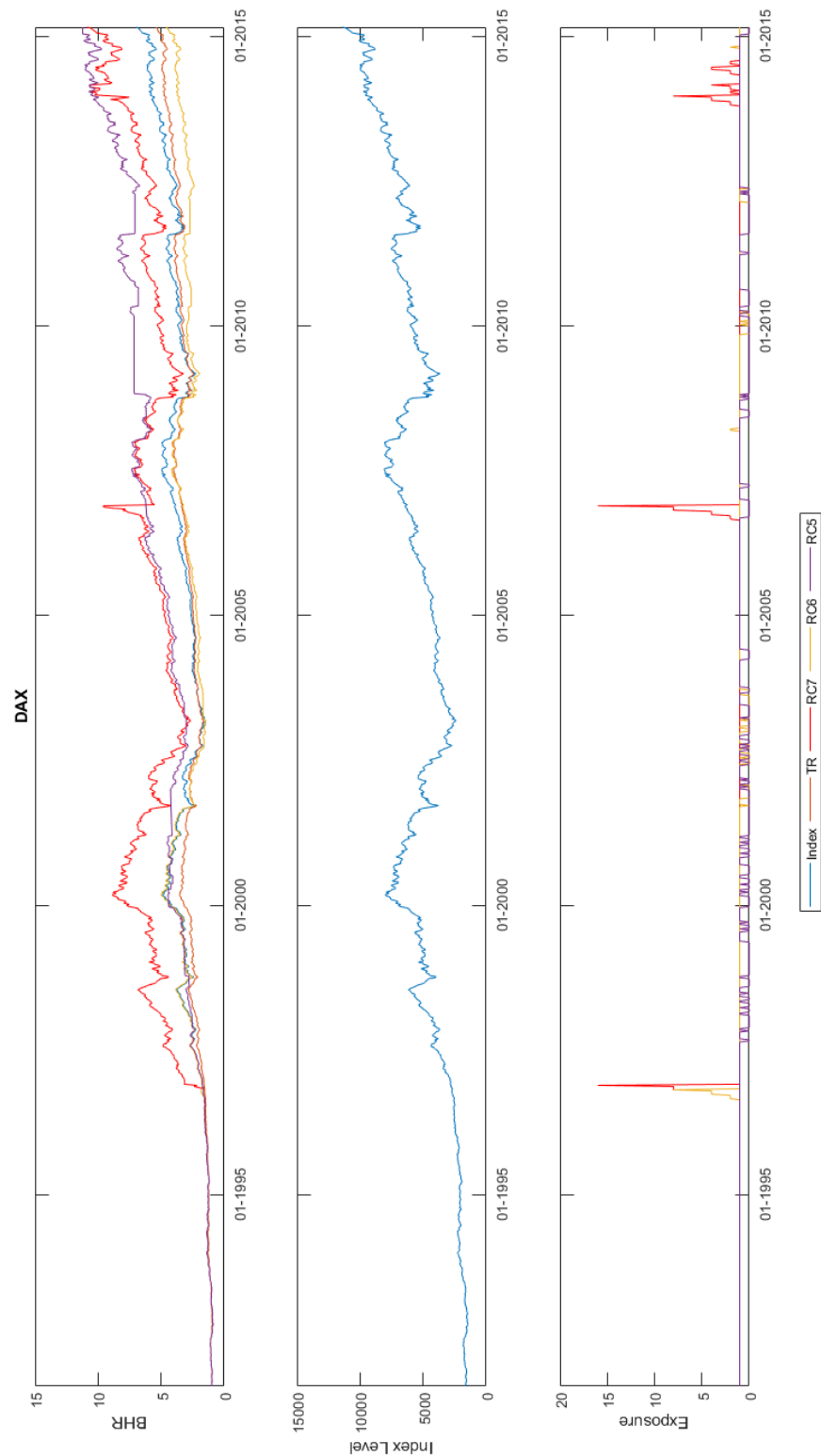


Figure 4.5: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

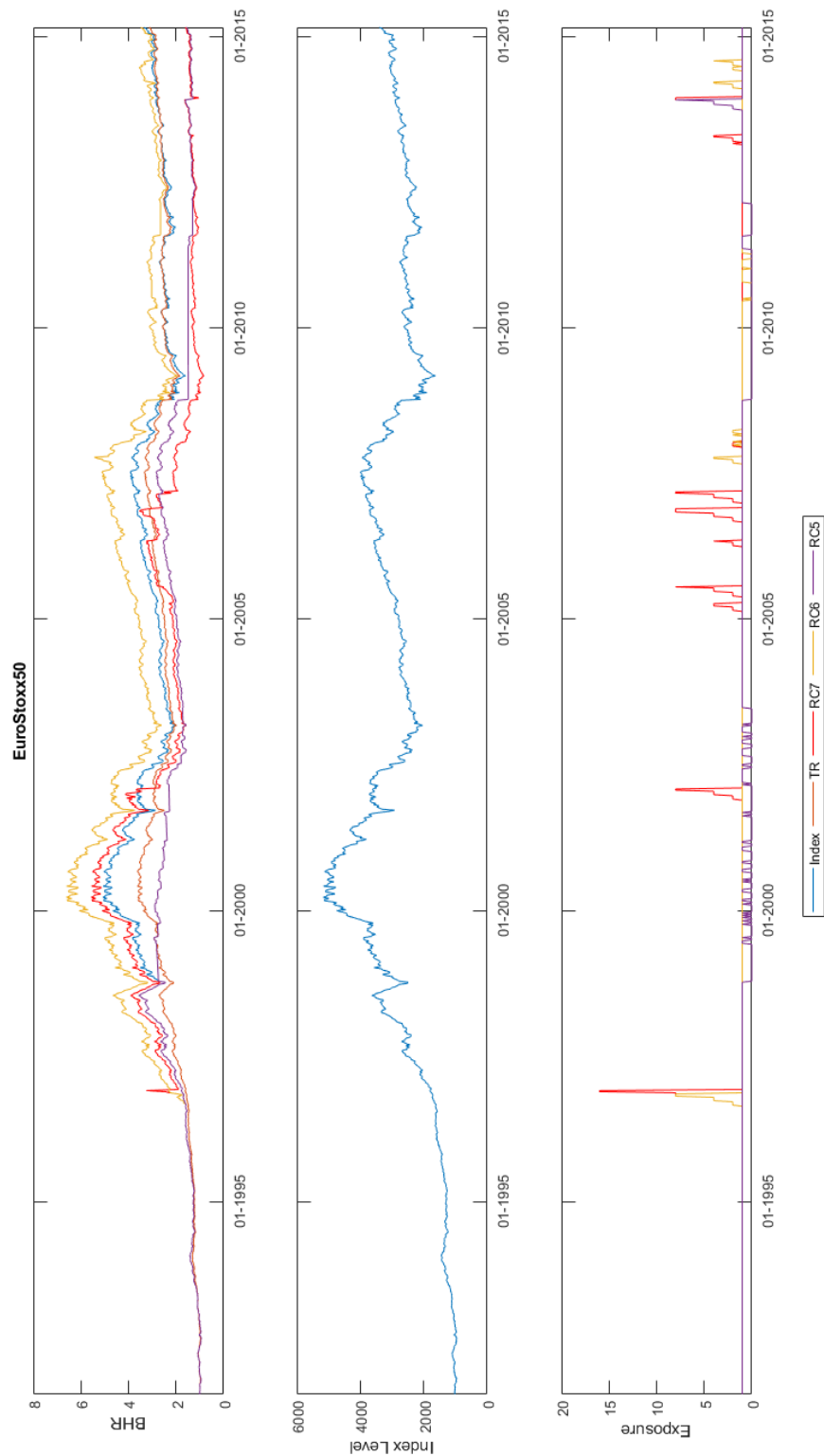


Figure 4.6: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

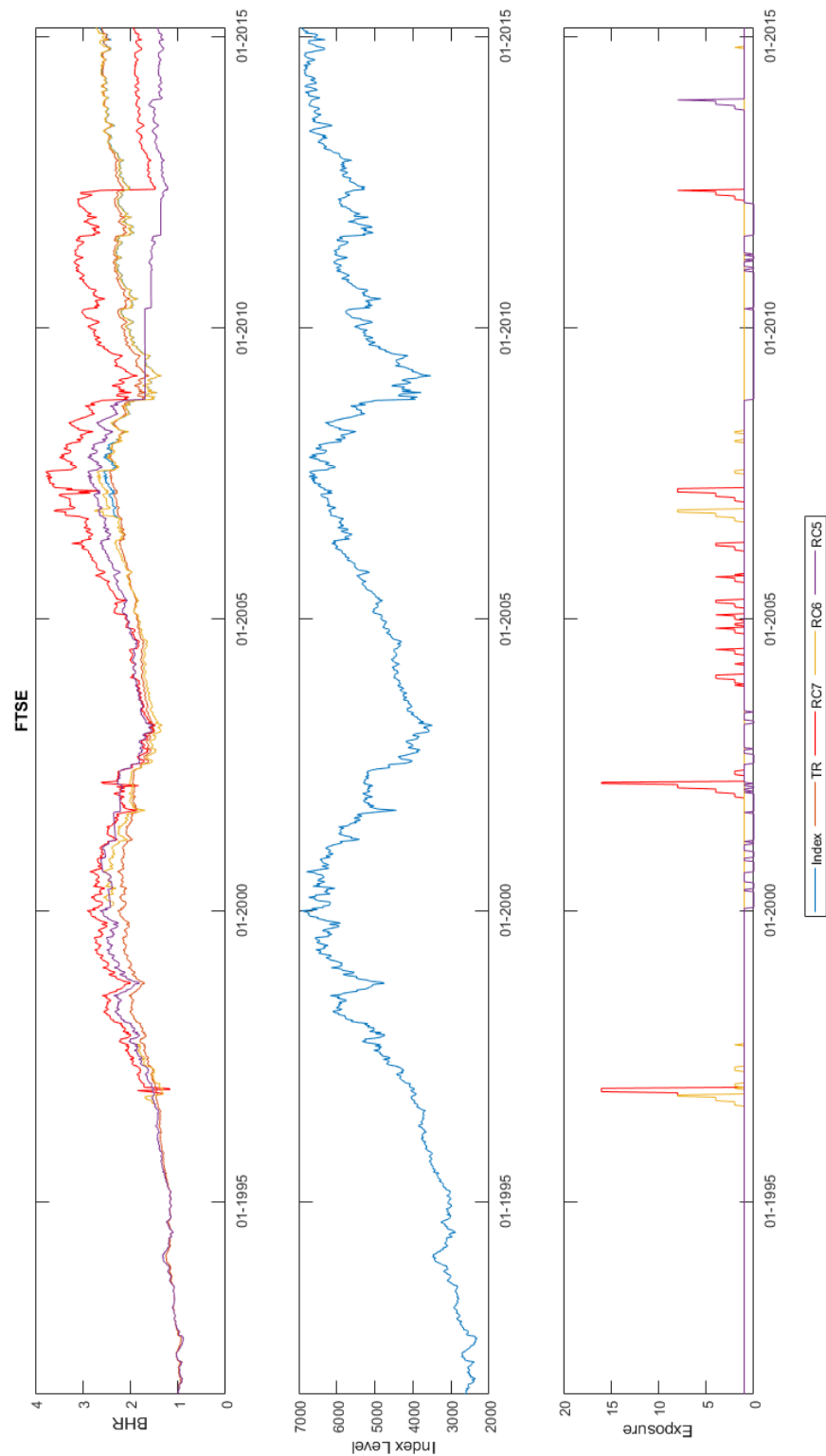


Figure 4.7: This figure displays the Buy and Hold return (BHRs) of the volatility based strategies, the index level and the exposures induced by the trading rule.

4.4.3 Risk Adjusted Returns

Without providing a clear - cut picture our analyses so far points at better performance of the volatility based strategies. Next, we run Fama and French (1992) Three-Factor regressions on the strategies to examine whether there is an economic value of the volatility strategy in equity markets accounting for the size and value effect. The factor data is obtained from Kenneth French's website.

$$E(r_i) = \beta_0 + \beta_1 * E(r_m - r_f) + \beta_2 * SMB + \beta_3 * HML + \epsilon_i \quad (4.2)$$

where:

$E(r_i)$ = Expected return of asset i

r_f = Risk free rate

$E(r_m)$ = Expected return of the market portfolio

SMB = The returns of the size factor

HML = The returns of the value factor

ϵ_i = IID error term

The results are presented in tables 4.2 and 4.3. As is visible from the table, with one exception none of the volatility based strategies applied to the indices yields alphas in either direction at relevant significance levels. Significant positive alphas at the 99 % - level can be observed for the NASDAQ, here for all risk classes. Risk class 5 for the DAX shows a positive alpha at the 95 % - level which supports the positive results for this risk class and the DAX from the analysis of the BHRs. Apart from these two exceptions no significant alphas could be found, so overall only very limited positive impact of the SRRI could be found accounting for size and value effect. On the other side we also did not find any indication for indirect costs induced by the volatility bands. Given the results above we abstain from adding further factors capturing momentum (Carhart (1997)) or liquidity (Pastor and Stambaugh (2003)) to the analysis.

4.4.4 Discussion

Overall we can state that the historical backtesting of a risk on - risk off trading strategy based on the SRRI proves to effectively control dispersion and tail risk on a longterm basis. Furthermore we find evidence in our analysis on historical data for equity indices that the volatility strategy imposed by regulators would actually be beneficial for equity investors in terms of higher SRs and BHRs compared to apassive investment in the index. It should however be noted that none of strategies clearly emerges either regarding

	S&P 500				SX5E				DAX				FTSE				CAC40			
	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat	Beta	T-stat
RC7	Constant	0.0685	0.84	-0.0978	-1.14	0.0464	0.54	-0.0777	-0.89	-0.0138	-0.14									
	Market	1.1343***	32.51	0.9613***	26.22	1.0226***	27.93	0.8963***	24.00	1.0552***	24.25									
	SMB	-0.3428***	-5.28	-0.1035	-1.52	0.0476	0.70	-0.1317*	-1.90	0.0009	0.01									
	HML	0.0363	0.58	0.1218*	1.87	0.1153*	1.77	0.1924***	2.89	0.2126***	2.75									
RC6	Constant	-0.0032	-0.12	-0.0497	-0.90	-0.0249	-0.41	-0.0752	-1.52	-0.1068	-1.84									
	Market	1.0233***	87.60	0.8353***	35.60	0.8116***	31.64	0.7750***	36.83	0.8472***	34.19									
	SMB	-0.2279***	-10.48	-0.1461***	-3.35	0.0217	0.46	-0.0592	-1.51	-0.0866*	-1.88									
	HML	0.0130	0.62	0.1144***	2.74	0.1188***	2.60	0.2034	5.43	0.1618***	3.67									
RC5	Constant	-0.0001	0.00	-0.0602	-1.20	0.1048**	1.99	-0.0681	-1.45	-0.0876	-1.53									
	Market	0.5737***	40.30	0.4229***	19.83	0.3912***	17.43	0.4256***	21.27	0.3948***	16.18									
	SMB	-0.2084***	-7.87	-0.1181***	-2.98	0.0113	0.27	-0.1478***	-3.97	-0.0211	-0.47									
	HML	-0.1120***	-4.42	-0.0277	-0.73	-0.0591	-1.48	-0.0375	-1.05	-0.0319	-0.73									

Table 4.2: This table shows the first set of results of the Fama-French Three Factor regressions that are performed to verify if the volatility based strategies yield significant outperformance. Significance at a confidence level of 99%, 95%, 90% is indicated with ***, **, *, respectively. No significant alphas at the 99% - level could be found for the investment strategies based on the risk classes.

	IBEX 35			Hang Seng			DJ Ind			MSCI World			NASDAQ		
	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	t-stat
RC7	Constant	0.0356	0.40	0.1103	1.10	0.1203	1.40	-0.0009	-0.01	0.1712***	2.41				
	Market	0.9319***	24.36	0.7233***	16.89	1.0593***	28.87	1.0258***	27.50	1.2930***	42.69				
	SMB	0.0581	0.82	0.0596	0.75	-0.4195***	-6.14	-0.2088***	-3.01	0.1175**	2.08				
	HML	0.2581***	3.79	0.0798	1.05	0.1551***	2.37	0.1370**	2.06	-0.8828***	-16.37				
RC6	Constant	-0.0367	-0.56	0.0971	1.22	0.0216	0.64	-0.0278	-0.80	0.1600***	3.31				
	Market	0.7509***	27.03	0.5266***	15.50	0.9444***	65.04	0.9010***	60.92	0.9265***	44.89				
	SMB	0.0104	0.20	0.0729	1.15	-0.3121***	-11.55	-0.0582**	-2.11	0.1575***	4.10				
	HML	0.1699***	3.44	0.0772	1.28	0.1214***	4.70	0.1450***	5.51	-0.2776***	-7.56				
RC5	Constant	-0.0266	-0.48	0.1123*	1.76	0.0139	0.40	-0.0279	-0.79	0.1054**	2.14				
	Market	0.3738***	15.71	0.2058***	7.57	0.5575***	37.25	0.5359***	35.49	0.4246***	20.17				
	SMB	-0.0217	-0.49	0.1371***	2.71	-0.2898***	-10.41	-0.1524***	-5.42	0.2569***	6.56				
	HML	-0.0122	-0.29	-0.0689	-1.42	-0.0503*	-1.89	-0.1572***	-5.85	-0.1775***	-4.74				

Table 4.3: This table shows the second set of results of the Fama-French Three Factor regressions that are performed to verify if the volatility based strategies yield significant outperformance. Significance at a confidence level of 99%, 95%, 90% is indicated with ***, **, *, respectively. Apart from the NASDAQ no significant alphas 99% - level could be found

BHRs nor the SRs. Further to this very high variations of the BHRs are observable. We can also observe that high leverage induced by low volatility levels or lagged reaction to cut exposures in downside markets may be detrimental to performance.

This is a pitfall of the longterm orientation of the set-up which aims to generate stable risk classes. Accounting for the size and value effect reveals no significant alphas in most of the cases. In the following we conduct a simulation study to gain further evidence on the impact of the volatility strategy on the distribution parameters of returns.

4.5 Simulation Study

4.5.1 Desgin of the Simulation

To examine the effect of the SRRI on the distribution of portfolio returns we conduct a simulation study. We generate 10.000 price paths of 1040 weekly returns (i.e. 20 years) and apply the strategy on these generated returns. We then use the obtained returns from the strategies to compute the distribution parameters and risk metrics for each price path. A paired t-test is subsequently performed on these parameters between the simulated passive returns and the returns of the strategies maintaining the risk classes as defined above. To limit the impact of extreme scenarios we constraint our investment strategy to a maxium leverage of 3200%. This level of leverage would only be surpassed after 6 months outside the selected risk band.

We generate the returns using two specifications. First we use a GARCH(1,1) - model as e.g. described in Engle (2001) or Engle and Patton (2001).

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (4.3)$$

Setting $\omega = \gamma V_L$, the GARCH(1,1) equation 4.2 can be written by:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (4.4)$$

In the second set-up we estimate a GJR-GARCH(1,1) - model as e.g. described in Glosten et al. (1993) which is then used to simulate the returns. This specification accounts for asymmetry (or leverage) within the volatility modelling and takes the following form:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 + \gamma_+ I(u_{n-1}^2 > 0) + \gamma_- I(u_{n-1}^2 < 0) \quad (4.5)$$

The model parameters are estimated on the return data described above using the full time series available. Within the simulation we assume a t-distribution for the innovations.

4.5.2 Results

As you can see from table 4.4, we find that applying the strategies has significant impact on the volatilities of the portfolios. That is to say for the strategy in risk class 7 the volatility is significantly higher at the 99% - level than the index volatility and vice versa for risk classes 5 and 6.¹⁷ The same picture with switched signs emerges for the tail risk measure (VaR), so overall the findings indicate that the volatility based strategies without leverage constraints have a significant effect on volatility and VaR. This is a pattern one would expect given the results from the analyses of historical data and once again underpins the effectiveness of the trading rule applied in controlling a portfolio volatility.

A part from risk class 7, where most of the indices do not show any significant difference in skewness, we observe significantly lower skewness for risk classes 5 and 6. The volatility based strategies show higher levels of kurtosis than the index itself which is a result of the risk on - risk off strategy as they will cumulate a lot of returns close to zero due to the periods of underinvestments. The higher levels of kurtosis also shows that the volatility strategy would broaden up the occurrences of returns, i.e. more extreme or higher values and less occurrences around the mean induced by higher leverage. So far the results are as expected considering the trading rule applied.

We could not find significant differences in the mean returns between the two samples, so the longterm volatility strategy imposed by the SRRI does not seem to materially affect average returns. Looking at the risk adjusted measure we can observe negative t-statistics for the SRs for all the indices. This indicates a negative impact on performance considering both risk and return. We can therefore state that the indications for positive impact found in the historical analysis were not confirmed in our simulation study. To the contrary our results suggest a negative impact on the results for investors. For robustness checks we change the time window taken into account when estimating the model parameters for both models. The results remain unchanged.¹⁸

Overall we can state that the SRRI yields significantly lower risk adjusted returns, while average returns do not seem to be affected in the same way. This suggests that higher variations induced by the volatility signal do not pay off on a risk adjusted basis.

¹⁷The results are very similar for both models. In order to be concise we only present the results for the GJR(1,1) - Model.

¹⁸The results are available upon request.

As we have shown above, this finding may be related to the fact that the longterm volatility is used as a signal (weekly data from the last five years). Consequently, the strategy will be notoriously late as it will only react if there is a clear trend or a very large move that leads to a rather quick adaptation of the estimate. Shortterm volatilities might prove to be more efficient in creating a trading signal in a context of a volatility trading strategy, potentially at the cost of less stable risk classes, though.

Strategy	S&P 500	SX5E	DAX	FTSE	CAC40	IBEX 35	Hang Seng	DJ Ind	MSCI World	NASDAQ
Mean	-0.45	-0.15	0.67	1.00	0.47	0.52	1.27	-0.44	-2.14**	1.06
Volatility	223.61***	218.41***	151.93***	289.54***	181.54***	149.18***	71.90***	309.71***	495.76***	73.55***
Skewness	-2.58***	-2.99***	-1.23	-1.90*	-0.60	-0.60	-0.15	-2.00**	-2.28**	-0.41
Kurtosis	49.40***	47.85***	35.92***	54.08***	43.09***	39.23***	22.91***	54.19***	61.87***	23.35***
VaR	-152.95***	-151.11***	-111.59***	-177.70***	-126.74***	-109.31***	-57.70***	186.22***	-227.48***	-58.57***
SR	-16.31***	-13.79***	-10.00***	-12.23***	-11.24***	-10.89***	-6.57***	-13.09***	-11.17***	-7.08***
Mean	0.77	0.53	-0.46	0.31	0.10	0.11	0.25	0.16	-0.30	0.60
Volatility	-19.62***	-25.18***	-43.51***	-8.17***	-39.10***	-50.61***	-79.73***	-5.02***	68.79***	-78.83***
Skewness	-7.80***	-8.98***	-11.37***	-4.38***	-11.84***	-11.13***	-7.81***	-4.67***	-1.73*	-5.30***
Kurtosis	16.82***	12.34***	3.50***	15.81***	10.02***	11.43***	38.42***	15.27***	26.10***	25.56***
VaR	16.21***	18.79***	29.29***	8.20***	25.52***	32.54***	53.06***	6.07***	-42.59***	52.31***
SR	-15.12***	-12.19***	-11.62***	-12.02***	-10.76***	-11.22***	-10.68***	-11.50***	-10.66***	-10.56***
Mean	-0.87	-0.84	-1.15	-0.22	-0.68	-0.80	-0.47	-0.47	-1.10	-0.44
Volatility	-91.68***	-134.49***	-241.36***	-111.24***	-233.53***	-251.96***	-176.97***	-103.69***	-78.84***	-177.97***
Skewness	-8.04***	-4.77***	-0.30	-11.58***	-3.84***	-1.66	5.26***	-7.93***	-12.31***	4.41***
Kurtosis	21.85***	26.29***	46.92***	24.02***	66.47***	79.86***	99.96***	12.55***	10.91***	82.13
VaR	56.56***	73.28***	111.20***	64.02***	104.82***	109.13***	89.16***	60.56***	46.49***	89.21
SR	-15.62***	-11.95***	-7.13***	-12.97***	-7.79***	-7.37***	-4.83***	-12.89***	-12.32***	-4.89***

Table 4.4: Results of the paired t-test on the distribution parameters. Significance at a confidence level of 99%, 95%, 90% is indicated with ***, **, *, respectively. The returns are generated with a GJR(1,1) - Model, where the parameters for each index are estimated on the full history available and a t-distribution is assumed for the innovations. We generate 10.000 price paths of 1040 weekly returns and apply the risk on - risk off strategy. Then the distribution parameters and the Sharpe Ratios are calculated and the t-test is performed against the same parameters of the passive strategy. There is no significant difference in mean return, but the strategies based on volatility display significantly lower SRs.

4.6 Conclusion

We examine the impact of the longterm volatility strategy imposed by the SRRI on the returns of equity investment strategies. In our historical backtesting of the volatility strategies we initially find indications that for some indices they actually yield higher SRs and also higher BHRs than passive investments in the index. The latter albeit at the cost of notably higher variations. Besides a few exceptions the analyses of the BHRs revealed that realized volatility as the signal chosen for the risk classes does not provide robust protection in downside markets. It should also be noted that none of the risk classes clearly stands out as an optimal risk class.

For most of the worldwide indices no significant alphas emerge for the SRRI based strategies accounting for the size and value effect. In further analyses through a simulation study we couldn't find evidence for a significant effect on mean returns in a paired t-test. The results do, however, reveal significantly lower Sharpe Ratios earned by the volatility based strategies. This suggests that investors may have to bear additional indirect costs through lower risk adjusted returns. Consequently, controlling a portfolio's volatility according to the SRRI can lead to additional regulatory costs. Furthermore distortions when attributing fund performance are evident.

Potential future research could focus on improvements regarding the return effects induced by the SRRI by e.g. considering flexible boundaries or a more refined set of indicators for the determination of the risk class.

Selbstständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Trier, den 30.05.2018

Martin Ewen

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