Statistical Methods of Strategic Portfolio Management for Fund of Funds

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für Wirtschaftswissenschaften

des Karlsruher Instituts für Technologie

genehmigte

DISSERTATION

von

Diplom-Volkswirt Michael Stein

Tag der mündlichen Prüfung: 13.12.2010

Referent: Prof. Dr. Svetlozar T. Rachev

Koreferent: Prof. Dr. Detlef Seese,

2010 Karlsruhe

Danksagung

Zuerst möchte ich meiner Frau Alona danken. Ohne ihre große, bedingungslose und immerwährende Unterstützung und Liebe wäre diese Arbeit nicht möglich gewesen. Sie hat mich auch in schwierigen Situationen immer mit großer Fürsorge und Verständnis unterstützt und ich widme ihr diese Arbeit von ganzem Herzen.

Des Weiteren möchte ich meinen Eltern Renate und Jürgen danken, durch die ich seit jeher Unterstützung erfahren habe und die immer an mich und meine Vorhaben glaubten. Ebendies gilt für meinen besten Freund Tobias.

Dank auch an alle anderen Familienmitglieder in Deutschland und der Ukraine sowie meine Freunde und Kollegen. Hier sind besonders Stephan Brünner und Dr. Werner Bals zu nennen, welche mich als meine Vorgesetzten bei der Credit Suisse während der Promotionszeit mit großem Verständnis und wertvollen Ratschlägen unterstützten, sowie Lidia Bonifacio, welche die Hardwareanforderungen der großen Analysen unterstützte.

Für eine hervorragende ökonometrische Grundlagenausbildung zu Freiburger Zeiten, welche mir bei dem Erarbeiten meiner Studien und der statistischen Weiterbildung immer geholfen hat, möchte ich Prof. Roland Füss und PD Dr. Harald Nitsch danken.

Allen Mitarbeitenden der Universität Karlsruhe und allen der Universität sowie dem Lehrstuhl Verbundenen möchte ich für die Hilfe und die vielen wichtigen Ratschläge danken. Hier ist besonders Stoyan V. Stoyanov zu nennen, welcher vor allem bei den Codierungen in MATLAB mit Rat und Tat zur Seite stand.

Dank auch an Jürgen Dietrichkeit von The Mathworks, welcher auf der Softwareseite hinsichtlich MATLAB und den Erweiterungen exzellenten Support leistete.

Dank für die Unterstützung als Co-Supervisor gebührt Professor Frank J. Fabozzi von der Universität Yale, der durch seine große Erfahrung ein unschätzbar wichtiger Ratgeber war.

Abschließend geht großer Dank an Professor Svetlozar T. Rachev, meinen Doktorvater, welcher mich vom ersten Tag an mit großer Unterstützung und uneingeschränktem Vertrauen

geleitet hat, sowohl bei inhaltlichen Fragen, als auch hinsichtlich der nicht immer leichten Verbindung von Theorie und Praxis.

Michael Stein, Frankfurt am Main im Oktober 2010

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Abstract

A “fund of funds (FoF)” is an investment fund that invests in other investment funds rather than investing directly in shares, bonds, or other securities. Sometimes referred to as multi-manager funds, these investment funds pose – apart from the challenges that arise for every portfolio to be managed – special problems to their management teams. Most of those must be addressed with appropriate statistical or mathematical methods. We show how this may be done, using - among others - both state-of-the-art tools like post-modern portfolio optimization as well as using accessible and comprehensive representations.

1. The World of Funds of Funds

1.1. Introduction

The fund of funds (FoF) concept has its origin in the 1960s, with the industry steadily growing since then. A FoF is a fund, which invests in other funds and is sometimes referred to as a multi-manager fund. There are many different types of FoFs. They include funds of hedge funds, funds of private equity funds, funds of mutual funds, and funds of real estate funds among many others. Being the most popular FoF type, funds of hedge funds had about US $600 billion assets under management at the end of 2009, compared to total hedge fund assets under management of about US $1.500 billion according to Barclay Hedge (managed futures had about US $214 billion assets under management).

Investments in FoFs can be advantageous for both retail and institutional investors due to the distinct features of this kind of financial product. However, as with any other investment product, disadvantages and sources of possible dissatisfaction exist as well.

One out of several striking advantages of FoF concepts is the possibility for retail investors to get access to financial products in which they could not directly invest. Many funds — and especially hedge funds — are not accessible for most private and retail investors due to high minimum investments, prohibitive high transaction costs, lack of information or simply because of missing distribution channels.

With FoFs, retail investors are able to get exposure to sectors, asset classes, markets, and products which otherwise would not have been included in their portfolios. Such structural aspects, albeit largely differing between countries, markets, and sectors, stem from the fact that business ties and related costs are crucial in determining the investment product universe.

With most FoFs pooling money from large and diverse investor bases, they are able to invest in assets that demand high minimum investments or that offer discounts to management fees, costs or loads when investing amounts above specified marks. Investing in special share classes of funds that are generally open for all kinds of investors with pre-defined minimum investments and lower management fees, is another path to cost reduction. Because banks and fund management companies generally have their own trading infrastructure, accounting, and clearing offices and desks as well as special agreements with other market players and counterparties, absolute and relative operational costs also can be reduced significantly.

However, on the con side, the double cost structure of FoFs caused debates in the past and is still subject to discussions both in the academic world and among practitioners.

In addition to these organizational economies of scale, direct contracting between financial institutions may impose another beneficial factor when it comes to market access. With direct contracts between financial institutions, banks, endowments, management companies, and/or advisors, discounts to fund load fees for example may be agreed on, or the institution may be able to trade without paying issuance fees. Structural aspects and the effects of business ties in the fund industry have been the subject of numerous studies, which will be discussed in the fund (of fund) industry review in Section 1.2.

Besides constraints at the cost-of-investment side or barriers to entry, retail investors face another problem when building portfolios out of a large variety of assets and financial products: The problem of information and overview. As the fund industry is offering a huge range of products, it is difficult for retail investors to get an overview concerning funds in which they are interested. Performing the task of market screening may be both time-consuming and inefficient. Furthermore, even when having found a pool of investment possibilities, selecting the ones that suit the investor's needs and preferences is a challenging task, sometimes even for experienced investors.

As is the task to define an investment universe, the evaluation task is challenging, because based on the respective needs each single investor has, information building with respect to the quality of target funds is crucial. This stems from two interrelated facts. First, retail investors generally do not have access to sophisticated data systems or information systems. Second, even if such sources are at their disposal, retail investors may find it difficult to use such information properly.

Being exposed to some kind of informational blinkers, the only way to remedy may be delegating investment decisions. This can happen in various ways, for example with investment advisors or wealth managers. Investing in pension funds or insurance plans could be a solution, too. However, none of the mentioned forms of investment decision delegation is free from shortcomings or disadvantages. Costs have to be incurred in any case, and one is always exposed to the classical problems of moral hazard, divergence of interests, uncertainty, and, once again, insufficient information. For FoFs, the same holds true of course, and one may argue that indirectly paying a FoF manager via management fees may result in the same problems as paying directly for investment consultancy or wealth management.

However, the emergence of the industry in recent years and the steady path of growth that the branch has found, suggests another view. Seemingly, the FoF industry delivers products and investment possibilities that attract retail investors all over the world. If it would not pay in the most direct sense of the word, why should people put their money into FoFs? Is it the inexistence of better solutions, advertisement effects, or do FoFs really suit retail investors that well? These questions have yet to be answered, where attention should be drawn on the double cost structure imposed by FoFs and their management fees. This often-emphasized double fee structure of FoFs is subject to the studies of Brown et al. (2004) and Reddy (2007).

Many of the problems that retail investors face when making investment decisions do not arise for institutional investors in the same manner. As mentioned above, information flows are completely different for institutional investors such as pension plans, asset managers, wealth managers, endowments, or state-owned investment funds than they are for private, retail investors. The same holds true for different cost burdens, resulting from the structures discussed above. Reconsidering the decision to choose between types of delegating investment decisions, questions concerning the value added by market professionals have to be answered.

Naturally related to management fees and advisor compensation is the question of how well the services provided suit the investors. When deciding on the sector, asset class or country to invest in, the problem is not only to separate the ones which one wants to be exposed to, but to decide on how this can be achieved. Investing in index or basket certificates or exchange traded funds (ETFs), for example, are ways to gain exposure to specific markets, sectors, countries or strategies. Most index products are very transparent when it comes to underlying constituents, have very low management fees, and offer the ability to participate directly in the movements of the underlying index. If exposure is gained through index or asset tracking products, the investor receives a return profile with zero alpha (no excess returns over the benchmark or index) and a beta of one (the returns are – or should be - proportional to the underlying benchmark or index).

Passively managed ─ or at least benchmark oriented ─ funds are another way to participate (almost) one-by-one, although some funds exist, which are marketed as actively managed ones, but are merely tracking their benchmark. In contrast to investing in index profiles, both retail and institutional investors are demanding excess returns from their investments, that is, they expect the managers to outperform their benchmark.

Finding fund or portfolio managers which seem to possess superior ability to outperform the market and thereby keeping track of the imposed costs is also a strain of research of its own. Questions that arise when searching for alpha include ─ among many others ─ the following: Is past performance due to pure luck or ability? Are the returns achieved driven by timing, selectivity, superior strategies or are unobservable factors responsible? May the investors expect the past performance to persist over time? As even market professionals and academics may struggle to identify winners and losers, the quest for alpha is understood as being one of the most challenging. Selection problems, performance analyses, and efforts to identify winners and losers are the subject of Section 1.3. These problems arise on both sides of the FoF ─ investors are interested in selecting the best FoFs and in turn FoF managers are seeking to invest in the best funds.

After discussing selectivity and identification problems that arise when deciding on investments, we lay out a problem that is very much a special FoF problem. FoF managers may choose among a large variety of funds depending on the branch they are investing in. Building portfolios out of funds may result in multiple exposures to one and the same asset or risk factor. For example, when investing in European real estate equity funds like the Henderson Horizon Pan-European Property Equity Fund or the Morgan Stanley European Property Fund, one has significant exposure to the shares of Unibail Rodamco, a real estate company that makes up more than 10% of the European Public Real Estate Association (EPRA) Europe Index.

One should be careful when selecting related funds in order to avoid the trap of ending up with a market-representing portfolio of top-holdings, while at the same time incurring higher costs than when investing in the related indices. From this, it should be clear that limits to diversification arise not only from the structure of the underlying assets but also from the paralleling of holdings. Benefits of including additional funds therefore need to be weighed against the disadvantageous increased monitoring burden and the diversification drain. Of course, this problem is not limited in dimensions, as FoF-Squared (fund of fund of funds) structures exist as well, for example when institutions decide between building portfolios out of funds or investing in FoFs. We will cover FoF specific portfolio construction problems in Section 1.4.

1.2. The Fund (of Funds) Industry

As noted earlier, many different FoF types exist. Although the variety is large and growing, hedge FoFs (HFoFs) have attracted the majority of capital invested in FoFs. The large fraction of HFoFs in the industry has a straightforward structural interpretation, as one crucial benefit from investing in this type of FoF is the possibility of investing in hedge funds at all. Generally, hedge funds are not accessible for most non-institutional investors except high-net-worth individuals, and by pooling investors' money, the HFoFs open the door to this asset class for nearly everybody. Of course, minimum investments exist for HFoFs too, but especially when accessing investible hedge fund indices those are found to be lower.

Diversification benefits are another source of attractiveness of all FoFs, especially when multiple hedge fund strategies such as Event Driven, Convertible Arbitrage, Distressed Securities or Global Macro for example are included in the HFoFs. Large and growing, hedge funds show a wide range of investment possibilities. Due to the fact that hedge funds are way less transparent than mutual funds and do not have the strong and strict reporting obligations that are imposed on mutual funds, the task of selection and identification in the investment process is especially tough when building portfolios that consist of or at least contain hedge funds. In this respect, HFoFs deliver a precious service to investors by screening the hedge fund market, performing due diligence processes, and by selecting the most prospective investment possibilities.

As with any other asset class, the layout of the investment process is crucial to the success of the investments made. Following the due diligence process and the manager selection, the HFoF asset allocation (bottom-up or top-down approach, diversification considerations, expectation building among others) is done, followed by continuously monitoring the risks and returns of the investments made. Investment processes' setup and quality are the determining factors for the success or failure of HFoFs. For example, Standard & Poor's defines fund rating criteria that are underlying their decisions such as investment culture, due diligence approach, portfolio monitoring systems and controls, operational risk assessment, experience of fund management teams, selected managers' experience, and performance success.

Private equity FoFs (PEFoFs) parallel many features and advantages of HFoFs outlined above. These invest in leveraged buyout (LBO) or venture capital (VC) funds and by doing so serve as investment channels to otherwise not accessible investment possibilities. PiperJaffray, who offers a variety of PEFoFs, published a special report – hereafter referred to as PiperJaffray (2003) – on this type of FoFs, which describes the distinct features of this sort of investment, some of which are explained in the following.

LBO or VC funds invest directly in companies that are not traded publicly on stock exchanges and are not listed. While LBO funds make use of leverage after purchasing part of a target company, VC funds typically make serial equity investments without taking debt. Of course, both sub-types of private equity try to identify companies that seem to be the most promising concerning actual and future returns. Due diligence and subsequent close monitoring enhance the possibility of high prospective returns on capital invested. Especially LBO funds when taking over whole firms are directing the path of the companies in which they are investing. The difference between VC and LBO funds can be roughly seen in the maturity of their target companies, with the former commonly investing in young, immature companies and the latter targeting more mature firms with more or less stable cash flows. High capital amounts are demanded to perform this kind of business, and the pooling of money by PEFoFs serves as an appropriate way of raising those.

In addition to the HFoFs and the PEFoFs, which make up most of the industry, many other FoF types have emerged in recent years. For example, FoFs that consist of stock funds and bond funds provide high diversification benefits due to the opposing movements that the fixed income and equity markets naturally take. Investors do not need to shift between bonds and stocks; the adjustments are made by the FoF managers, whose timing on the markets is crucial to the performance of this type of investment vehicle.

Sector specific or industry mutual FoFs exist as well, being portfolios that comprise investments in a certain sector, country or class of investments. For example, some real estate FoFs invest in both open-ended real estate funds (which are directly investing property funds with a bond-like risk and return profile) and real estate equity funds. Depending on their market expectations, the fund management teams can quickly increase their real estate equity exposure or stick to the "safe-haven"[1] directly investing real estate funds.

Not all FoFs are limited to invest solely in other funds. Some have the possibility to invest certain fractions of the fund volume in shares of companies, corporate or government bonds, certificates or derivatives. While increasing the flexibility and enlarging the investment universe of these FoFs, additional investment possibilities represent both opportunities and threats. Consider a fund manager who has a strong bullish view on one single company, to which he wants to get more exposure than is possible through the underlying fund holdings. By buying ordinary shares or derivatives on that company, the fund manager may tweak the exposure to that company to the desired level. Another strategy example would be to use derivatives or reverse index trackers to isolate underlying fund performances or alpha, or to reduce exposure to certain parts of the underlying funds while maintaining the remaining structure. Non-fund investments may therefore be a tool for sophisticated FoF strategies, with hedge fund-like strategies then being accessible by managers of long-only funds. However, if FoF managers are able to discretionally invest in non-fund assets, the FoF concept may loose its stability or the structure that was

[1] Please note however, that the developments following the financial market crisis has set some funds under stress and several funds had to devalue parts of their portfolios.

expected by investors. Put another way, the abilities of FoF managers need to be high enough to reap the benefits of non-fund investment possibilities.

Therefore, the skills of the management team are once again the crucial determinant of the success of investments. When it comes to performance measuring and attribution, a variety of questions and problems arises, such as comparability, factor selection, statistical or technical problems, measurement decisions and many more. To address these issues, the next section will be devoted to an overview concerning performance analysis and identification problems in the fund and fund of fund world.

1.3. Performance Analysis and Identification Problems in Fund (of Funds) Management

This section highlights the problems of performance analysis, the search for alpha and identification problems inherent in FoF business. In doing so, we turn the focus on several problems which especially apply to FoF investments.

When building FoFs, the product management and portfolio management teams are confronted with a large set of questions. First, one has to choose how the investment universe should be defined. Generally, FoFs are set up as products that focus on a certain industry, a country, a sector, or an asset class of financial products. Several possible types of FoFs have been discussed in Section 1.1. After the "topic" of the FoF is selected, the next step is whether to constrain the investment universe further. For example, if a FoF is bond oriented, the question is whether the FoF should be able to invest in bond funds of any kind, or whether certain profiles or countries may be excluded or limited.

In addition, some FoFs are allowed to allocate a certain fraction of their assets under management to non-fund investments, such as single stock shares, bonds, derivatives or others. As mentioned above, this may lead to two opposing outcomes. On the one hand, the profile of the FoF could be greatly improved. With FoF managers having the ability to (partly) hedge fractions of their investments, to gain or tweak exposures to preferred sectors or companies which may be underrepresented in the fund holdings, or to circumvent structural and institutional constraints, able managers may perform better than they would when being limited to fund-only investment schemes.

A striking example is that of real estate company Unibail-Rodamco. The EPRA (European Public Real Estate Association) Europe Index, which serves as the benchmark for most European real estate equity mutual funds, consiste of about 19% of Unibail-Rodamco in March 2010. As UCITS (Undertakings for the Collective Investment of Transferable Securities) regulation limits the single allocation of mutual funds in one company to 10% of the fund volume, this has led to all funds underweighting Unibail-Rodamco relative to the benchmark. If the FoF management team is bullish on Unibail-Rodamco, they may heal the expected underperformance of their regulated fund holdings by investing directly in Unibail-Rodamco shares or derivatives. Another example would be if the FoF managers want to pursue a strategy of picking small companies for which they have promising information, but which are only small fractions in the target fund holdings due to their small role in the benchmark index.

On the other hand, non-fund investment allowances for FoF managers may lead to undesirable effects. If managers take the wrong steps and have a large amount of discretionary freedom, they may dis-stabilize the FoF and introduce performance flaws. Put another way, the possibility of non-fund investments is increasing both risk and uncertainty concerning future performance from the perspective of FoF shareholders. As the investment universe and therefore the allocation possibilities may be exploding due to non-fund investments, the investor holding a FoF is confronted with increased problems concerning expectation building. Therefore, fund manager ability is the crucial factor dividing pro and con of non-fund investment possibilities for FoFs.

When it comes to ability and performance attribution as well as the identification of “better” funds and FoFs, i.e. investments that deliver “alpha”, we are in the favourable position of having a huge research work body concerning performance measurement at our disposal. While the several studies are differing largely in their very nature, the aim of the most is to conduct an analysis that may be useful for selecting funds, i.e. managers. Before the various approaches will be discussed and put in relation to the FoF world, some preceding arguments are due.

One important aim of performance analyses and identification in the search for alpha should be comparability, that is, when trying to analyse various mangers’ skills and fund performances, the study needs to focus on the right factors and benchmarks. The classical model of portfolio selection and the single-index model by Markowitz (1952 and 1959) as well as the Capital Asset Pricing Model (CAPM) that has been developed by Sharpe (1964) and Lintner (1965), use simple linear ordinary least squares regressions (OLS). The regression is run on the excess return of an asset on its benchmark’s (the market portfolio) excess return, with the excess return generally being defined as over a risk-free rate. In these models, the higher the intercept that represents the alpha, the higher the risk adjusted return, while risk is measured as beta, relative to the benchmark.

Fama and French (1992) in their seminal study augment the analysis with additional factors. They introduce two factors in addition to the benchmark or market portfolio, the excess return of small capitalisation stocks over large capitalisation stocks (small-minus-big, SMB) and the excess return of stocks with high ratios of book-to-market-value over ones with low book-to-market-value (high-minus-low, HML). Not representing the end of the factor model developments, the Fama and French (1992 and 1993) model had an invention by Carhart (1997), who introduced the momentum of one-year stock returns as an additional characteristic component, after Jegadeesh and Titman (1993) having proposed the momentum factor. The resulting four-factor model has been used extensively in the past and builds the baseline for many studies on performance analysis. The initial work on portfolio theory and benchmark-oriented performance measurement has triggered a lot of following research work, such as the arbitrage pricing theory by Ross (1976), an alternative to the CAPM.

Before discussing the nature of performance analyses for selection processes, a few technical facts concerning the use of alpha and beta as a measure of superior fund (manager) quality are noteworthy. As alpha is simply the intercept of an OLS regression, it tells the analyst about the (excess) return that a fund would achieve if all the explaining factors (for example, the SMB excess return) were set to zero. It is understood that the intercept is somehow a bin for all non-random effects not caught up by the explaining factors and therefore may be the result of a large variety of effects, not only representing the superior ability of a funds' manager. When it comes to beta, used as a measure of fund exposure to the explaining factors, the use of linear regression analyses may be inappropriate especially when analysing funds that show highly non-linear dependencies, for example hedge funds and other vehicles that are subject to option-like payoff structures. However, the non-linear effects may be included even in linear regression analyses when using respective explaining factors.

Not criticizing the use of the four-factor model or related setups, we stress that the four-factor model is not suitable for all kinds of performance analyses, especially when constructing FoF portfolios. For example, if the universe of the funds under review is not restricted very much, that is, if fund managers may have invested in a large variety of stocks (for example a country oriented mutual fund), the four-factor model lets conclude about the source of performance. Nevertheless, the alpha, the regressions' intercept, is not measuring the ability of the fund manager.

An intuitive example: A fraction of fund managers in a study sample overweighs small caps against large caps stronger than other fund managers. In a year where small caps subsequently perform better than their blue chip counterparts, the higher returns of the small cap biased funds are a result of their superior ability to forecast the small cap outperformance. In the four-factor model, this ability is not identified as ability, but is "soaked up" by the SML term in the regression, leaving an alpha that neglects the good decision made by the fund managers overweighing small caps. If the aim of the study is to identify where the performance comes from, this is a favourable effect, if the study was to compare fund managers in a selection process, it is not. This problem is crucial to any performance analysis in the fund universe and calls for sensible selection of the factors in relation to which information is to be obtained, thereby carefully interpreting the results obtained.

Especially when analysing funds in a FoF portfolio building process, the caveats of simply picking high Carhart-alpha funds are clear-cut. As FoFs should be well diversified portfolios build out of the most promising target funds, the misleading effects discussed above may introduce biases that lead to significant deviations from this goal. In the mentioned example, one would be underweighting funds that successfully chose the right strategy, possibly harming future performance. Therefore, it is key to use factor models such as the Carhart (1997) model in the right way. If the FoF management team is aiming at identifying the strategy or sector relations of target funds, the factor models may suit them well, for example when aiming at including a heterogeneous set of target funds. If they want to identify the ones that made the right investment decisions, they should change the respective view.

In the fund selection process for a FoF, we propose a multi-step use of the Carhart (1997) model or similar factor models. First, the model should be used to identify by which of the observable and identifiable factors or characteristics a fund's performance was driven, on a very aggregated level, for example indeed with the four factors proposed by the Carhart (1997) model. Second, from the initial analysis, separate classes are built for which the analysis is re-run, yielding a more reliable picture of the underlying funds' quality. In the re-run(s), the factors may be adjusted in relation to the class characteristics. For example after separating the small cap-benefited funds, one could introduce further more dis-aggregated sector benchmarks such as the S&P Technology or the Wilshire Micro Caps. Obviously, the use of the multi-step procedure may better suit FoF selection processes due to the possibility of both finding different characteristic classes of funds and finding the ones that are the best performers in the respective classes. How deep the analyses are conducted, and in which order the analyses are performed, depends on the respective needs and the structures of the target funds under consideration.

The arguments proposing a multi-step approach to fund selection are broadly in line with Daniel et al. (1997), who favour characteristic benchmark portfolio models over the four- factor model by Carhart (1997). However, even when using the proposed multi-step analysis or benchmark portfolio building processes, the analyst may struggle to identify the funds which steadily perform in the way that is found in the analysis.

As for any other investor, the search for performance persistence and the interpretation of past fund returns (and the projection of those into the future) is an important task in the FoF portfolio building process. Besides the problems discussed above, one has to take the analysis from the cross-section to the intertemporal dimension. Work on this subject goes back to Jensen (1969) and Beebower and Bergstrom (1977), and it were Grinblatt and Titman (1989a, 1989b, 1992), Brown and Goetzmann (1995), Hendricks et al. (1993), Malkiel (1995), Elton et al. (1996), Daniel et al. (1997) and Carhart (1997) heavily influencing the work on performance persistence. The issue of survivorship bias in performance persistence studies is an often-discussed problem, as are the problems of short-history samples and non-normally distributed alphas across the funds. The latter two problems have led to the use of Bayesian and bootstrap methods, see

Pastor and Stambaugh (2002a and 2002b) and Kosowski et al. (2006 and 2007) among others.

Concerning FoF performance, Rachlin and Castro (2007) discuss hedge fund performance measuring for FoF managers and on the FoF layer, Chiang et al. (2008) investigate the performance of real estate mutual FoFs.

As all of the studies above are related to analysing the performance of funds and/or assets, the question being addressed is how to identify winners and losers, and to identify which of them tend to be of the same type in the future. Following the performance analysis and identification problem, the process of fund of fund portfolio building necessitates an appropriate selection process in the task of picking the respective funds to include in the portfolio. This leads to a discussion of the problems concerning portfolio optimization and is covered in the next section.

1.4. Building Funds of Funds

When constructing portfolios of funds, it is critical to consider both the nature of any fund, as well as the common factors driving them. Diversification benefits stemming from low or even negative correlations and relationships among assets are important for the expected risk and return structure of the resulting portfolio. Since the seminal work of Markowitz (1952 and 1959), this topic has been among the most researched and discussed by both academics and practitioners, see Steinbach (2001) for an overview on mean-variance optimization.

Black and Litterman (1990 and 1992) have developed a framework that lets the investor include his subjective views, a setup being more robust to estimation errors. Extensions to the Black-Litterman approach have been made by Giacometti et al. (2007) who use stable distributions and therefore propose models that do not suffer from the shortcomings caused by the normality assumption of the classical models. The use of stable Paretian distributions in financial and portfolio modelling has been studied in detail by Mittnik and Rachev (1993 and 2000), Samorodnitsky and Taqqu (1994), Rachev and Han (2000), and Ortobelli et al. (2002 and 2003).

When it comes to FoFs, a few words concerning the distinctiveness of FoF portfolio optimization are due. In the FoF building process, one often has to choose one or several funds out of a family of funds with very similar exposures and/or strategies. This introduces the possibility of very high correlations among underlying funds, stemming from the fact that those may be invested in the same companies, assets, sectors or markets. It is therefore crucial to identify the holding structures or risk factors of target funds, as well as common factors that are influential to the funds' performances. Only by doing so does the FoF management team avoid the risk of unnecessary and inefficient double or multiple exposures to the same companies, assets, sectors or markets. This may be done by either running factor analyses on the funds' data or by investigating the reports of funds and/or taking into account information available on them. If the unique and common features of the respective funds are found and a set of funds in which the FoF management wants to invest is defined, the question remains how the FoF portfolio will be build. Thereby, it is not possible to build a FoF by viewing any target fund as a single asset.

Using an appropriate risk measure is crucial for FoF portfolio building, with Goodworth and Jones (2007) focussing on non-parametric risk measurement for hedge funds and FoFs, and Christie (2007) using downside leverage and event risk measures in FoFs. For a general discussion of risk measures, see Rachev et al. (2008).

As is the choice of the appropriate risk measure far from trivial, so is its interpretation, especially when being applied for optimizing a FoF portfolio. When viewing any target fund as a single asset, one ignores the possibility that the risk that is included in one fund may also be included in other funds.

Related to this problem is the issue of choosing not only which funds or what kinds of funds to include in a FoF, but also how many. The question is whether including additional funds really helps in diversifying the portfolio and thereby not averaging or counter-investing away the characteristics of the target funds. Among others, Connelly (1997), O'Neal (1997), Park and Staum (1998), Saraoglu and Detzler (2002), Brands and Gallagher (2005), Louton and Saraoglu (2006), Amo et al. (2007) and Kooli (2007) discuss the problem of FoF portfolio building. Especially the Connelly (1997) paper hits the point with the discussion surrounding so-called unintended indexing, which means that by choosing too many funds, one could end up with a costly index-type investment portfolio. This does not only come from the fact that especially many mutual funds label themselves as being actively managed and thereby only slightly over- or underweight their holdings relative to their benchmark. Connelly (1997), in citing a speech of William E. Jacques at the Institute for International Research sponsored conference of Active vs. Passive Investment Management argues that mixing for example a growth fund with a value fund counters the investment strategies, thereby increasing the portfolio holdings deadweight.

With all the problems introduced in the preceding discussion, it is clear that FoF portfolio building is by no means a trivial or at least easy task. While only a few studies on fund portfolios exist, the literature did not yet provide a concluding answer on the questions raised, leaving open the door for further investigations and insights.

1.5. Outlook and Structure of the Thesis

Being a large and growing part of worldwide financial investment possibilities, funds of funds are increasingly in the focus of both practitioners and academic researchers. In this initial section, we lined out some specific features, (dis) advantages, developments, questions and problems that are special to FoFs. By doing so, we reviewed past research work in both the FoF world as well as in the field of funds as the natural FoF underlyings.

Among the most crucial questions and challenges that we found are the following: FoFs are very diverse according to their investment universe and need to be treated accordingly; the fees charged by FoFs have initiated the discussion of the double-cost fee structure; fund portfolios have to be build by taking into account that the target funds may not be seen a single assets.

With these problems and many more still being unresolved, we stress the importance that FoF research needs to be done with tools that are sensible in light of the special nature of fund portfolios. Identifying the nature, risk factors and exposures of the target funds, thereby assessing their similarities and differences, needs sophisticated and sensible approaches and techniques.

Especially when it comes to non-linear (inter)dependencies and relationships, classical measures and methods may not be sufficient to perform the needed analyses. Copulas, simulation models and other inventions may be needed to identify the factors that are crucial in FoF management. Of course, the obtained results need to be used with other information from the due diligence and compliance assessment processes.

When building portfolios out of funds, it is clear that one cannot rely on the classical models with an assumed normal distribution. As both the most target funds as well as their investments exhibit non-normally distributed returns, we propose the use of stable distributions in the portfolio building process for FoFs. Furthermore, the fact that several target funds may be influenced by the same factors calls for methods that detect multiple exposures or holdings.

In this study, a large variety of issues and topics regarding FoF management that have been mentioned in this introductory chapter are addressed using post-modern tools of portfolio analysis and portfolio management:

In Chapter 2, we pick up a classical topic, the one of style investing, in a FoF context. We use not only the common moments of absolute and relative performance of growth, value and style-neutral FoFs of different sizes, but use a post-modern reward-to-risk measure in the analysis to find out whether style-neutral FoFs provide value added.

Chapter 3 is devoted to the problem of optimizing portfolios using different approaches, from classical mean-variance to tail dependent performance ratio measures. In addition, the approach presented provides an elegant solution to non-linear optimization problems, which are especially severe when dealing with heterogeneous assets, non-linear performance measures and a large span of different portfolio optimization outcomes.

The effects of broad market movements on sector FoFs are in the focus of the study presented in Chapter 4, where again post-modern tools are used in a parsimonious approach of measuring asset and market interdependencies. A comparison with traditional approaches and a careful assessment of the results shows that the approach is superior to its peers and may be highly beneficial in practical FoF management.

Chapter 5 is devoted to a problem that was at the core of many discussions during the subprime meltdown, the credit crunch and financial crisis that emerged since 2007, the problem of money flows and liquidity. As not only single assets like stocks, bonds, derivatives or commodities may be largely affected by liquidity issues, FoFs may face a special problem when target funds restrict asset flows to protect from flow-induced issues.

We sum up the study in Chapter 6, and come back to the results found in the studies comprising the thesis, with an eye on the asset management world.

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2. Style-neutral Funds of Funds: Diversification or Deadweight ?

2.1. Introduction

Style-neutral portfolios are built by investing equally in opposing styles, the objective being to generate risk-adjusted returns that are superior to those obtained from investing with a tilt towards one or the other style. While there are many possible style classifications, we focus on a pair of the most important and widely accepted style classifications, namely “value” and “growth”. Generally, the definition of “value” and “growth” stocks are as follows: Shares of companies classified as value stocks are shares for which the price-to-book ratio is low and those classified as growth stocks have a high price-to-book ratio. Value managers therefore are investors who expect upside potential in companies with a low price-to-book ratio, as those seem to be undervalued by the market.

The style of value investing has its origin in Graham and Dodd (1934 and1949) which had a tremendous influence on investment theory and practice, although the focus increasingly turned on price-to-earnings rather than price-to-book. In contrast to value investors, growth managers focus on capital appreciation with companies mainly reinvesting their earnings and with good prospects for further expansion. The value and growth classifications are not directly defined as mutually exclusive counterparts based on a single measure. The term growth at a reasonable price (GARP) further relates the price and expansion potential characteristics to each other.

Being defined that way, the value versus growth distinction has found its way into the above mentioned three-factor model by Fama and French (1992 and 1993), with Fama and French (1998) providing evidence concerning value and growth investing. In the extension of the Capital Asset Pricing Model (CAPM), the factor "high-minus-low" with respect to the book-to-market ratio is used to control managers' performance against the benchmark for their growth or value style. The other factor being used to augment the CAPM is the excess return of small capitalisation stocks over large capitalisation stocks ("small-minus-big")[2].

The discussion surrounding style investing has led to extensive research regarding timing styles and employing neutral approaches. Gerber (1994), Fan (1995), Sorensen and Lazzara (1995), Ahmed et al. (2002) and Amenc et al. (2003), for example, focus on style timing, mainly implemented in a market-neutral framework.

In this study, we do not analyze value versus growth style investing within a market-neutral approach, but investigate the properties of style-neutral portfolios including both value and growth strategies. We analyze style-neutral portfolios by building synthetic funds of funds (FoFs) out of both value- and growth-oriented equity funds. This is also interesting in the light of two contrary notions regarding FoFs, namely, the view that style-neutral FoFs may deliver the best of both worlds against the view that they will result in costly benchmark replicators. The latter argument was brought forward by Connelly (1997) for FoFs in general and may be amplified in the case of style-based fund portfolio building. Connelly's view implies that the countering of styles results in obtaining a FoF that has countered and erased most or all active bets of the target fund managers, resulting in so-called portfolio deadweight and unintended indexing as mentioned in Chapter 1.

Because the analysis in our study is performed for funds rather than for individual common stocks has several implications. First, the identification

[2] As discussed above, another popular extension is provided by the four factor model of Carhart (1997) who augmented the analysis with a momentum factor. See Haugen and Baker (1996) for a discussion of 50 possibly influencing factors.

problem of value and growth is more complicated, as not only fund managers must properly identify the respective stocks but FoF managers must also carefully select their target fund managers. This may cause a dampening of effects and a diluted result. Second, we need to take into account an extra layer of fees because FoF managers charge their own fees[3].

Using a five-year sample of 25 value-oriented and 56 growth-oriented equity funds that focus on U.S. equities and are listed and classified in the Morningstar database and eligible in Germany, we build style-neutral FoFs and compare them with their most representative benchmark, the S&P 500. As the analysis aims at finding an answer to the question of whether style-neutral FoFs investing in both value and growth strategies could be beneficial, we use a rolling window approach in order to see the time-changing properties of the style-neutral fund portfolios. To get insight into the sources of the results obtained, the respective value- and growth-style portfolios also have been analyzed.

We find that diversification benefits in terms of return dispersion occur when investing in at least six to eight funds, a finding which is in line with earlier studies. However, the first four moments of the simulated FoFs and the benchmark did not yield a conclusive picture of the benefits and disadvantages of the style-neutral FoFs. Whether they are well-diversified portfolios of use to investors or resulting in costly portfolios that are merely the result of portfolio deadweight was therefore investigated by using the R ratio, which is a tail-dependent reward-to-risk measure.

The analysis shows that investing in more funds successively improves the R ratio in the style FoFs as well as in the style-neutral FoFs. However, the building of style-neutral FoFs results in an averaging process with time-dependent differences. This points at the notion that on average it is not a priori beneficial to build style-neutral FoFs, only when being able to select the best performing funds of the respective classes.

[3] See Brown et al. (2004) for a discussion of fees on fees in FoFs.

The chapter is organized as follows: In Section 2.2 we discuss the theoretical aspects of diversification and deadweight and explain our approach to measure style-neutral FoFs against the benchmark in Section 2.3. The presentation and discussion of the empirical findings follows in Section 2.4., our conclusions are summarized in Section 2.5.

2.2. Diversification and Deadweight

In this section, we briefly contrast the opposing views related to the general benefits and caveats of FoFs before discussing those in the context of style-neutral FoFs. Proponents of FoF structures highlight the ability of FoFs to benefit from diversification effects and from picking the best managers and strategies, but FoF critics stress the danger of countering styles or inefficiencies owing to the double layer of fees.

A general question related to FoF building is the one concerning the number of investments, as one may reduce both volatility over the course of time and terminal wealth dispersion by increasing the number of target funds. O'Neal (1997) shows that for growth equity funds, four funds may be sufficient to decrease most of the uncertainty concerning the FoF returns, whereas L'habitant and Learned (2003), for example, find the number to be between 5 and 10 for hedge fund portfolios. The effects of different fund portfolio sizes were also examined by Park and Staum (1998), Brands and Gallagher (2005) as well as by Gallagher and Gardner (2006) among others.

Apart from the general possibility of diversification benefits delivered by FoFs, the danger of countering styles or the correlation of target managers' styles has led to work by diBartolomeo (1999) and Gallagher and Gardner (2006), who demonstrate that while providing diversification, fund portfolios may end up resembling the benchmark and may be unable to outperform the index. Their results are in line with the theoretical arguments mentioned in Connelly (1997), who stresses the danger of countering the active bets of target fund managers. Connelly defines the measure of portfolio deadweight in a fund as the sum of the minima of each company's share in either the benchmark or the fund under consideration[4]. Therefore, funds which have large off-benchmark holdings would have the lowest deadweight score.

Connelly (1997) in his critique of FoFs states that by investing in funds that have different styles and therefore bets against the benchmark, a FoF may end up as a costly benchmark product. Labelling this problem as the law of unintended indexing, Connelly proposes the use of a benchmark tracking product and a future overlay. While this argument is generally appealing, we reject this proposal in our analysis of FoFs because we assume the FoF managers invest only in funds.

In the light of style-neutral FoFs, we find it of particular interest to analyze whether a fund portfolio that is balanced between value and growth target funds is delivering superior performance than the benchmark and/or fund portfolios focussing on one of the respective styles. As target fund managers select the stocks of their investment universe that best suit their style and for which they expect the best performance, it may be possible to benefit from their selection abilities through fund investments. By combining several managers with different styles, one could expect both diversification benefits and a superior benchmark-relative performance. On the other hand, correlations between stocks in the target markets as well as the countering of styles may result in the indexing schemes introduced above and a costly benchmark replication product.

[4] Connelly acknowledges that this measure is obtained from a presentation by William Jacques at a conference on active versus passive investment management sponsored by the Institute for International Research.

2.3. Data and Methodology

To examine the opposing effects and structures discussed in the preceding section, we focus on the return patterns of the funds in the analysis due to the limitation that fund holdings are available only from time to time, and often for differing dates. While the top positions in a mutual fund are usually reported on a monthly basis, complete fund compositions can be observed only once or twice a year in most regulated fund markets (with different reporting deadlines for different fund business years), making a holding structure analysis impossible or at least highly complicated.

We used Morningstar's database for selection purposes that includes solely funds that are permitted for distribution in Germany, with a total of about 15.000 funds. As we need to base our analysis on comparisons with a sensible and representative benchmark, we have chosen to do the analysis for equity funds with a focus on the United States. This stems from the fact that for this group the number of funds was largest and is not broken down into sub-regions as it can be seen for European focused funds (EU-15, EU-27, Eurozone or Europe-ex-UK are examples). Using U.S. dollar-denominated funds is straightforward with the chosen country focus and rules out conversion or hedging distortions. We used the S&P 500 as the benchmark. Accordingly, we restricted the sample further to large capitalization focused funds, ruling out any biases stemming from size tastes of fund managers. This was done by using Morningstar's 3-by-3 fund classification matrix, which indicates whether a fund is focussing on small, mid or large capitalization stocks and whether the fund management is pursuing a value, blend or growth investment approach. The Morningstar fund classifications resulted in 47 value and 84 growth funds.

Our approach is sensible in the way that we can rule out any distortions and biases due to legal or regulatory constraints, have no currency conversion issues, and can rule out any size effects, home or foreign biases[5].

We considered a time span of five years to be sufficient for the analysis, and have therefore chosen the sample time from July 1, 2003 to June 30, 2008. Because data were not available for the 47 plus 84 funds for the entire five-year period[6], our sample was reduced to 25 value and 56 growth funds that were in existence prior to the commencement of the study period.

Using total return data from DataStream Financial Thomson in weekly frequency, we have 261 weeks of performance data as our basis. The use of weekly data is beneficial as the results are not cursed by accounting discrepancies. This means that the funds' return series and therefore those of the synthetic FoFs can be compared more easily to the benchmark as there need not be done any time shifts induced by pricing differences[7]. The latter problem would be even further complicated as we use funds that have their investment focus in a time-zone other than the fund domicile's time-zone.

Checking how style-neutral FoFs performed against the benchmark was done by using synthetic style-neutral FoFs and the S&P 500 Composite Index. Although not all funds included in the analysis have the S&P 500 as their official benchmark, the index serves as the most important benchmark in evaluating fund managers. With respect to the used sample, it is straightforward to use the index representing the 500 U.S. companies with the largest capitalization to serve as orientation for FoFs with a large set of U.S. focused target equity funds.

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[5] See Chan et al. (2005) for an examination of managers' foreign and domestic biases.

[6] According to information from Morningstar, 3 value and 13 growth funds were obsolete from the dataset chosen. The aim of the study is on the effect of style-neutrality however, such that the survivorship influence is not crucial.

[7] While some funds report prices end of the day, others report prices for the day before. The latter method being called forward-pricing aims at preventing speculative trading against the fund.

To gain insight into the behaviour of the synthetic FoFs, we perform a time-varying analysis. With the 261 weekly fund and benchmark returns, the analyses were done by rolling 209 spans of 52 weekly returns through the sample. By comparing the characteristics of the style-neutral FoFs and the benchmark over time this enables us to carefully assess pros and cons of the style-neutral FoF investments.

As we want to analyze style-neutral FoFs we have to use even numbers of funds included in the portfolios. Furthermore, because there are only 25 value funds, we cannot compare the neutral FoFs to style FoFs containing more than 25 funds for an unbiased picture. These limitations have led to the bounds of 2 and 24 funds for the simulated portfolios. Consisting of 1 to 12 funds for each investment style, we build style-neutral funds by assigning 50% weight to each investment style class. Accordingly, we have built synthetic style-neutral FoFs and style FoFs of the same sizes between 2 and 24 funds for the sake of comparison.

Using this approach, we rule out the possibility of short selling and fulfill the constraint of full investment, as those constraints are most representative for real- world investment bounds. We generate 10.000 synthetic portfolios for each of the 3 FoF types, 209 time periods and 12 portfolio sizes. Afterwards, the return series of the synthetic FoFs are generated and compared with the benchmark. This is done to see how style-neutral funds in all varieties of compositions and sizes behave in comparison with the used benchmark and the style based FoFs. Analyzing windows of observations that are rolled through the sample enables us to see whether the findings are robust in different market periods.

The comparison of the simulated FoFs with the benchmark is done in various ways. As the stated arguments both in favour and against FoFs in general and style-neutral FoFs in particular are related to the diversification argument as well as performance considerations, we use not only dispersion measures for the portfolio and benchmark returns, but employ more sophisticated measures to examine the nature of the simulated FoFs.

Focussing on the tails and extreme returns is done by using the Rachev ratio (R ratio). For extensive discussions and applications concerning the R ratio and related risk and performance measures see Biglova et al. (2004), Rachev et al. (2005), Okuyama and Francis (2007), Rachev et al. (2008) and Farinelli et al. (2009).

To understand the R ratio, it is necessary to consider first the measure of expected tail loss (ETL, equivalent to the conditional value at risk, CVaR, for continuous distributions), which accounts for the concentration in the tails of the distribution. While the traditional value at risk (VaR) measure only indicates the value of the distribution at the threshold and therefore the maximum loss not to be exceeded with a certain confidence, the ETL measures the expected loss in the case of a tail event:

$$ETL_{1-\alpha}(r_p) = E\left(\max\left(-r_p, 0\right) \middle| -r_p > VaR_{1-\alpha}\left(r_p\right)\right)$$

Therefore, $ETL_{1-\alpha}(r_p)$ is the expected tail loss with tail probability α for portfolio returns r_p. Common choices for α are 1% or 5% in accordance with common choices of the 99% and 95% confidence levels used for VaR measures. Of course, the ETL for any given probability or confidence is always higher than the respective VaR. In the R ratio, the ETL of the difference of any portfolio's returns in comparison with the benchmark is serving as the denominator, giving a term for the severity of portfolio underperformance against the benchmark. By choosing the measure in that way, one does obtain a benchmark relative portfolio risk measure.

While the ETL based measure is used for the downside, a corresponding measure for the additional gains versus the benchmark is also needed. The ETL of the difference between the benchmark returns and the portfolio returns therefore serves as a relative gain measure and represents the nominator of the R ratio. Therefore, the R ratio may be interpreted as a benchmark relative reward to risk measure. Below the R ratio is expressed with confidence levels α and β for the two measures on the lower and upper tail of the performance differences between FoFs and the benchmark:

$$R(r_p) = \frac{ETL_{1-\alpha}(r_b - r_p)}{ETL_{1-\beta}(r_p - r_b)}$$

As we will analyze the portfolios versus the benchmark, r_p and r_b denote the corresponding return series. With the R ratio we have a very flexible performance measure at our disposal, which is free from distributional assumptions or comparable flaws. Sensible percentages for α are, for example, 30% to 40% to adequately measure the extra portfolio gain while β could be chosen to be 1% or 5% to control for the severity of underperformances against the benchmark[8].

2.4. Simulated Style (Neutral) Funds of Funds Analysis

In this section, we present the empirical results of the analysis of the synthetic FoFs against the benchmark and against their style-focused FoF counterparts. Starting with the first four statistical moments of the respective return distributions, i.e. the mean, the standard deviation, the skewness and the kurtosis, we compare the FoFs over time and with differing portfolio sizes. Following the first statistical examinations, we used the R ratio to deliver a conclusive picture of the benefits and disadvantages from building style-neutral FoFs.

Exhibit 2.1. shows the difference of the average annualised geometric mean return between the style-neutral FoFs and the S&P 500. The synthetic FoFs seem to be outperforming and underperforming against the benchmark, depending on the time period analyzed, although FoF underperformance seems to occur more often, and the underperformance periods are more severe than outperformance periods. As the average of the geometric mean

[8] Other possibilities include setting the upper and lower percentage to equal values in order to get a symmetric reward-to-risk measure rather than one that controls for large underperformances that serve as risk measures in the denominator.

returns represents a cross-sectional average of the first moment, the straight line for 2 to 24 funds for any period is natural and shows that a reasonable number of simulations was chosen. Looking at the respective style FoFs in Exhibit 2.1.a. and 2.1.b. (i.e. the value and growth FoFs), we can see that there is a large difference in the performances of the two styles over time, as expected. While the performance against the benchmark of the value FoFs is much centered around zero until the later time periods, the growth funds exhibit more pronounced periods of better or worse performance. Interestingly, during the sub-prime crisis beginning in 2007, the growth funds performed much better against the benchmark while the value funds have underperformed, indicating that the value funds had more exposure to companies being related with the financial market crisis and the following credit crunch.

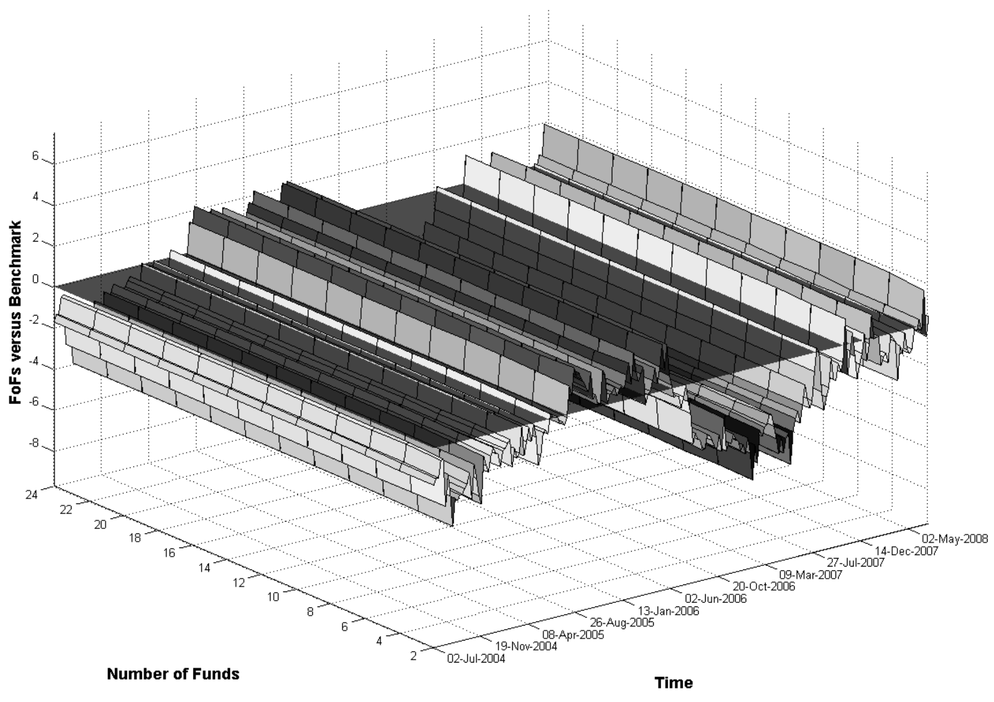

Exhibit 2.1. Difference in average annualized geometric mean return for style-neutral FoFs against the benchmark

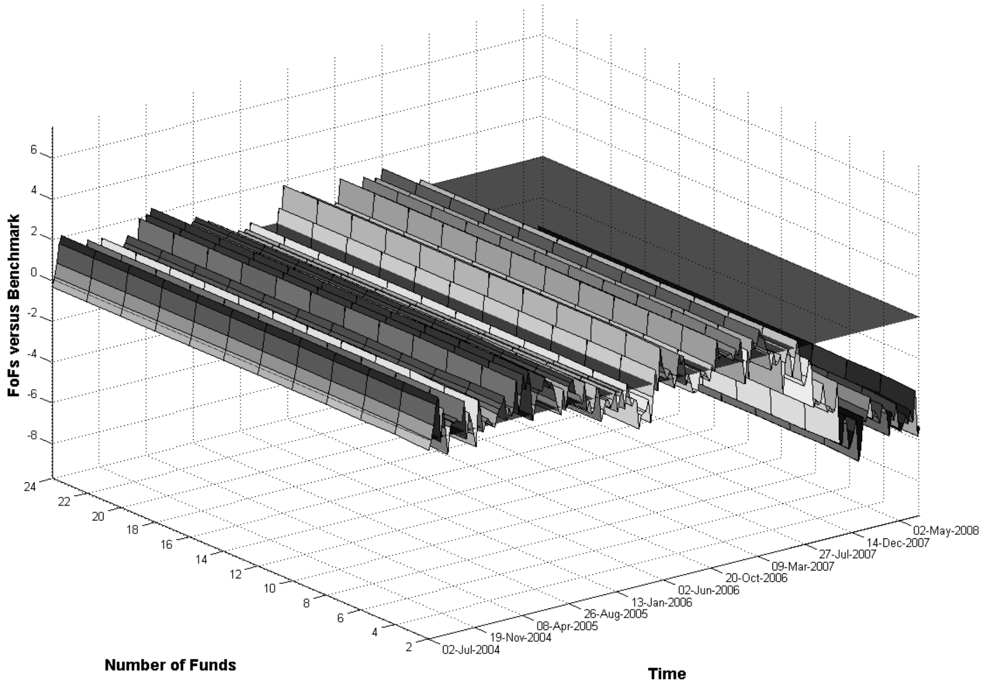

Exhibit 2.1.a. Difference in average annualized geometric mean return for value FoFs against the benchmark

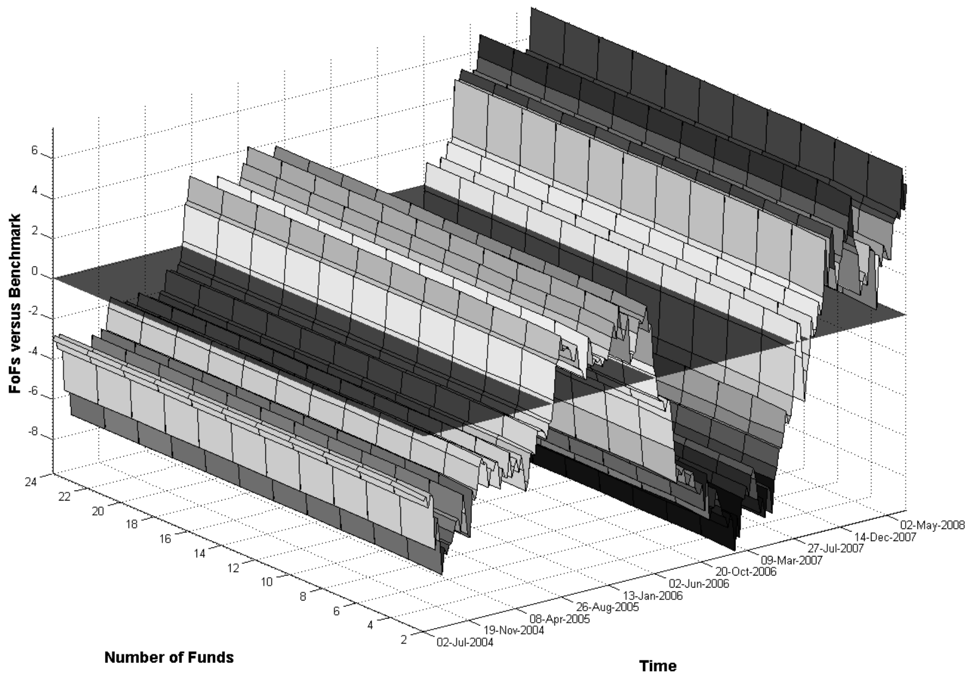

Exhibit 2.1.b. Difference in average annualized geometric mean return for growth FoFs against the benchmark

However, the fact that the style-neutral FoFs result in the picture we see in Exhibit 2.1. seems to show that the effect of style countering may be beneficial or disadvantageous depending on the time interval. While the general effect of more pronounced underperformance may be due to a general inability of fund managers to beat the benchmark, the comparison between the style FoFs and the style-neutral FoFs is showing that combining the two styles is resulting in a general process of averaging. In addition, the extra layer of fees induced by FoFs would lead to an even lower net performance against the S&P 500.

By analyzing the minimum and maximum geometric mean returns, i.e. the worst and best style-neutral FoFs and the respective style class FoFs in Exhibits 2.9. in the appendix, we can see again that the value funds are more stable over time when being compared to the benchmark than their growth counterparts.

The next important step when analyzing the synthetic FoFs over time and sizes is to take into account the resulting standard deviation of the FoFs and the benchmark, represented in Exhibit 2.2. As most of the reduction in the standard deviation is obtained with six to eight funds in the synthetic portfolios, this is roughly in line with other empirical findings. The synthetic FoFs seem to provide a reduction in the return dispersion against the benchmark in most time intervals.

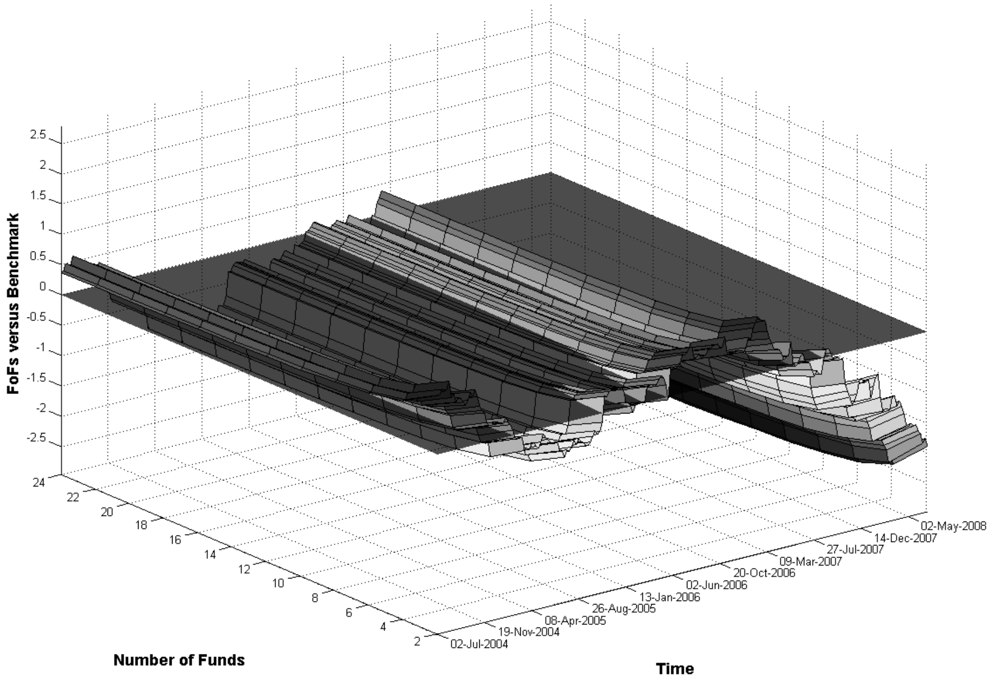

Exhibit 2.2. Difference in average annualized standard deviation for style-neutral FoFs against the benchmark

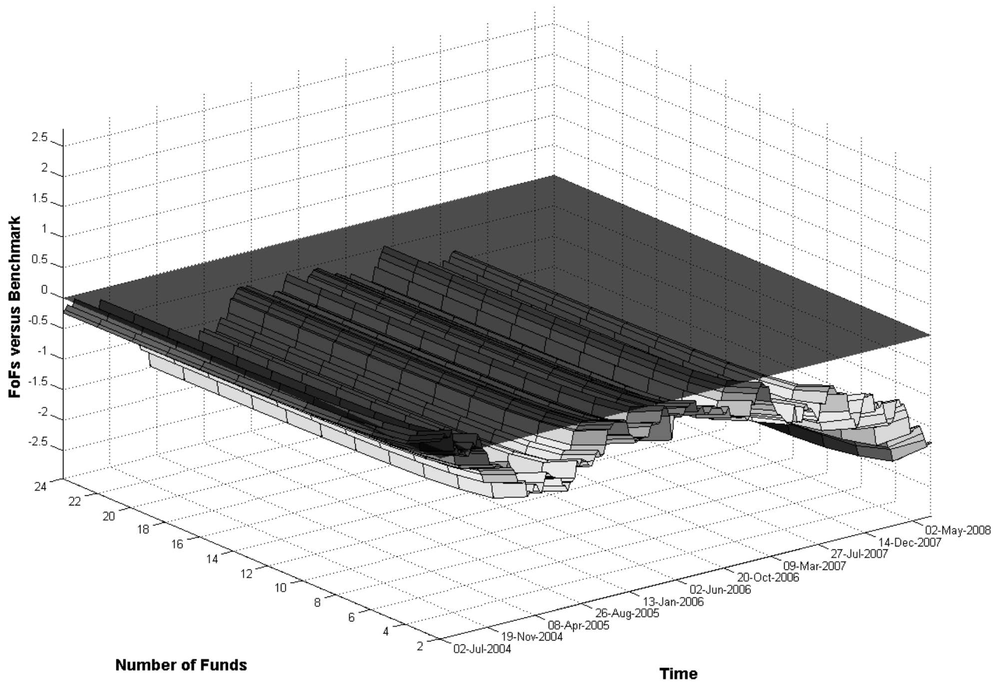

Exhibit 2.2.a. Difference in average annualized standard deviation for value FoFs against the benchmark

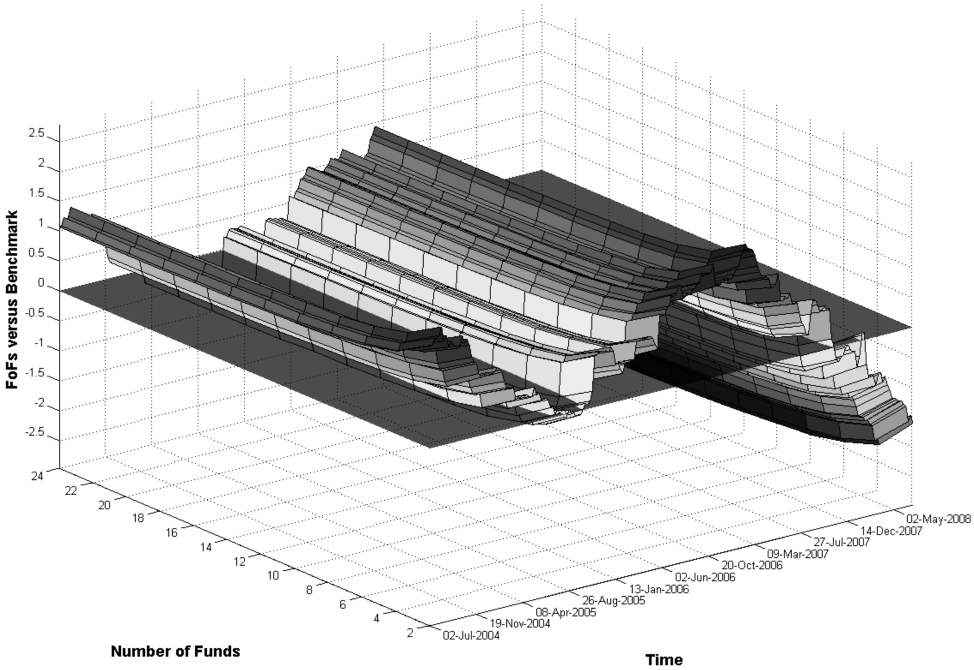

Exhibit 2.2.b. Difference in average annualized standard deviation for growth FoFs against the benchmark

What is striking in this analysis is that the most favourable reduction in the returns' dispersion is obtained during the sub-prime meltdown and the following credit crunch. Two possible explanations for this observation are most likely: First, during pronounced downturn phases and crashes, fund managers tend to hold more cash than during other phases. Second, the credit crisis was hitting most the companies and financial intermediaries that were exposed to the mortgage market, were highly leveraged or were related with the real estate market and fund managers could have reduced their holdings in these companies and sectors.

Again, looking at the style FoFs in Exhibits 2.2.a. and 2.2.b. reveals further insight, as the value FoFs are always less volatile than the benchmark, while the growth FoFs seem to be more or less dispersed in their returns compared to the benchmark depending on the time interval under consideration.

Analyzing the minimum and maximum annualized standard deviations, i.e. the best diversifying and worst diversifying style-neutral FoFs and the respective style counterparts in Exhibits 2.10. in the appendix, we obtain the usual picture of more stable value and more dynamic growth funds versus the benchmark.

Having analyzed the first and second moments of the synthetic FoFs versus the benchmark, we can state the following intermediate results: The average return of the fund portfolios against the benchmark shows that over- and under-performance change during the course of time and under-performance versus the benchmark appears to be first, more likely and second, more severe. The more dynamic and time-dependent nature of the growth funds is partially offset by the value funds, which holds true for both the mean returns as well as the returns' dispersion. For the measure of dispersion (i.e. the standard deviation), we find that building style-neutral fund portfolios is indeed reducing the volatility of returns when being compared to the S&P 500. The clear reduction however, is merely the result of the fact that the value funds are less volatile than the index in almost all periods.

Considering only the first two moments of the portfolio and benchmark returns does not yield a satisfactorily clear picture of whether a style-neutral FoF may be advantageous over a benchmark investment or style FoFs and whether the benefits of diversification are more powerful than the disadvantages caused by countering styles and the so-called portfolio deadweight. A deeper insight is possible by taking into account higher moments of the returns and the tail behaviour.

Looking at the skewness differences in Exhibits 2.3.a. and 2.3.b., we can see that in contrast to the mean and standard deviation graphs, the value and growth parts that constitute the style-neutral FoFs are more similar to each other with respect to the behaviour against the benchmark over time. In addition, we see that the building of style-neutral fund portfolios does not result in a significant smoothing of the returns skewness. This may stem from the fact that the skewness of the funds is a more characteristic and time-dependent measure than a style or skill dependent measure for asset returns (although more variation is seen in the growth sub parts again).

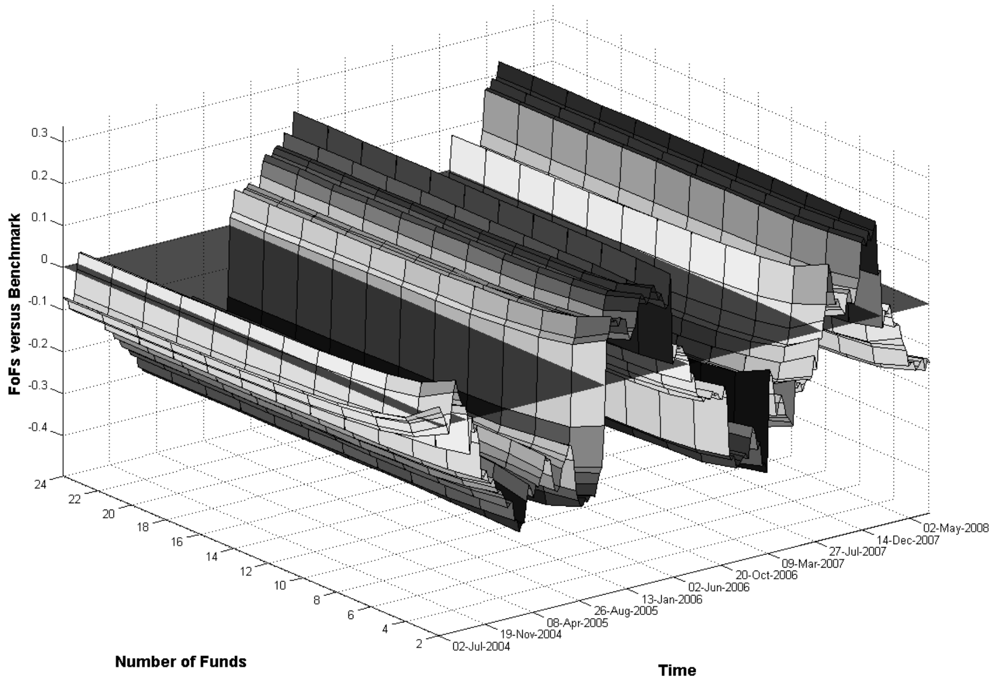

Exhibit 2.3. Difference in average skewness for style-neutral FoFs against the benchmark

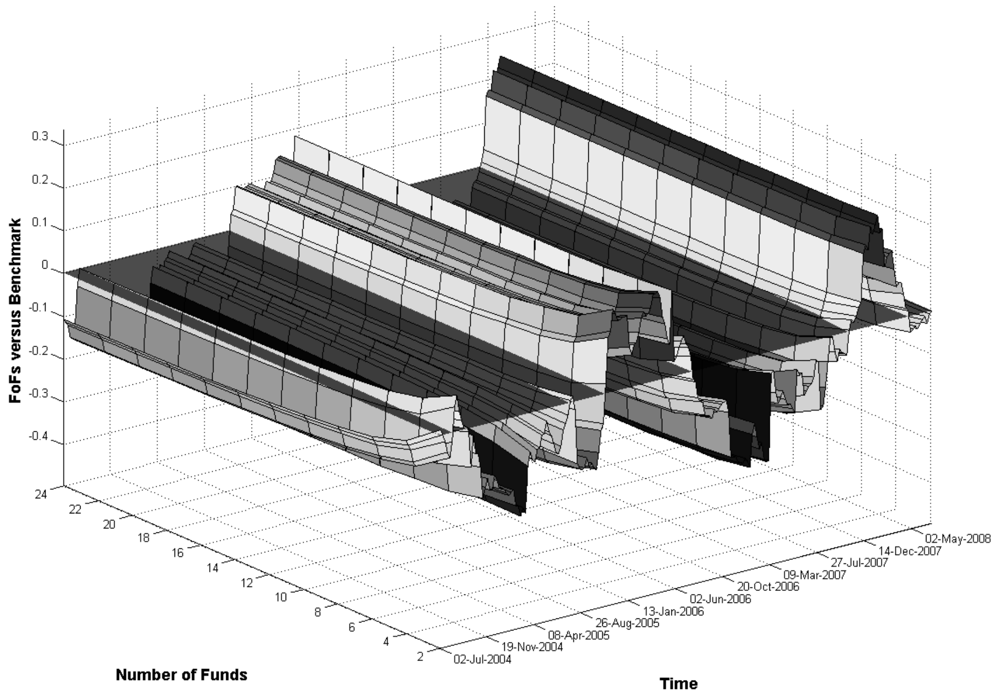

Exhibit 2.3.a. Difference in average skewness for value FoFs against the benchmark

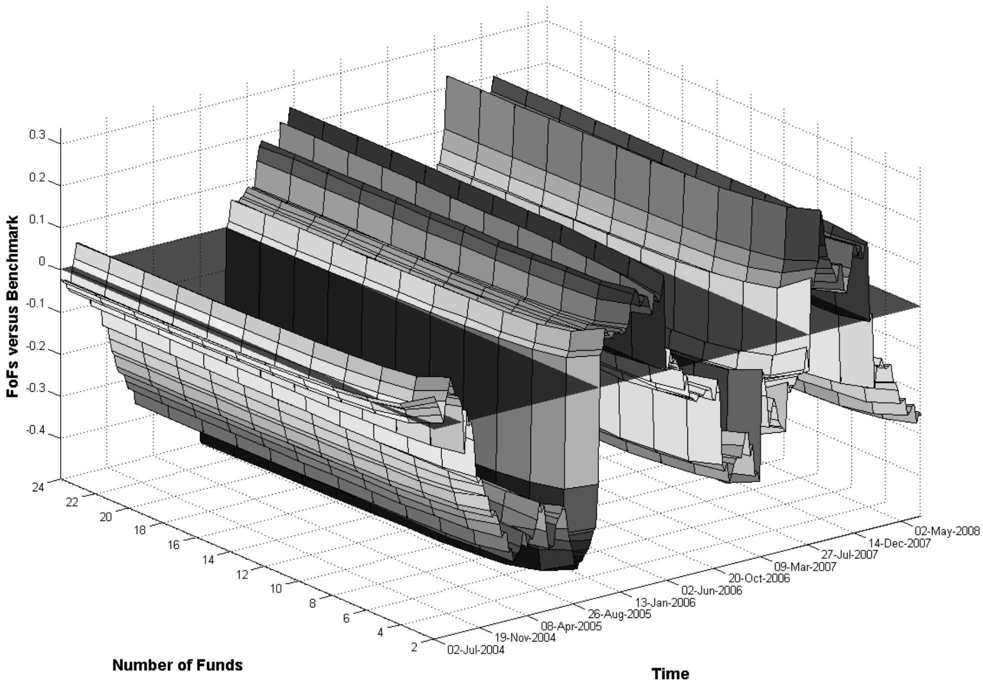

Exhibit 2.3.b. Difference in average skewness for growth FoFs against the benchmark

The difference in kurtosis for the FoFs and their sub-parts are shown in Exhibits 2.4.a. and 2.4.b. Although we can see a similarity to the skewness difference plots above with the two styles not differing as largely as when being investigated via the first two statistical moments, we see that the kurtosis is not reduced against the benchmark returns' kurtosis. This result is puzzling due to the following reasons: As one might expect that the building of style-neutral FoFs should result in a reduction in the tail concentration and a return distribution more centered around the mean, the expected result on the kurtosis is ambiguous. The technical fact that the kurtosis measure is increasing for larger tail concentration as well as for higher probability around the mean does not allow for a final conclusion concerning the style-neutral FoF behaviour, as the two expected effects have opposing influences on the value of the kurtosis.

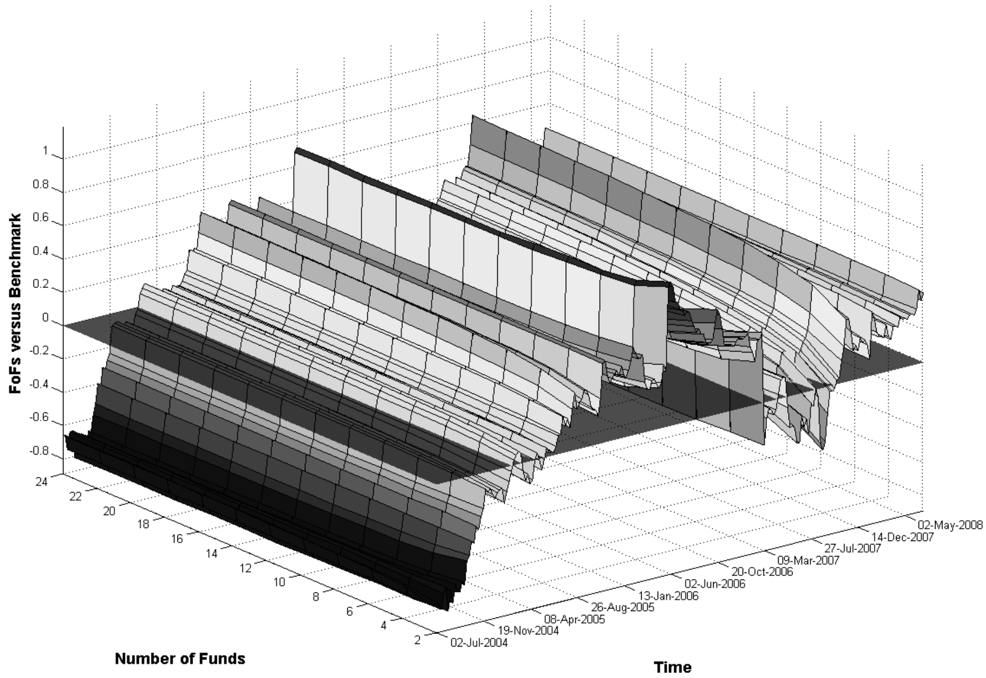

Exhibit 2.4. Difference in average kurtosis for style-neutral FoFs against the benchmark

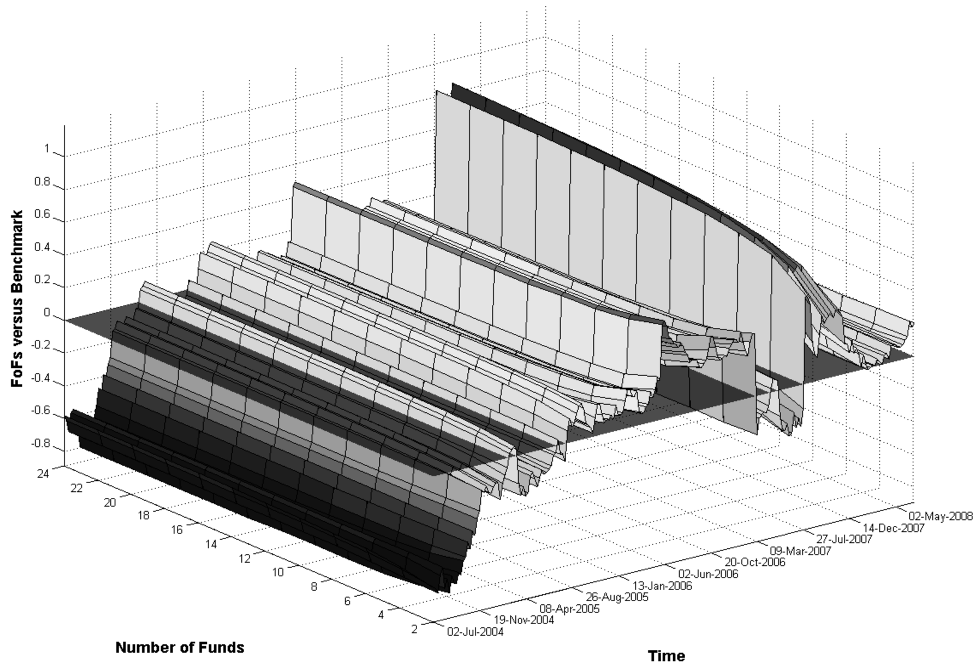

Exhibit 2.4.a. Difference in average kurtosis for value FoFs against the benchmark

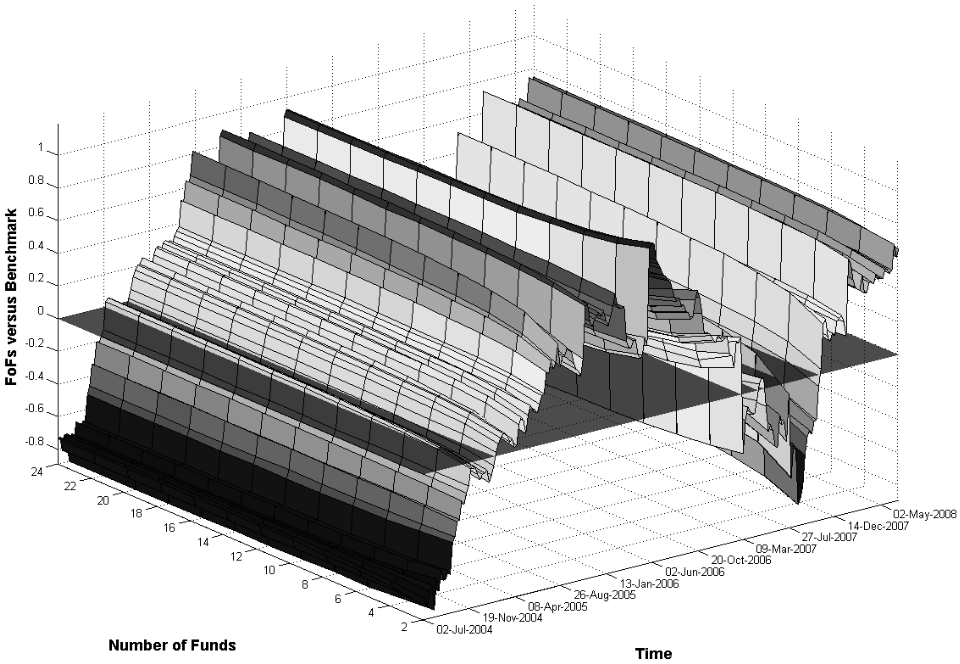

Exhibit 2.4.b. Difference in average kurtosis for growth FoFs against the benchmark

As for the mean and standard deviation plots, we have left the minimum and maximum plots in the Appendix, where in Exhibits 2.11. are the skewness differences, and in Exhibits 2.12. the kurtosis plots are found.

The fact that the amplitude of all results is greater for the growth sub FoFs may be the result of either the fact that the growth funds had a larger variation against the benchmark over time and portfolio sizes or because of the fact that the sample size consisted of more growth than value funds (making the possible range larger although restricting single portfolio sizes to 24), or a combination of both. Besides delivering interesting insights, having analyzed the first four moments separately did not yield a final conclusion concerning the appropriateness and usefulness of building style-neutral FoFs. We therefore take the analysis to the field of performance and risk measures. As described in Section 2.3., the R ratio serves as a measure that takes into account both reward and risk, while not being flawed by any assumptions and restrictions, like many classical risk and reward measures.

Furthermore, the behaviour of FoFs against the benchmark is adequately tracked by this reward to risk ratio, a feature that is highly desirable when considering equity markets in general and especially when recalling the somehow puzzling results from the kurtosis plots.

For the analysis of the R ratio over time, we have chosen to use 40% and 1% as the percentages for the reward (or outperformance) term and the risk (or underperformance) measures that constitute the R ratio. In the explained interpretation, the ratio serves as a measure that is putting the "average" excess returns against the risk of severe underperformances on the weekly horizon. Put another way, it is the average excess returns in the nominator controlled for misplaced aggressive bets of fund managers that lead to underperformance as measured by the denominator.

The R ratio in this context is informative on whether we can expect that building style-neutral FoFs is resulting in a controlled outperformance of the benchmark. As there is no pre-defined number indicating whether the ratio is high or low, we can compare the ratios of value, growth and neutral FoFs with each other, thereby getting a glance at the differences in the benchmark-relative performance. Exhibits 2.5.a. to 2.5.d. depict the R ratio over time. We can see the direct comparison in Exhibit 2.5.b., where the style-neutral FoFs are covered by the dark value and growth FoF R ratios. Only in periods where the light-gray surface is above the dark coverings, the style-neutral FoFs have outperformed both types of style FoFs with the same number of funds included. As we can see, this seldom happens, pointing towards the notion of a countering of styles and therefore a mediocre mixture of both investment styles.

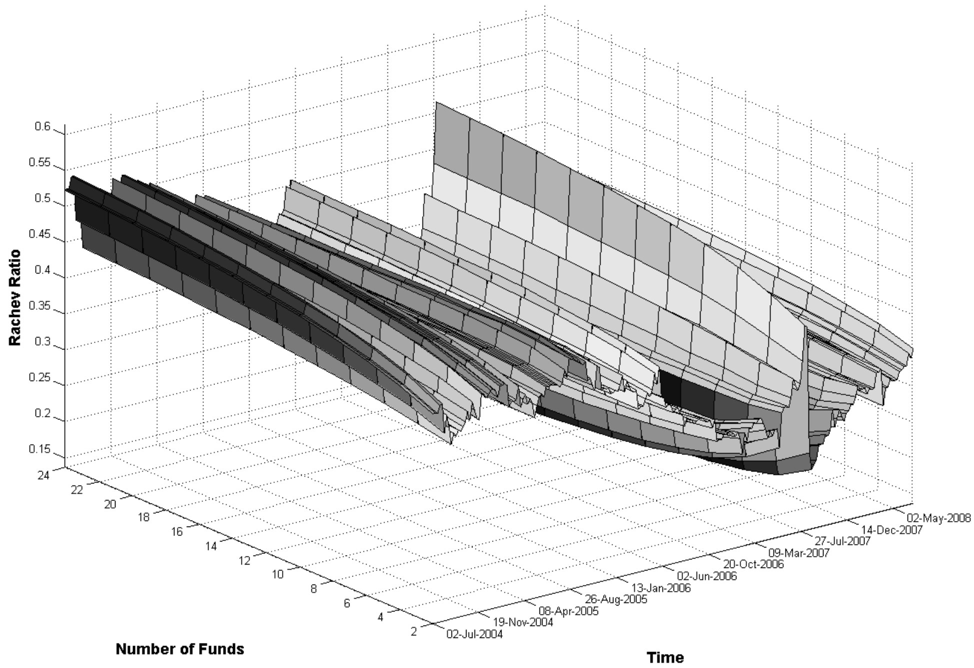

Exhibit 2.5.a. Average R ratio of the style-neutral funds of funds.

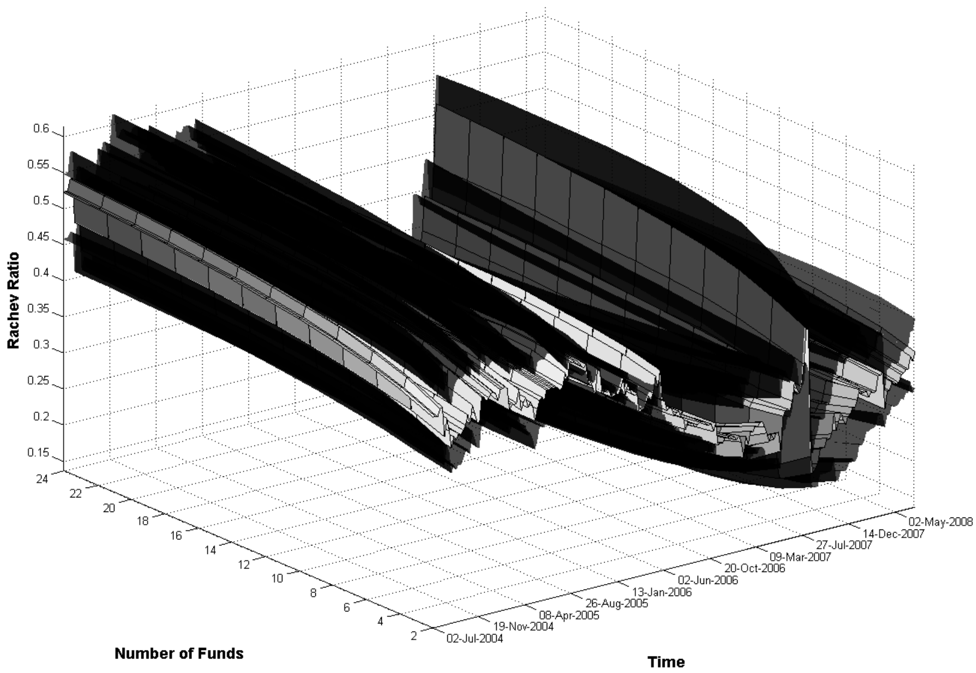

Exhibit 2.5.b. Average R ratio of the style-neutral funds of funds and the sub funds of funds

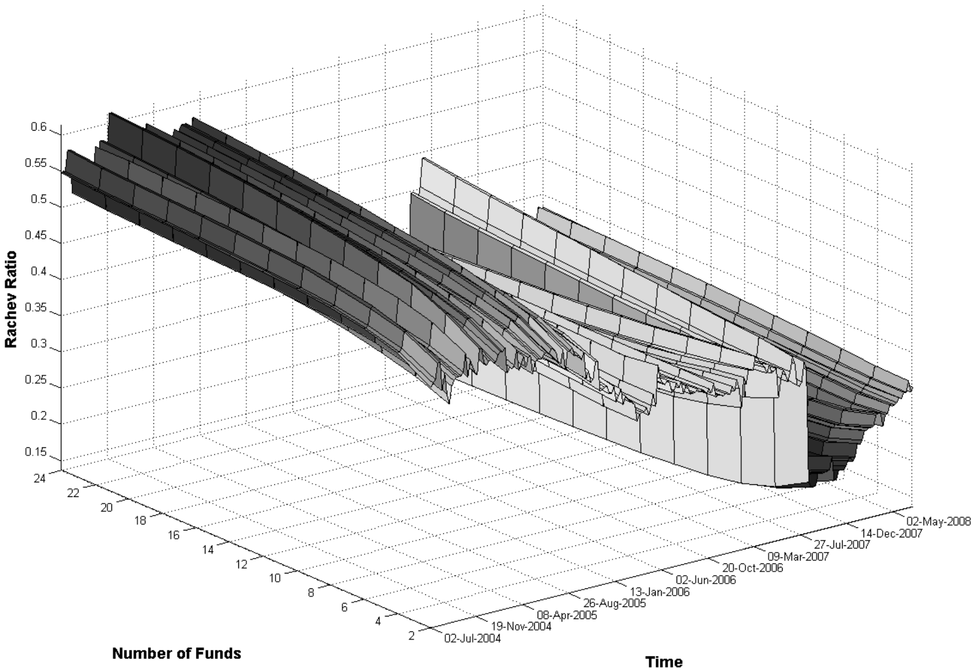

Exhibit 2.5.c. Average R ratio of the value sub funds of funds

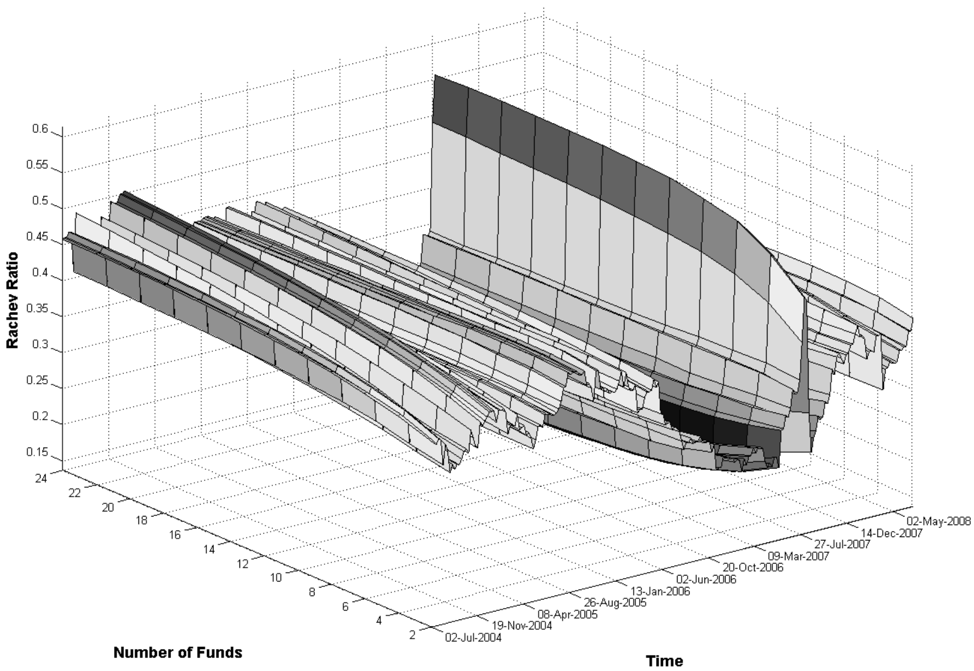

Exhibit 2.5.b. Average R ratio of the growth sub funds of funds

While it comes as no surprise that the mixture of differing styles results in an averaging out of characteristics, we can state that the "best of both worlds" may perhaps be obtained, but seemingly not with a 50/50 allocation to the two opposing strategies. As the differing styles are resulting in largely differing return and risk schemes in the various periods, we expect a FoF shifting between styles to be superior to a FoF locked in at 50/50 - given the ability to identify the best time to shift, of course. This result is related to the findings from the geometric mean analysis, where a similar pattern of time-depending performance differences was observed and pointed at an averaging process that may be beneficial or harmful, depending on the time period analyzed.

The implication of an averaging process caused by the mixture of both styles in equal proportion is further strengthened when building the average for all statistics over all 209 periods. Getting rid of the time-dependent effects, we present in Exhibit 2.6., 2.7. and 2.8. the average of the mean, minimum and maximum of the descriptive statistics and the R ratio for the 10.000 simulated portfolios of each class.

We can see that there is no a priori benefit of building style-neutral FoFs when analyzing the mean returns, the returns' standard deviations and the R ratios that are obtained on average, as seen in Exhibit 2.6. While both classes seem to underperform against the benchmark, the neutral FoFs do so too, of course. The averaging process and the effects of diversification nevertheless reduce the volatility of the returns, but to a moderate degree only. Regarding the R ratio, we can state that the process is leading to a result that again implies that style-neutrality is not generally beneficial to risk adjusted returns, although we need to take into account that the average values are not telling the whole story concerning the risk-adjusted performance measure. Therefore, the respective minimum and maximum values for the respective statistics for the 10.000 FoFs of all classes are shown in Exhibits 2.7. and 2.8.

Size	Mean Return			Standard Deviation			R ratio		
	Neutral	Value	Growth	Neutral	Value	Growth	Neutral	Value	Growth
2	-1,14%	-0,84%	-1,39%	0,02%	-0,56%	0,75%	0,36	0,38	0,35
4	-1,10%	-0,81%	-1,34%	-0,30%	-0,82%	0,39%	0,36	0,38	0,36
6	-1,08%	-0,80%	-1,32%	-0,40%	-0,91%	0,26%	0,36	0,39	0,36
8	-1,08%	-0,79%	-1,31%	-0,46%	-0,95%	0,20%	0,36	0,39	0,36
10	-1,07%	-0,79%	-1,31%	-0,49%	-0,98%	0,16%	0,36	0,39	0,36
12	-1,07%	-0,79%	-1,31%	-0,52%	-1,00%	0,13%	0,36	0,39	0,36
14	-1,07%	-0,79%	-1,30%	-0,53%	-1,01%	0,12%	0,36	0,39	0,36
16	-1,07%	-0,79%	-1,30%	-0,54%	-1,02%	0,10%	0,36	0,40	0,36
18	-1,07%	-0,78%	-1,30%	-0,55%	-1,03%	0,09%	0,36	0,40	0,36
20	-1,06%	-0,78%	-1,30%	-0,56%	-1,03%	0,08%	0,36	0,40	0,36
22	-1,06%	-0,78%	-1,30%	-0,57%	-1,04%	0,08%	0,36	0,40	0,36
24	-1,06%	-0,78%	-1,30%	-0,57%	-1,04%	0,07%	0,36	0,38	0,36

Exhibit 2.6. Average statistics for FoFs versus the S&P 500 over all 209 time periods of the average of the respective statistic for 10.000 simulated portfolios for value, growth and neutral FoFs

A large dispersion of results is obtained, implying that it greatly depends on which funds were selected by the random number generation for the time spans. For the R ratio as an example, the measure is becoming very low for the worst FoFs, while the highest ratios are more than twice the average. While this is seemingly in contrast to the implied notion of countering styles and cancelling out of active bets of target fund managers as discussed above, one may not interpret these results as evidence against those notions. This is because the average values for minimum and maximum achieved results are very unlikely to be obtained in practice, as it is most unlikely that a fund selection process would result in the minimum or maximum attainable of the respective statistic all of the time. In addition, the fact that the neutral FoFs maximum R ratios are higher than those for their style counterparts, but the minimum R ratios are lower, points in the direction that the extremes are merely based on the respective FoF mixture, rather than due to a general effect. However, the extreme values averages over time show how dispersed the results may be, owing to the large differences in the fund sample selected.

Size	Mean Return			Standard Deviation			R ratio		
	Neutral	Value	Growth	Neutral	Value	Growth	Neutral	Value	Growth
2	-11,56%	-8,51%	-12,60%	-2,57%	-2,29%	-2,48%	0,12	0,17	0,13
4	-9,47%	-6,99%	-10,13%	-2,44%	-2,22%	-2,25%	0,11	0,17	0,14
6	-7,99%	-5,82%	-8,47%	-2,22%	-2,07%	-1,94%	0,14	0,20	0,16
8	-6,98%	-4,99%	-7,42%	-2,06%	-1,93%	-1,73%	0,16	0,23	0,18
10	-6,28%	-4,33%	-6,70%	-1,92%	-1,83%	-1,56%	0,18	0,25	0,20
12	-5,79%	-3,81%	-6,15%	-1,81%	-1,73%	-1,41%	0,19	0,27	0,21
14	-5,37%	-3,36%	-5,68%	-1,73%	-1,65%	-1,31%	0,20	0,29	0,22
16	-5,01%	-2,96%	-5,32%	-1,66%	-1,57%	-1,20%	0,21	0,31	0,23
18	-4,75%	-2,57%	-4,98%	-1,59%	-1,50%	-1,11%	0,22	0,32	0,24
20	-4,49%	-2,18%	-4,71%	-1,54%	-1,41%	-1,03%	0,23	0,34	0,25
22	-4,27%	-1,72%	-4,45%	-1,49%	-1,30%	-0,96%	0,24	0,36	0,26
24	-4,09%	-1,14%	-4,23%	-1,44%	-1,15%	-0,90%	0,24	0,38	0,26

Exhibit 2.7. Average statistics for FoFs versus the S&P 500 over all 209 time periods of the minimum of the respective statistic for 10.000 simulated portfolios for value, growth and neutral FoFs

Size	Mean Return			Standard Deviation			R ratio		
	Neutral	**Value**	**Growth**	**Neutral**	**Value**	**Growth**	**Neutral**	**Value**	**Growth**
2	10,45%	7,01%	11,70%	4,29%	2,21%	5,55%	0,77	0,68	0,74
4	8,22%	5,60%	8,44%	2,92%	1,35%	3,99%	0,80	0,70	0,73
6	6,40%	4,42%	6,49%	2,13%	0,78%	3,10%	0,72	0,63	0,67
8	5,31%	3,54%	5,28%	1,67%	0,40%	2,58%	0,67	0,59	0,63
10	4,52%	2,86%	4,44%	1,35%	0,11%	2,22%	0,63	0,56	0,59
12	3,91%	2,33%	3,82%	1,11%	-0,11%	1,95%	0,60	0,53	0,57
14	3,47%	1,86%	3,34%	0,94%	-0,28%	1,75%	0,58	0,52	0,55
16	3,09%	1,43%	2,92%	0,80%	-0,42%	1,60%	0,56	0,50	0,53
18	2,79%	1,05%	2,55%	0,68%	-0,56%	1,43%	0,54	0,48	0,52
20	2,53%	0,64%	2,22%	0,58%	-0,68%	1,32%	0,53	0,47	0,51
22	2,28%	0,20%	1,98%	0,48%	-0,81%	1,21%	0,52	0,45	0,50
24	2,05%	-0,41%	1,73%	0,42%	-0,96%	1,12%	0,51	0,42	0,49

Exhibit 2.8. Average statistics for FoFs versus the S&P 500 over all 209 time periods of the maximum of the respective statistic for 10.000 simulated portfolios for value, growth and neutral FoFs

2.5. Conclusion

By building simulated FoFs for the classes of value, growth and style-neutral, we analyze whether those fund portfolios are able to outperform the benchmark and how they compare with each other. Choosing a simulation size of 10.000 portfolios for any of the 3 types of FoFs, 209 windows of 52 weeks and 12 fund sizes, we first separately analysed the mean, standard deviation, skewness and kurtosis of the resulting synthetic portfolios.

While one could conclude that the average mean return, in comparison to the benchmark, is very time-dependent and differing between the style FoFs, the style-neutral FoFs seem to average out these characteristics. The combining effect is more beneficial when looking at the standard deviation, as the standard deviation of the style-neutral FoFs is reduced versus the benchmark. However, this effect is strongly influenced by the generally lower dispersion of returns in the value sector.

As the skewness and kurtosis effects are not as easy to judge as the first two moments, and since the kurtosis results are especially difficult to interpret, we focused on the tails of the synthetic FoF benchmark relative return distributions, using the R ratio. Being informative on the average outperformance distribution of a portfolio versus the benchmark and controlling for severe underperformances, the R ratio shows that building style-neutral FoFs do indeed result indeed in an averaging process, i.e. the style-neutral FoFs are merely composites of two opposing styles. This indicates that a mixture of those is not yielding a structure of style-neutral FoFs outperforming both styles in a period.

We can therefore conclude that building style-neutral FoFs is reducing uncertainty and the amplitude of various return and risk measures, but a distinctive “best of all worlds” effect is not obtained. For a FoF manager willing to achieve a mediocre and stable pattern of returns, the style-neutral approach may serve the purpose, but for strong risk-adjusted outperformance – and this has to be the aim for any manager – a shifting between the styles could yield more favourable results if the timing is right. However, as most combinations analyzed in the study already underperform the benchmark, there is no need to dig into fee discussions or any survivorship bias effects.

Further research could be done in the field of shifting between styles in FoFs, or put another way, how to find the optimal proportion of the style and growth allocation in a FoF that is investing in both styles and is not locked in at 50/50. In addition, the financial market crisis and the credit crunch with severe drawdowns in global equity markets have surely had their impact on the results, which was obvious in the mid and late 2007 periods as well as in the beginning of 2008. While the fund managers could, of course, have chosen to hold more cash and to reduce the holdings of companies most affected, the crisis had its impact not only through the raw performances but also through the changing of valuations of companies and therefore a changing picture of price-to-book ratios. While the rapid decline in prices of stock led to a decline in this ratio, companies may have become more of the value type in general until depreciations were made and book values changed or the markets recovered. This makes the identification of value and growth more complicated and the shifting in the funds' compositions would be highly interesting in case of data availability.

However, the general results found and conclusions made are fairly stable over time and are not the result of the particular stage of time of the credit crisis. The fact that the style-neutral FoFs are protecting from the worst, but make the best unattainable, holds throughout the time span analyzed, only with changing levels.

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2.7. Appendix

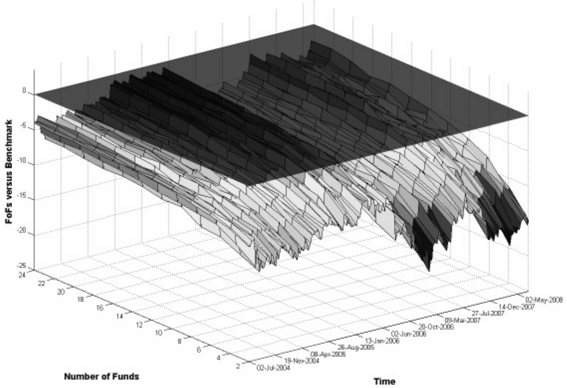

Exhibit 2.9.a. Difference in lowest annualized geometric mean return for style-neutral FoFs against the benchmark

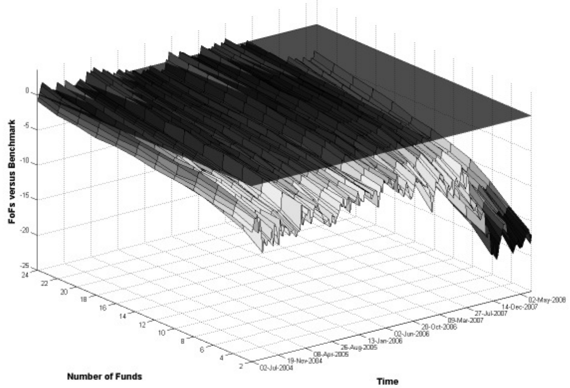

Exhibit 2.9.b. Difference in lowest annualized geometric mean return for value sub FoFs against the benchmark

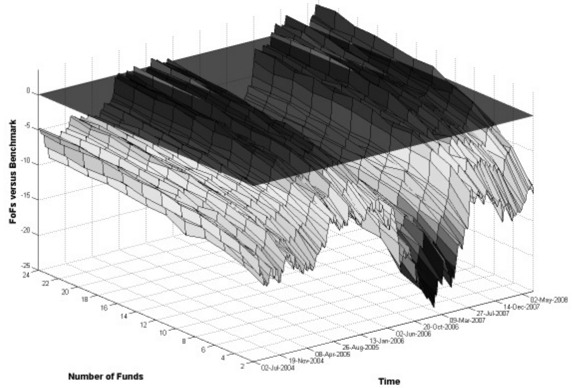

Exhibit 2.9.c. Difference in lowest annualized geometric mean return for growth sub FoFs against the benchmark

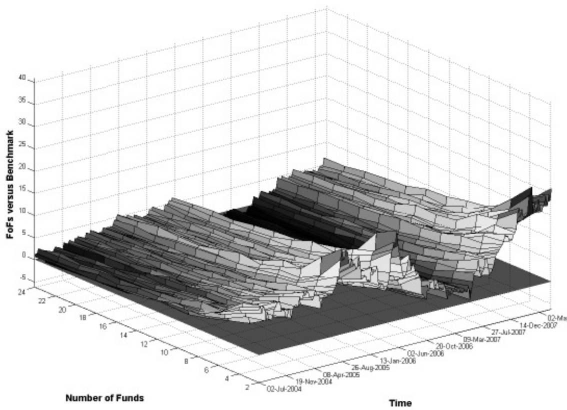

Exhibit 2.9.d. Difference in highest annualized geometric mean return for style-neutral FoFs against the benchmark

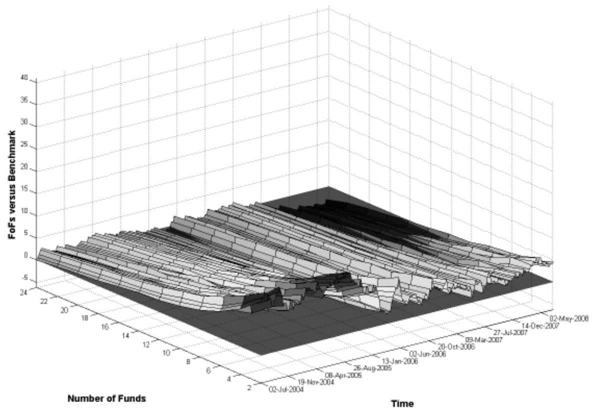

Exhibit 2.9.e. Difference in highest annualized geometric mean return for value sub FoFs against the benchmark

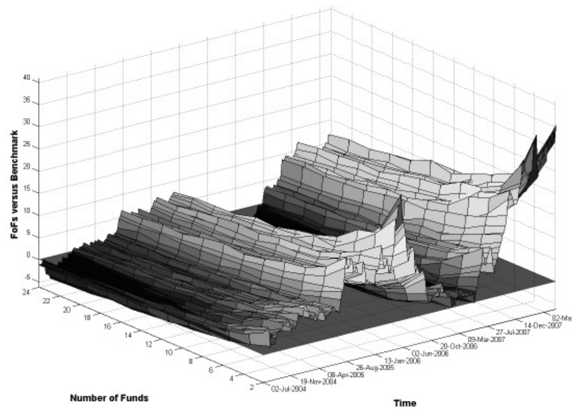

Exhibit 2.9.f. Difference in highest annualized geometric mean return for growth sub FoFs against the benchmark

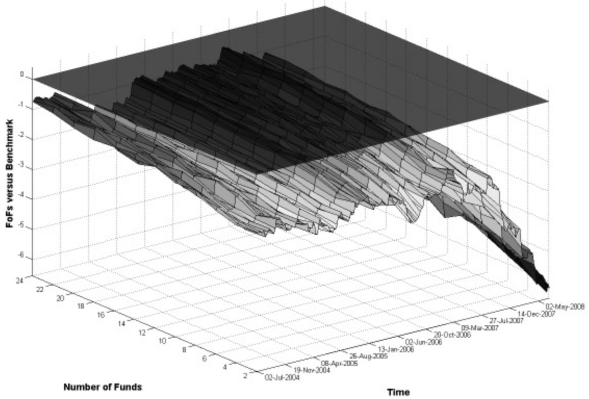

Exhibit 2.10.a. Difference in lowest annualized standard deviation for style-neutral FoFs against the benchmark

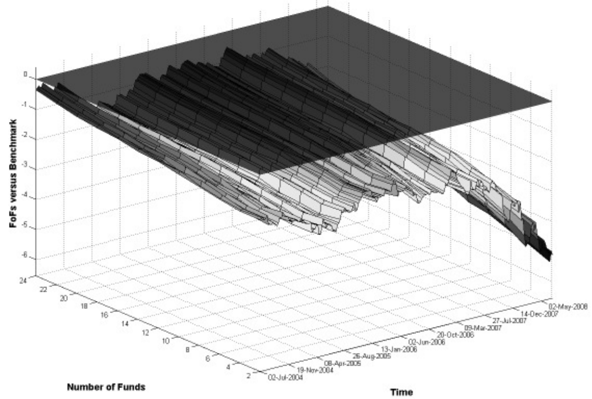

Exhibit 2.10.b. Difference in lowest annualized standard deviation for value sub FoFs against the benchmark

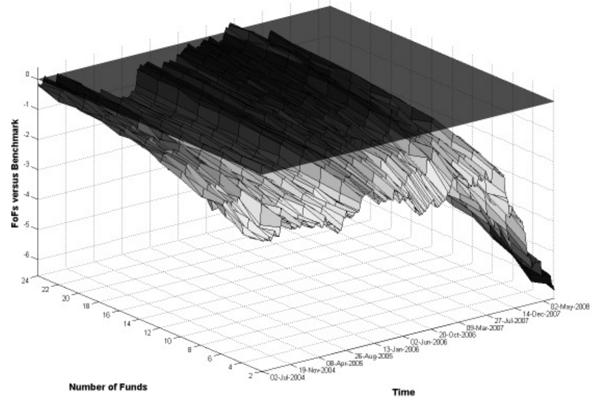

Exhibit 2.10.c. Difference in lowest annualized standard deviation for growth sub FoFs against the benchmark

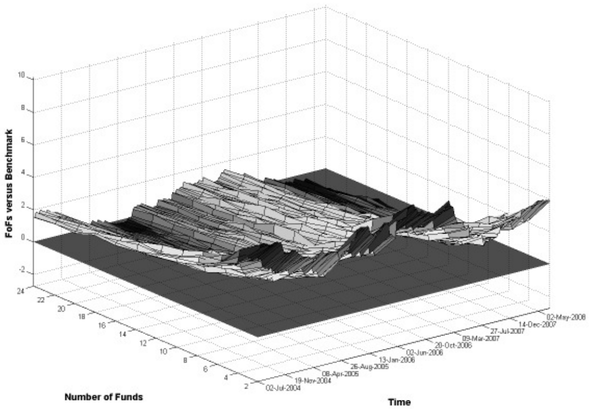

Exhibit 2.10.d. Difference in highest annualized standard deviation for style-neutral FoFs against the benchmark

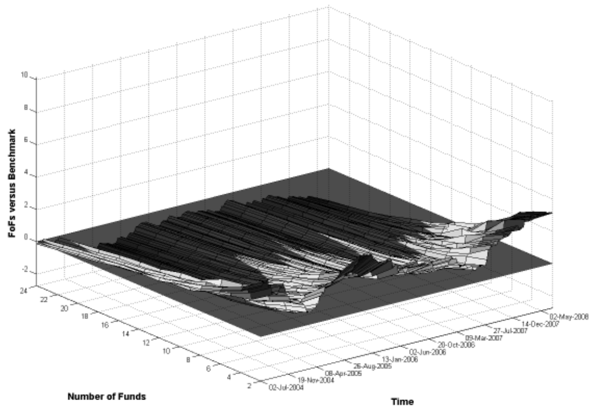

Exhibit 2.10.e. Difference in highest annualized standard deviation for value sub FoFs against the benchmark

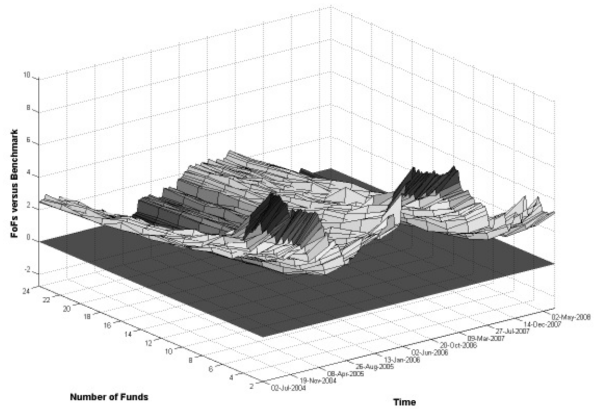

Exhibit 2.10.f. Difference in highest annualized standard deviation for growth sub FoFs against the benchmark

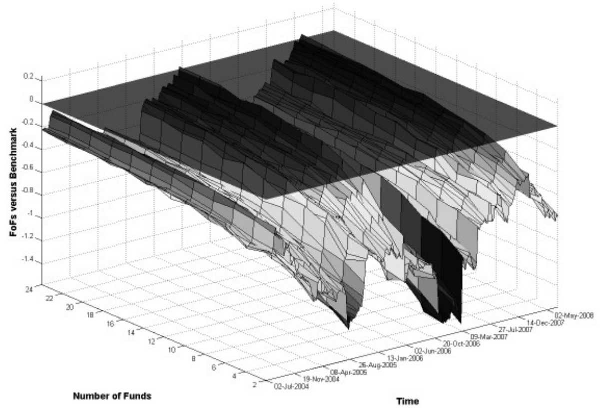

Exhibit 2.11.a. Difference in lowest skewness for style-neutral FoFs against the benchmark

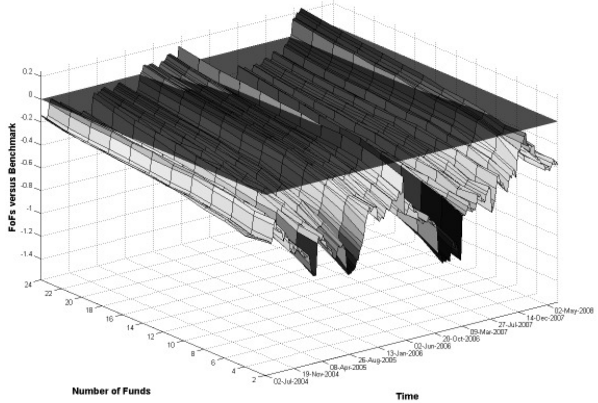

Exhibit 2.11.b. Difference in lowest skewness for value sub FoFs against the benchmark

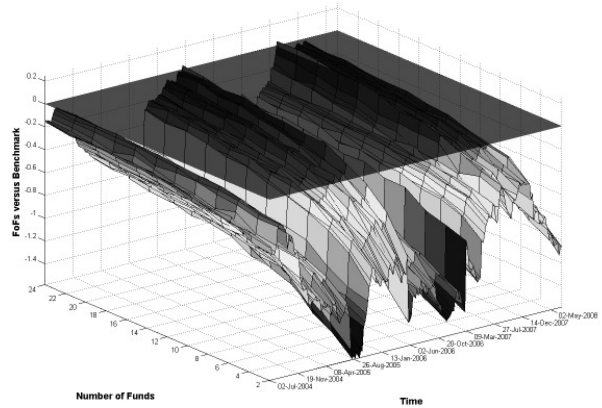

Exhibit 2.11.c. Difference in lowest skewness for growth sub FoFs against the benchmark

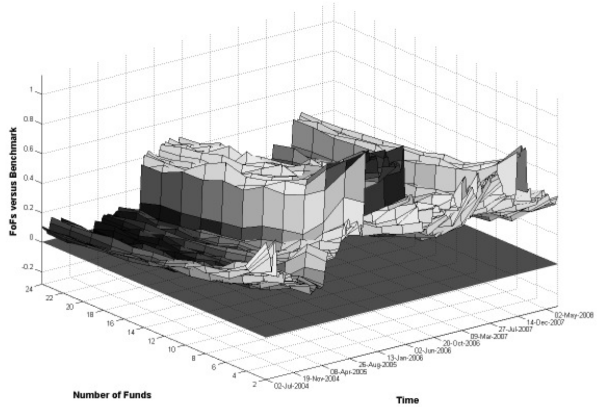

Exhibit 2.11.d. Difference in highest skewness for style-neutral FoFs against the benchmark

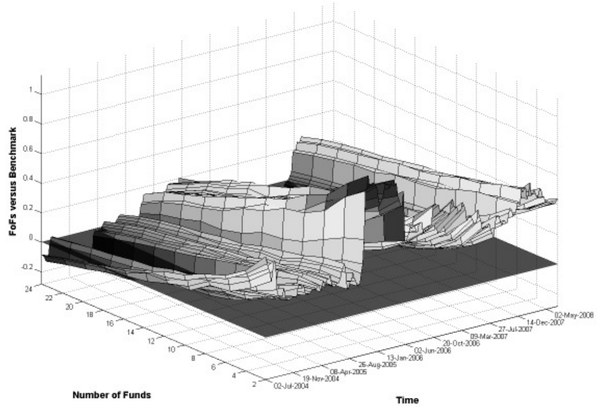

Exhibit 2.11.e. Difference in highest skewness for value sub FoFs against the benchmark

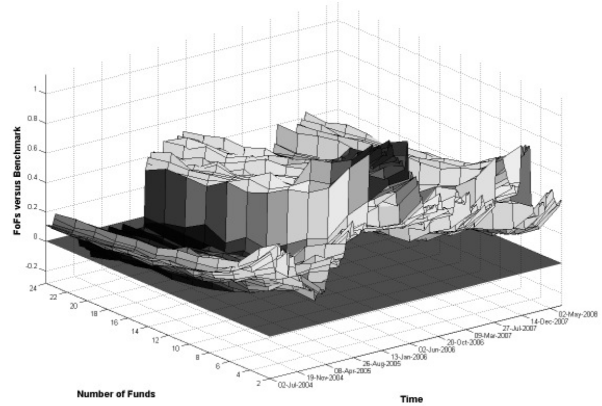

Exhibit 2.11.f. Difference in highest skewness for growth sub FoFs against the benchmark

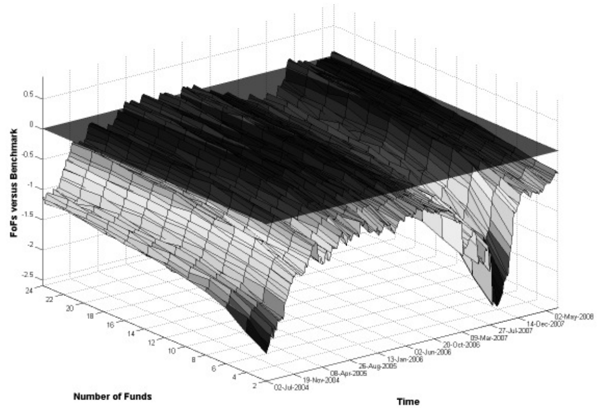

Exhibit 2.12.a. Difference in lowest kurtosis for style-neutral FoFs against the benchmark

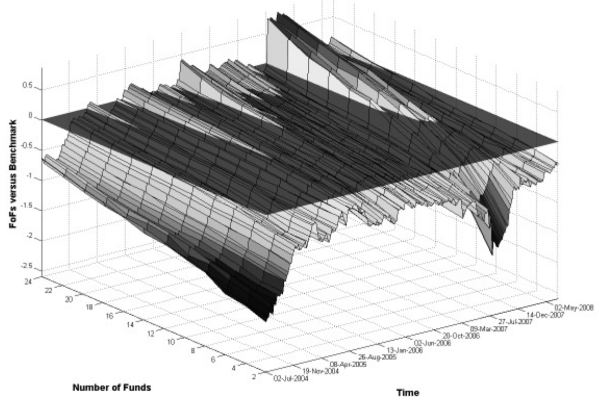

Exhibit 2.12.b. Difference in lowest kurtosis for value sub FoFs against the benchmark

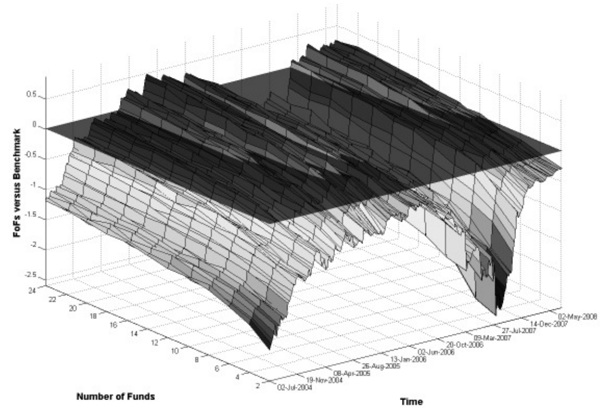

Exhibit 2.12.c. Difference in lowest kurtosis for growth sub FoFs against the benchmark

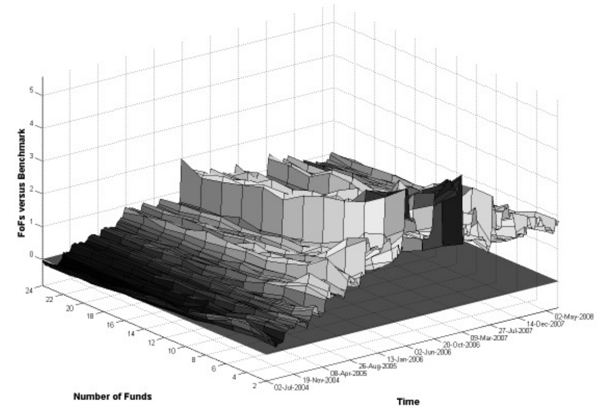

Exhibit 2.12.d. Difference in highest kurtosis for style-neutral FoFs against the benchmark funds

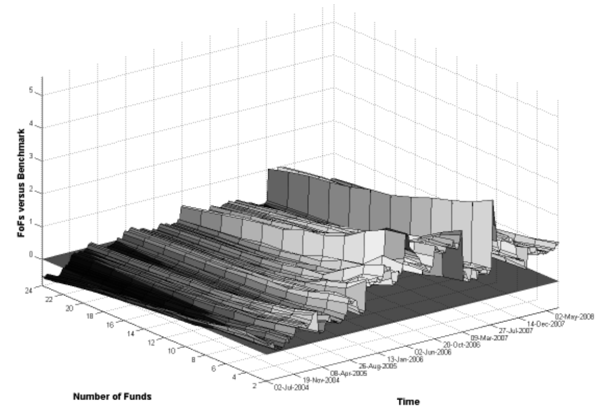

Exhibit 2.12.e. Difference in highest kurtosis for value sub FoFs against the benchmark

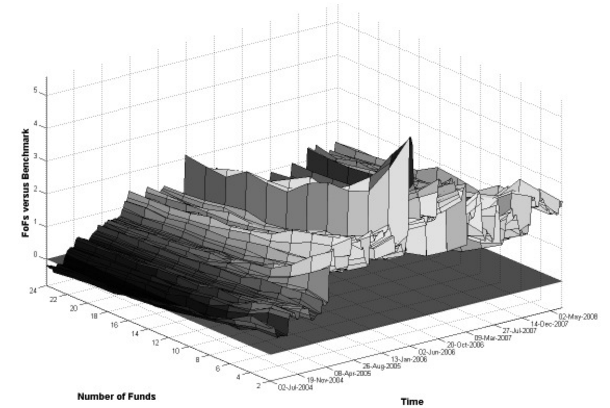

Exhibit 2.12.f. Difference in highest kurtosis for growth sub FoFs against the benchmark

3. R Ratio Optimization with Heterogeneous Assets using Genetic Algorithm

3.1. Introduction

In this chapter, we propose a framework to portfolio optimization that is superior to mean-variance approaches utilized for asset allocation. We show how a portfolio with heavily differing asset types in various market phases can be managed efficiently by using a ratio-based portfolio optimization approach and provide a general solution to related optimization problems and the technical challenges arising from them.

Since the formulation of the portfolio selection theory, as formulated by Markowitz (1952), portfolio selection has been among the most discussed finance topics in both the theory and practice of finance. As a result, a large body of research work has emerged. Although the mean-variance approach allows a portfolio manager to identify the efficient frontier, risk-reward measures must be utilized to select the optimal portfolio given the investor's risk aversion. The most commonly used measure is the Sharpe ratio proposed by Sharpe (1964) and its extension (Sharpe, 1994). The Sharpe ratio focuses on portfolio compositions of assets that maximize the ratio of expected portfolio returns to the variability of the returns.

While the combination of the basic objectives of investing ─ maximizing reward and minimizing return variability or risk – is still the baseline for portfolio optimization approaches and frameworks, the measures and tools employed have changed. The mean-variance framework and the Sharpe ratio generally refer to the trade-off between reward and uncertainty (or variability); however, measures that try to capture risk instead of uncertainty have become increasingly popular. While there is still considerable debate on the most desirable and important properties of risk measures in portfolio theory[9], recent approaches mainly share the same crucial characteristic, namely a focus on the tails of the return distributions. Among those measures, ratios that relate portfolio reward to portfolio (tail) risk have gained greater attention[10].

With this chapter, we contribute to the existing literature by providing a portfolio optimization method that is both independent of any distributional assumptions and may be used with any combination of assets, not being limited to benchmark-related problems. These properties are especially important when considering flexible and complex financial market products and the active management of portfolios containing them. One example is the fund of funds (FoF) product because it requires careful allocation of capital by FoF managers in order to achieve value added for investors[11]. This stems from the fact that for FoFs normally a very large universe of target funds may be available, depending on the products' specification. If the universe of possible fund investments is very heterogeneous, the task of portfolio management is even more complicated. We use such a heterogeneous set of target funds with a sample of two very different types of real estate investment funds that are highly suitable for our study. The framework presented in this chapter may be applied to any combination of assets though, for example for bond and equity portfolios or even for direct investments rather than fund investments.

We use a modified version of the Rachev ratio (R ratio) introduced in Chapter 2, which is a reward-to-risk ratio that is free from distributional assumptions. However, optimizing this ratio makes the solution of a non-quasi-convex optimization problem necessary. As this technical issue is

[9] See Rachev et al. (2007) for an extensive study of risk and reward measures in portfolio management.

[10] See Farinelli et al. (2009) for applications and comparisons of tail ratio measures.

[11] See Stein et al. (2008) for a general introduction to funds of funds.

very general and applies to all ratio problems that may have a negative denominator, we propose genetic algorithms as a general solution method for all ratio problems being non-quasi-convex. We show that although the span of possible solutions is very large due to the heterogeneous fund types that are candidates for inclusion in the portfolio, genetic algorithm solves the optimization problem efficiently and for all periods without the problem of numerical instability for the solution.

The chapter is organized as follows. In Section 3.2. we explain the methodology used in our study, namely the statistical measures, the optimization approach, and the genetic algorithm for solving the problem at hand. We introduce the data and the implications of the differing fund type properties in Section 3.3. The portfolio optimization results are presented in Section 3.4. and our findings are summarized in Section 3.5.

3.2. Rachev Ratio, Portfolio Optimization and the Genetic Algorithm

We begin with the R ratio[12]. This return to risk measure uses the expected tail loss (equivalent to the conditional value at risk, CVaR for continuous distributions), generally being defined as:

$$ETL_{1-\alpha}(r_p) = E\left(\max(-r_p, 0) \middle| -r_p > VaR_{1-\alpha}(r_p)\right)$$

where $ETL_{1-\alpha}(r_p)$ is the expected tail loss with tail probability α for portfolio returns r_p. Common choices for α are 1% or 5% in accordance with common choices of the confidence levels 99% and 95% used for value-at-risk (VaR) and other risk measures. As noted earlier, ETL goes beyond

[12] For extensive discussions and applications concerning the R ratio and related risk and performance measures see Biglova et al. (2004), Rachev et al. (2005), Okuyama and Francis (2007), Rachev et al. (2008) and Farinelli et al. (2009).

traditional VaR by providing information on the expected loss in the case of a tail event instead of furnishing information only on the loss not be exceeded with the respective confidence level[13].

For the R ratio, the measure of expected tail loss is used in the following way: The nominator is defined as the ETL with probability α of the negative of the excess return of a portfolio over the benchmark. Conversely, the denominator is the ETL with probability β of the excess return of a portfolio over the benchmark. Defining the ratio this way, one obtains a measure of the estimated outperformance controlled for the severity of underperformances of a portfolio against the benchmark:

$$R(r_p) = \frac{ETL_{1-\alpha}(r_b - r_p)}{ETL_{1-\beta}(r_p - r_b)}$$

In this study, we do not use a benchmark because we combine very different fund types, so we set r_B to zero and therefore have the modified R ratio being defined as:

$$R(r_p) = \frac{ETL_{1-\alpha}(-r_p)}{ETL_{1-\beta}(r_p)}$$

By using this ratio, one obtains a measure for absolute expected gains at a given probability level divided by the absolute expected losses at another probability level. Sensible percentages for probability level α are, for example, 30-40% to get a reward term that focuses on the upper 30-40% of the return distribution, while probability level β could be chosen to be 1% or 5% to take into account the highest expected losses and to be in accordance with common risk metrics.

Having defined the ratio to optimize the FoFs, we need to impose sensible restrictions and bounds prior to solving the problem. As normally a FoF is of the long only type, we impose the typical no short-selling constraint. Furthermore, we restrict the maximum weight of any fund to 20% to obtain

[13] See Sortino and Sachell (2001) and Rockafellar (2002) among others concerning VaR and CVaR / ETL.

sensible results that are in accordance with practical portfolio management and often seen regulatory or compliance restrictions. In addition, we impose the classical full investment constraint and restrict the outcomes to portfolios with positive expected returns[14].

The problem therefore takes the following form:

$$\max_{w} R(r_p) = \frac{ETL_{1-\alpha}\left(-w^T r\right)}{ETL_{1-\beta}\left(w^T r\right)}$$

$\sum w_i = 1$ (full investment constraint)

$0 \le w_i \le 0.2$ (long-only constraint and upper limit of 20%)

$w^T r > 0$ (positive expected return)

with $r_p = w^T r$ being the portfolio returns for the vector of fund weights w and the vector of fund returns r. We have chosen to maximise the R ratio with probability levels of 33% in the nominator, i.e. the upper third of the return distribution and 1% for the denominator, i.e. the lower 1% of the return distribution. Defining the ratio that way, we obtain a moderate and not very aggressive measure for the reward, controlled for the most severe expected losses during one period:

$$\max_{w} R(r_p) = \frac{ETL_{67\%}\left(-w^T r\right)}{ETL_{99\%}\left(w^T r\right)}$$

We will contrast the results with other optimizations, for which the same restrictions and bounds were applied. The following optimizations were performed, thereby setting benchmark values as well as riskless rates of return to zero for achieving comparable results:

[14] The decision whether to impose the restriction for positive expected returns of a portfolio needs to be based on the available asset types, since depending on the market situation no solution may be obtained if all or most assets had a negative return in the estimation period. In our case, it is always possible to obtain positive expected portfolio returns.

Sharpe-ratio (SR) optimization: $\max_{w} S(r_p) = \dfrac{w^T r}{\delta(w^T r)}$

Expected Tail Loss (ETL) Minimization: $\min_{w} ETL_{99\%}(w^T r)$

Expected Tail Gain (ETG) Maximization: $\max_{w} ETL_{67\%}(-w^T r)$

Optimizations, as presented above, were performed due to the following considerations: The Sharpe Ratio is used to check whether the distribution and tail focussed measures are truly superior to their mean-variance counterparts. The minimization of the expected tail loss has become a popular approach in portfolio optimization in the recent past and the expected tail loss is the denominator of our non-benchmark related R ratio, i.e. the risk part of the ratio. As the risk part of the ratio is used for a stand-alone optimization, it is natural to use the reward term as a single objective too, in order to analyze whether it is one term or the interplay of the two terms that delivers the best result.

While the SR, ETL, and ETG optimizations can be done using derivative based solving routines or linear programming routines (the solutions may lead to local minima however), the R ratio introduces more challenging computational issues. Generally, performance ratio optimizations may cause several issues related to solving the problem at hand. The ratio may turn out to be unbounded, which is a very general argument that is valid for all performance ratios with a possibly negative denominator.

For the R ratio in particular, there are additional complications because the problem is not quasi-convex. This means it cannot be reduced to a convex problem with the usual techniques, implying there may be many local extremes. However, even if problems are not quasi-convex, they can still be solved with traditional convex techniques (we have to keep in mind that the solution is only local nevertheless) but on the condition that the ratio is continuously differentiable twice. As the ETL function used in the R ratio does not have a first derivative for all portfolios as well as for small sample sizes and/or low tail probabilities, the issue of numerical instability may arise nevertheless. Thus, the optimization may not converge generally because of two reasons – either we have a case in which the ratio is unbounded, or the derivatives which the traditional convex optimization methods require are numerically unstable.

We resort to the class of genetic algorithms to solve the optimization problem outlined above. Classified as heuristic methods for global search problems, genetic algorithms are procedures that behave like natural, evolutionary processes. The origin of genetic algorithms dates back to the 1950s with Barricelli (1954 and 1957), Fraser (1957) and Fraser and Burnell (1970) heavily influencing the use of genetic algorithms in computer applications. Over the course of time, genetic algorithms have found their way to applications and research in finance and economics. For recent examples, see Dempster and Jones (2001), Hryshko and Downs (2004), Lai and Li (2008), and Lin and Liu (2008), among others.

Generally, optimization using genetic algorithms is done by successively generating "populations" of solutions. Starting the search, random combinations of individuals are formed, for which all individuals are evaluated concerning their fitness, i.e. their contribution with respect to the objective function. In any following iteration, the current population is used to build the next generation. This is done by selection based on the fitness of individuals, randomly re-combining populations and mutating individuals. In our case the fitness function is the R ratio as a function of the return vectors and of the weights of the funds in the FoF, the population is the portfolio composition. This means that the genetic algorithm is successively building fund compositions and the evaluation of any fund's contribution to the fitness (i.e. to the maximization of the R ratio) is indicative on the following compositions.

While the use of genetic algorithms is often induced by computational necessities as in our case, they have a very beneficial side effect: The genetic algorithms search for global minima and therefore one obtains a very robust solution to the problem at hand and is not left with a local minimum or corner solutions.

3.3. Real Estate Funds: Data and Implications for Portfolio Optimization

In this section we describe our data sample and the implications of the data properties. The two types of funds used in this study are real estate mutual funds and German open-ended real estate funds. The former funds invest in companies in the real estate sector and in real estate-related companies. These companies need not be Real Estate Investment Trusts (REITs). Candidate companies are those doing business mainly through the development, management or trading of real estate properties. In addition, real estate companies that are qualified as REITs are tax-exempt under the requirement of an almost complete distribution of their capital gains. As with any type of stock, the stocks of real estate companies that the mutual fund managers invest in are traded on exchanges and are therefore priced through demand and supply interactions in the equity market. The share value can trade at a premium to or discount to net asset value of the properties held by the company. According to the share price of the target stocks, the daily net asset value of the real estate mutual funds is derived, at which fund shares may be redeemed on a daily basis.

The second asset type used in this study is the German regulated open-ended real estate funds. According to German investment law, the special type of open-end fund must invest directly in property, and most funds focus on commercial real estate. As with U.S. open-end funds (mutual funds), the fund issues shares at net asset value; that is, there is no premium or discount as in the case of a closed-end fund and redemptions are also possible at net asset value on every trading day[15]. Daily net asset values of the funds are determined via rents received, re-valuations of property held (normally once per year for each building), sales and acquisitions of properties as well as on costs and fees (from property management, consulting services, construction, refurbishments). In addition, the funds need to hold large amounts of liquidity (mainly cash, overnight money and very conservative bond investments) because their investments in very illiquid assets and the daily fund inflows and outflows. Due to the German practice of valuation, the changes in property values are small and provide a stable and smooth pattern over time. This is caused by basing the valuations on the long-term expected rents to be received (a long-term sustainable rental income method) by holding the property and is in contrast with mark-to-market oriented valuation methods seen in many other jurisdictions. In addition, especially for large portfolios, the smoothing effect is even greater because the assets re-valuation is distributed over the year, rather than taking place at one time for all properties held. For these reasons, open-ended real estate funds typically exhibit a very stable and non-volatile pattern over time[16].

Using these two kinds of real estate investments results in a very heterogeneous sample what represents a common problem for FoF managers. The problem of not having a benchmark for portfolio selection is apparent in this case, too. While FoFs investing in these two types of real estate funds (and in related fund types of the real estate sector) are spreading in Europe at the time of writing of this study, the combination of safe-haven investments and more risky and volatile assets is also common for other

[15] If any, there was only very little trading volume of these funds in secondary markets during normal market phases. However, the suspension of redemptions by some funds (caused by large outflows of money and deteriorating liquidity) in October 2008 has led to trading activity on stock exchanges since then.

[16] However, in the following of the suspensions of redemptions and the severe market downturn, pronounced de-valuations of property have led to drops in assets prices for many German open-ended real estate funds. Nevertheless, this does not impose a flaw into our study with the focus being on the framework for managing very heterogeneous assets.

asset classes. Balanced funds or mandates comprising both bonds and stocks or bond and equity funds are examples of related problems. The nature of those changes primarily with respect to the combination of the differing asset types and the respective weightings.

As indicated above, the two types of real estate funds differ significantly with respect to their return characteristics and statistical properties. Apart from some exceptions the typical open-ended real estate fund were returning between 3% to 6% per year with small daily movements in the net asset value and an annualized standard deviation of less than 1%. In contrast, the real estate mutual funds are exhibiting high volatility and leptokurtotic, skewed return distributions, and are prone to tail events that are typical for equity investments.

For each class we have included 10 funds with Europe as their main investment region. Using weekly total return data from Thomson Financial DataStream until end of October 2008, we have chosen end of October 2003 as our beginning date to have five years of data. As we use a rolling window of 52 weeks, we have 209 periods and therefore four years with largely differing market periods for the fund portfolio optimization.

Exhibits 3.1. and 3.2. show the used funds and the descriptive statistics. From the statistics it is evident that the two fund types are very different from each other and that any assumption of normality of the return distributions fails.

Furthermore, Exhibit 3.3. is displaying the very time-dependent performance of the real estate equity funds and the fairly stable return patterns of the German open ended real estate funds.

German Open Ended Real Estate Fund	Mean	Stand. Dev.	Weekly Min	Weekly Max	ETL 99%	Max. Drawdown	Jarque-Bera
AXA Immoselect	4,78%	0,60%	-0,21%	0,68%	-0,16%	-0,21%	2.352,18***
Commerz Real Hausinvest Europa	4,27%	0,83%	-0,19%	0,72%	-0,18%	-0,36%	691,43***
Credit Suisse Euroreal	4,21%	0,31%	0,00%	0,23%	0,00%	-0,00%	59,51***
Deutsche Bank Grundbesitz Europa	6,59%	4,77%	-6,33%	4,32%	-3,19%	-6,33%	2.6969,81***
DEGI Europa	3,18%	0,90%	-0,08%	1,71%	-0,05%	-0,08%	193.716,98***
DEKA Immobilien Europa	4,27%	0,77%	-0,19%	0,72%	-0,18%	-0,19%	1.400,83***
iii Euro Immoprofil	-0,57%	1,66%	-2,81%	0,69%	-1,61%	-3,61%	92.949,90***
UBS Euroinvest Immobilien	5,89%	0,98%	-0,14%	1,24%	-0,11%	-0,14%	5.421,51***
Union Investment Uniimmo Deutschl.	3,83%	1,66%	-1,45%	2,63%	-0,78%	-1,45%	60.209,68***
WestInvest 1	2,87%	1,06%	-1,32%	0,66%	-0,80%	-1,32%	12.933,74***

Exhibit 3.1. Statistics of Data for German Open Ended Real Estate Funds

Notes: Annualized (linear) returns and standard deviation. ***, **, *and* * *denote significance at the 1%, 5%, and 10% levels (rejection of the normal distribution). Data source: Thomson Financial Datastream*

Real Estate Equity Fund	Mean	Stand. Dev.	Weekly Min	Weekly Max	ETL 99%	Max Drawdown	Jarque-Bera
Amadeus European Real Estate Securities Fund	-9,63%	22,36%	-21,86%	6,60%	-15,74%	-72,36%	1.316,72***
Credit Suisse European Property	-4,74%	21,31%	-17,60%	7,09%	-14,66%	-64,72%	492,47***
Dexia European Property Securities	-4,09%	20,62%	-19,00%	7,18%	-15,13%	-62,84%	1.036,17***
Henderson Horizon Pan European Equities Fund	-5,23%	20,33%	-18,26%	5,73%	-14,70%	-68,86%	874,33***
Morgan Stanley European Property Fund	-6,38%	21,62%	-19,48%	5,81%	-15,22%	-66,67%	794,58***
AXA Aedificandi	0,87%	21,30%	-20,92%	6,73%	-15,57%	-58,79%	1.462,06***
ESPA Stock Europe Property	-0,55%	18,14%	-13,69%	5,49%	-10,92%	-58,94%	243,19***
Pioneer Eastern Europe Stock	-2,16%	30,49%	-24,56%	18,87%	-19,58%	-68,11%	633,07***
ING Invest European Real Estate	-2,28%	20,93%	-16,65%	6,96%	-13,24%	-60,57%	347,92***
Constantia European Property	-5,14%	20,58%	-12,84%	8,24%	-10,65%	-64,94%	84,28***

Exhibit 3.2. Statistics of Data for Real Estate Equity Funds

*Notes: Annualized (linear) returns and standard deviation. ***, **, and * denote significance at the 1%, 5%, and 10% levels (rejection of the normal distribution). Data source: Thomson Financial Datastream*

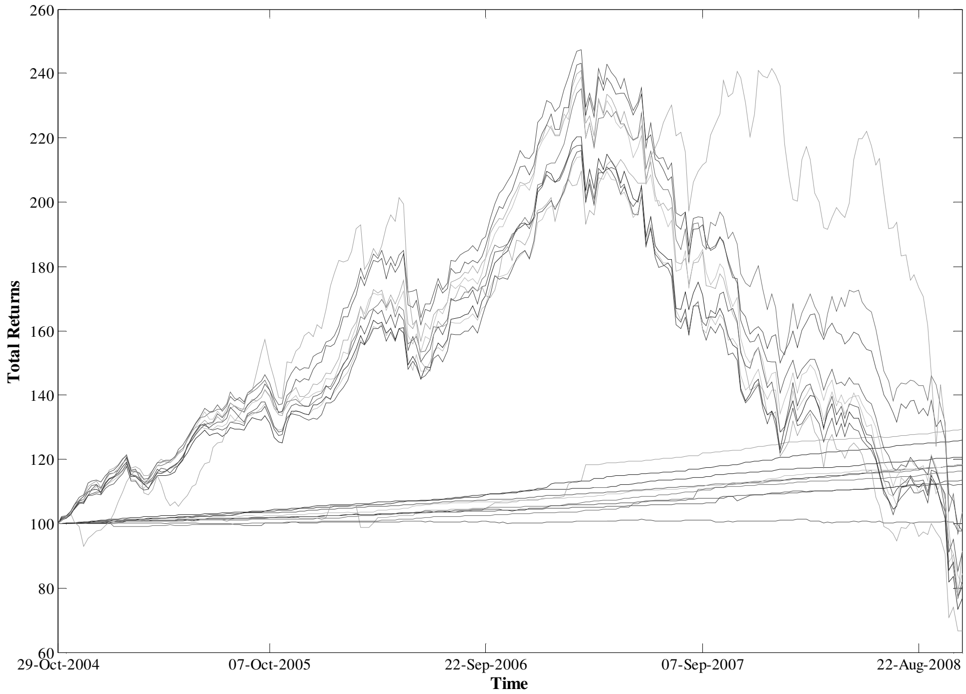

Exhibit 3.3. Total returns of the 20 funds used

3.4. Optimization Results

We show the results of the dynamically optimized fund portfolios in this section. As the algorithm is seeking to minimize the fitness function, we took the negative of the R ratio to maximize it. It is clear that the possible results can be very dispersed when considering the minimum (0,0587) and maximum (infinite for the fund with zero ETL and 21,391 for the other funds) values of the R ratio of the 20 funds during the testing period. Even though the imposed boundaries greatly reduce the span of possible results, the dispersion is, of course, still huge.

First, we checked whether a common derivative-based optimization routine would find solutions to the problem. In almost all periods this approach failed, although the maximum allowed iterations and function evaluations have been set to almost impractically high values. This comes as no surprise when keeping in mind the numerical problems discussed in Section 3.2. We therefore went on with the analysis using the genetic algorithm to optimize fund portfolios with respect to the R ratio.

Exhibit 3.4. shows an arbitrarily picked example (from the week ending September 15, 2006) of the 209 optimizations. From the subplot bottom left showing the cause of termination we see that the algorithm found a solution to the problem after only 19 generations, which was within the span of maximum iterations allowed (set to 100).

Please note that while it is the aim to have a converging optimization result, the speed of achieving this depends on the calibration as well. If one opts to have a more precise maximization or minimization of the problem at hand, one may use a smaller grade of change in the fitness function from one iteration to the next that may be allowed before stopping and vice versa. For smaller changes allowed until stoppage, the points in the upper left part of Exhibit 3.4. then resemble sort of an asymptotic line approaching the minimal value of the fitness function found .

Furthermore, one can see that with the ongoing process of building fund compositions the algorithm approached both the minimum of the fitness function (the maximum attainable R ratio in our case, subplot top left) as well as the fulfilling of the constraints by minimizing the constraint violations (subplot bottom right). The population providing the best solution to the R ratio maximization problem is depicted in the subplot at top right, showing the composition of the expected R ratio-optimal FoF for the next period. For every period, the genetic algorithm converged to an optimum without exceeding the limits or constraints, showing the usefulness of its application to the problem.

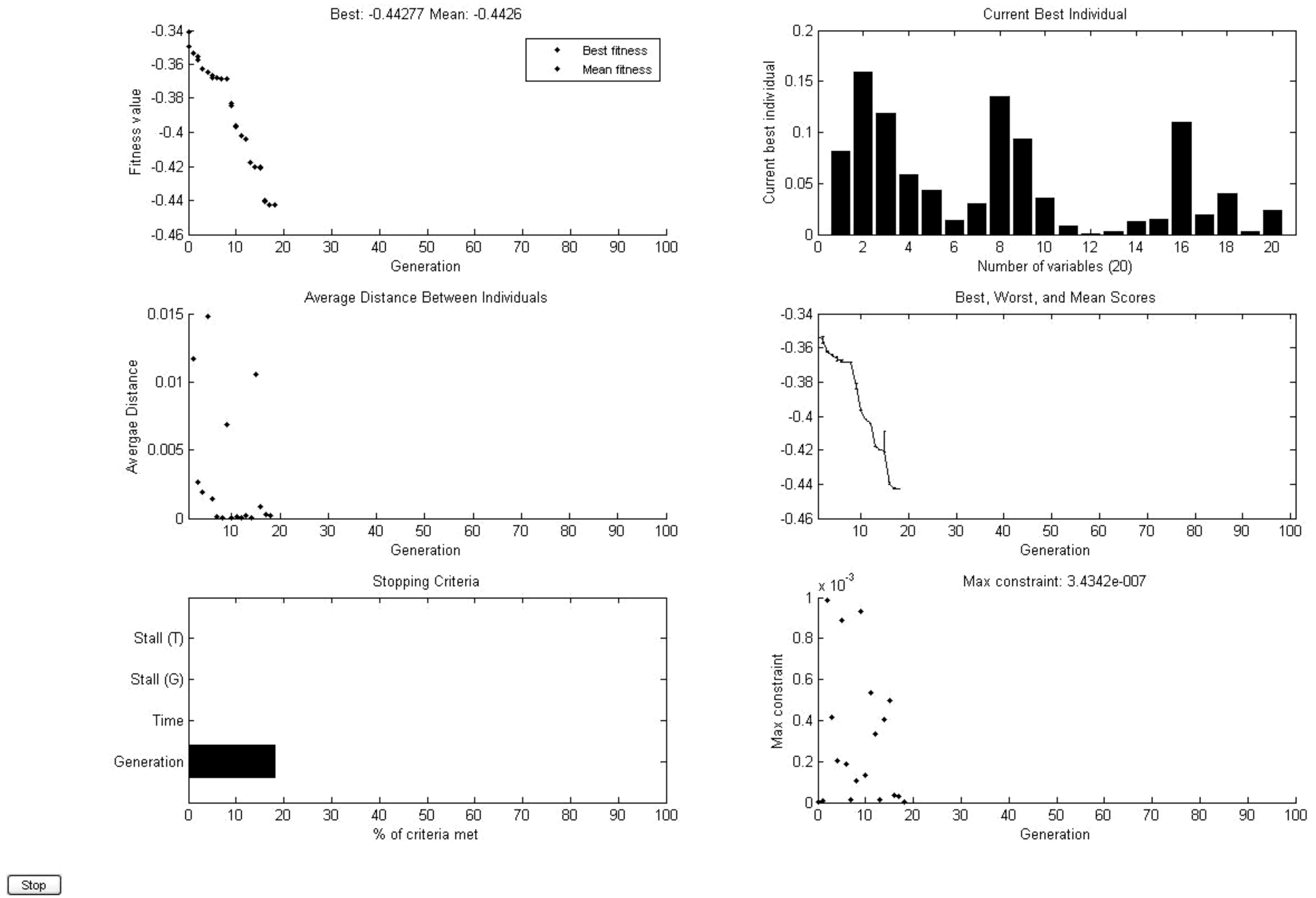

Exhibit 3.4. Example of genetic algorithm for solving the R ratio optimization for the estimation period September Week 2, 2005 until September Week 2, 2006

The SR optimization was done by a standard derivative-based optimization. For only a handful of periods, optimal portfolios were violating a constraint; we then used the previous allocation for that period, not significantly influencing the results. For the ETL and ETG optimizations, standard derivative-based solving methods were also sufficient and delivered results for all 209 periods for both approaches, we did not experience numerical instabilities in any of the periods.

By calculating the portfolio returns when investing the portfolio as indicated by the weekly ratio maximization, the performances shown in Exhibit 3.5. and summarized in Exhibit 3.6. are obtained. The R ratio optimized portfolio clearly outperforms both its Sharpe ratio counterpart that focuses on returns to variability as well as the two approaches using either the reward or the risk term. As expected, the R ratio FoF has a higher standard deviation than the Sharpe ratio portfolio, but only a slightly higher one than the risk reduction focused minimum ETL portfolio (the ETG oriented FoF has the highest dispersion, of course, as it does not control for either variability or risk). It is particularly interesting that the R ratio optimal portfolio has a somewhat smaller ETL than the portfolio focusing exclusively on that measure. This means that the orientation of the R ratio to realize gains and thereby to control for the highest risks works very well for our set of heterogeneous assets. A reward to risk ratio as used here is therefore highly effective on realizing risk-adjusted returns. This became even more clear when calculating the R ratio for all four approaches after the optimizations were done. As the ratio should naturally be the highest for the approach focusing on it, we can see that indeed this outcome is obtained, with a 42% (0,27 to 0,19) higher ratio when being compared with the Sharpe and ETL portfolio and a 29% (0,27 to 0,21) higher ratio when being compared to the ETG portfolio.

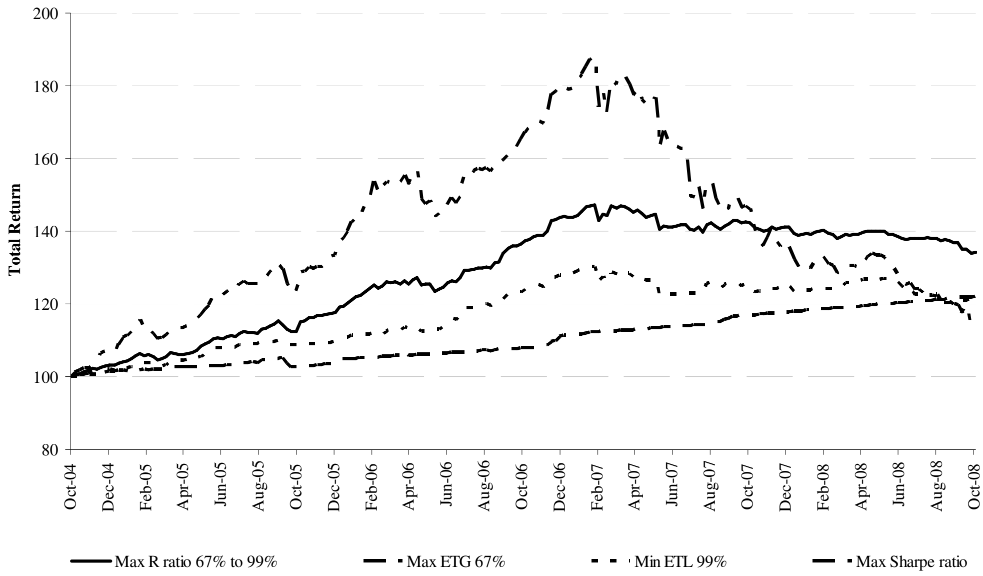

Exhibit 3.5. Total returns of the four portfolio optimization approaches

Optimized funds of funds over time	Mean	Standard deviation	Weekly Min	Weekly Max	ETL 99%	Max. Draw-down	R ratio (67% to 99%)
R ratio optimized portfolio (67% to 99%)	7,61%	4,68%	-2,93%	2,31%	-2,76%	-9,08%	0,27
Sharpe ratio optimized portfolio	5,06%	1,69%	-1,43%	1,23%	-1,31%	-2,38%	0,19
Expected Tail Gain optimized portfolio (67%)	3,20%	12,59%	-7,81%	4,89%	-7,71%	-39,53%	0,21
Expected Tail Loss optimized portfolio (99%)	4,89%	4,36%	-3,51%	2,11%	-3,11%	-7,91%	0,19

Exhibit 3.6. Statistics of Optimized Portfolios

Notes: Annualized (linear) returns and standard deviation.

As the statistics of the FoFs discussed, so far, focused on the weekly measures and the distributions, the inter-temporal measures also deserve attention. As we can see from Exhibit 3.5., the four approaches led to very different return patterns over time. While the ETG portfolio generates large returns during the bull phase of the real estate equity markets, the same portfolio took a large hit during the correction in the market and the financial market crisis, since no control for risk is implemented. On the other side, the large standard deviations of the real estate mutual funds lead to very defensive FoF allocations when using the Sharpe ratio. The return pattern merely resembles the ones of the German open-ended real estate funds, i.e. the Sharpe ratio is missing the upside possibilities due to investing heavily in the safe-haven funds. While all three approaches result in a lower terminal wealth than the R ratio FoF, the comparison between the portfolios based on the R ratio and the ETL turns out to be most interesting again. After the R ratio portfolio has realized far more upside returns in the bull phase of the real estate equity markets, the drawdown in the following post-peak phase (which was in February 2007), was only slightly worse than that of the ETL FoF (-9,08% versus -7,91%). This shows again that R ratio optimized portfolios may be able to realize upside potentials and, on the other hand, limit the severity of losses during downward phases as well.

However, none of the approaches delivered a return pattern that realized the good performance of the equity markets and switched completely into safe-haven investments during the drawdown period, but this is merely a fact that is due to the chosen exemplary estimation window of 52 weeks. Although it is questionable that perfectly fitting portfolios are realistic, shorter durations, higher frequencies, and other estimation methods for the tails or combinations of estimation periods could further enhance the return patterns of all four approaches.

3.5. Conclusion

In this chapter, we propose a framework to portfolio optimization that is superior to mean-variance approaches utilized for asset allocation. Using a very heterogeneous set of funds for which we used real estate funds as an example, we show how a portfolio can be managed efficiently by using a ratio-based portfolio optimization approach. We also provide a general solution to related optimization problems and the technical challenges arising from them.

The modified R ratio approach used for our benchmark-free optimization delivers a FoF performance that is superior to the one obtained when performing a Sharpe ratio-based optimization approach as well as when employing other tail-dependent optimization frameworks. Our results show the appropriateness of the approach that is due to the capability of taking into account tail risks and simultaneously realizing gains on the upside.

Arising computational challenges caused by the non-quasi-convex type of the optimization problem are addressed by using a genetic algorithm. The genetic algorithm solved the optimization problem efficiently and resulted in robust optima, while classical derivative-based algorithms, which in addition may result in local minima, failed to solve the problem at hand. As the problem of non-quasi-convexity of the optimization is apparent for all ratio-based optimizations that may have a negative denominator, we propose the use of genetic algorithms for solving such problems in general.

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4. Broad Market Risk for Sector Fund of Funds: A Copula-Based Dependence Approach

4.1. Introduction

If there were still doubts concerning the dependence of sectors in broad market downturns, the recent crisis following the sub-prime meltdown and the so-called credit crunch have erased those in an impressive manner. While sectors or industries may be largely affected by the fundamentals and structures in their very own part of the global economy or sub-sectors of markets, disruptions and downturns in the general financial markets affect them, too. For this reason, it is crucial for managers of sector funds or sector fund of funds (FoF) to take into account the dependence structure of their underlying industry portfolio on broad market movements. The impact of economic and political changes that affect all markets and sub-sectors impose a certain minimum of similarity in the behaviour of stock markets in different aggregation levels (say from the very specialized sub-part of an industry up to the MSCI World). These minimum similarities are pronounced when financial market effects lead to broad market movements that show up in all industries and sectors, for example through flow-effects, market sentiment, de-leveraging and flights to substitute asset classes. While these effects are not new in nature, appropriate approaches to deal with them are still scarce in nature, and often include strong assumptions or non-flexible concepts.

As the degree to which a sector portfolio is affected by market movements is a problem of measuring the interdependence between financial variables, it is a part of research that has undergone tremendous developments in recent decades, from correlation or covariance-based methods to the use of more sophisticated multivariate distribution functions and copulas. We combine an asymmetric *t* copula and stable marginals to measure the dependence of a sector FoF on the broad stock market, thereby modelling the univariate randomness of the variables adequately as well. As information on investment or market risks must be updated in high frequencies and on a regular basis, we show how the modelling of the sector exposure to broad market risk can be done with a very parsimonious approach that reduces the dimensionality of the problem at hand, thereby using all relevant information available. A slim approach that is applicable even in the presence of few data is of special interest nowadays with the industry being highly dynamic and financial assets being generated very quickly.

The estimation procedure has one crucial benefit in practical applications, as it may be used on both sides of a FoF, meaning that FoF managers may use the approach to model their own broad market dependence structure on the one hand, and investors in a specific sector FoF may use the approach to model their investment risks with respect to the index which they are willing to diversify away from.

Employing a copula approach with an asymmetric *t* copula as chosen form for the dependence modelling, and stable distributions for the marginal distributions of the variables respectively, we generate simulations for the market index as well as for the synthetic FoFs of the sector under consideration. Both the dependence structure and the univariate randomness appear to be modelled very well with our approach, showing the need to apply the right sophisticated concepts for modelling financial assets prone to tail events, and even more important, tail dependence. From the time-varying, rolling window estimations we can see that increases in broad market tail risk lead to increases in sector portfolio tail risk, but not vice versa, indicating a good and unbiased representation of the dependence structure as well as the simulation of the realizations for each period under consideration.

The fact that simulations are generated using the combination of methods at hand is especially comforting when it comes to the calculation of measures that demand a lot of observations and do not possess closed-form solutions. In addition, the fact that the asymmetric approach allows for differing tail-dependencies on the up-side and the down-side suits the analysis for a FoF very well, as the dependence may be skewed due to industry-specific characteristics as well as by fund characteristics. Furthermore, changes in those characteristics are well tracked by the approach because estimations are done using very recent data and therefore short memory.

Knowing the broad market exposure is especially important for managers of or shareholders of sector FoFs in industries for which derivatives are either not available or scarce, as in these cases it is especially difficult to reduce risk and market exposures. Unfortunately, for some industries, hedging considerations therefore simply fail due to the lack of hedging products. Employing an approach to measure the joint risks with the general stock market for which myriads of derivatives are available may enable sector-exposed portfolios to be isolated from the broad market movements or at least dampen the effects of extreme events.

Our parsimonious approach for measuring (inter)dependence between financial markets and assets where the data input must be very up to date or where only a short history of data is available is not limited to FoFs of course. However, we consider it especially appealing for the FoF class for the following reasons. While many funds are allowed to invest in derivatives to hedge their risks, they often abstain from doing so. Reasons for doing so include the lack of adequate tools (if the fund is sector focussed for example, as discussed above), the costs of hedging may be too high or the use of derivatives is regarded as being too exotic a tool in classical asset management. However, if the risks are not hedged on the fund level, but merely dampened by holding cash positions during downturns (thereby forfeiting partial exposures that would be beneficial and incurring a considerable inertia into the fund), the FoFs may fail to get the benefit of diversification and risk reduction by spreading their allocation over the target funds. This is a special problem for FoFs, because with an increasing number of target funds, the marginal contribution from diversification is decreasing and characteristics may cancel each other out. With reliable measurement of the risks and exposures of the FoF and the market, this problem of practical portfolio management may be easily overcome and therefore the approach presented in this chapter should be used in practical applications not only for risk measurement but for risk management and hedging on the FoF level as well.

The organization of this chapter is as follows. In the next section we review the methods used, namely the skewed *t* copula, stable distributions, and risk measures. In Section 4.3, we discuss the approach of the study and the data. The empirical results are presented in Section 4.4, showing the application of our framework to synthetic technology sector FoFs, and their dependence on the broad market represented by the S&P 500. Section 4.5 concludes the chapter.

4.2. Asymmetric t Copulas and Stable Paretian Distributions

In this section, we explain the method that we propose to model sector FoF dependence on broad market movements, as well as the type of distribution that we employ to model the univariate randomness of the single variables.

To model the dependence structure between the FoF and the index, we use a copula function. Copulas have found increasing attention first in academic research on financial markets and have made their way to Wall Street and many other parts of finance in the following. While the use of copulas brings a substantial improvement to the toolboxes that are available for financial and economic research, the methods have been discussed in heated debates in the financial industry as well[17]. We take the view that it is merely the application of the right concept for a problem at hand and the difficulty of choosing the right form of the copula that is decisive on the way a copula model suits the needs of the researcher or practitioner, see Rachev et al. (2009). Thus, the use of copulas is advantageous to all currently existing methods for measuring dependence if the right concept is applied.

Generally, the concept of copulas enables one to separate the univariate randomness of any variable from the multivariate dependencies by means of factorization. A copula represents the true interdependence structure between variables while the marginal distribution is informative on the univariate randomness of these variables. Therefore, a standardized measure of the purely joint features of a multivariate distribution is generated by using copulas. We briefly discuss the copula definitions below[18]. The cumulative distribution function of a one-dimensional random variable is called the *grade of a random variable* (uniformly distributed between 0 and 1), and the copula is the distribution of these grades, such that an n-Copula $C:[0,1]^n \rightarrow [0,1]$ is an n dimensional distribution function with univariate marginal distributions $U(0,1)$.

Archimedean (for example Clayton, Frank or Gumbel) copulas are calculated over a closed-form solution (being very hard to derive for multivariate applications beyond two dimensions however) and do not need to be represented by an application of well-known families of multivariate distributions using the theorem of Sklar (1959 and 1973). In contrast, elliptical (for example Gaussian or Student *t*) copulas can be derived via simulating these multivariate distributions taking advantage of their simple stochastic representations. In the recent past, the focus in both academia and practice turned to the elliptical class of copula forms. However, a caveat of

[17] See Whitehouse (2005) and Salmon (2009) for example.

[18] See Embrechts et al. (2003), Cherubini et al. (2004), Meucci (2006) and Nelsen (2006) for thorough discussions of copulas and their applications in finance.

general elliptical copulas is that the upper and lower tail dependence, being informative on joint extreme realizations, is identical, due to the radial symmetric shape of the elliptical copulas. In addition, a Gaussian copula has no tail dependence at all (see Bradley and Taqqu (2003)), and this is the main argument against its use in financial market applications from our point of view.

That the Gaussian copula is inappropriate for most financial applications due to the aforementioned inability of measuring tail dependence is especially interesting in light of the ongoing debate surrounding copula functions in financial markets and especially during the credit crisis (see Rachev et al. (2009)). The fact that the Gaussian copula has no tail dependence at all is stemming from the fact that a multivariate Gaussian distribution is the n-dimensional version of a Gaussian distribution, which assigns too low probabilities to extreme outcomes. While the use of Gaussian distributions in financial market applications is widely accepted as being flawed due to the fact that this distribution type attributes too low probabilities to extreme observations, the multivariate version still is frequently used in copula applications.

The *t* copula, or Student copula, does not share the shortcoming of the normal copula concerning the tail dependence and enables the modelling of joint extreme market outcomes. However, the radial symmetric shape of the t copula still leaves a concern regarding the use for financial market data, as the upper and lower tail dependence is identical. Thus, the probabilities of joint tail events on the downside are equally distributed as the ones on the upside. In reality, this may pose problems when modelling markets or assets for which this assumption may not hold.

Improving the features of copula models is the use of asymmetric *t* copulas, which in contrast to the general elliptical copula forms discussed above allow for differing tail dependencies as well. Especially in our application of a sector FoF and the broad market, this feature is highly desirable as the dependence of the FoF may be different when considering upside and downside events. Using the asymmetric t copula, we generate a large number of copula scenarios, thereby taking into account the dependence between the assets. These copula scenarios are then used to generate univariate scenarios for each variable, thereby making use of the inverse of the cumulative distribution function of the marginal distribution used for the univariate modelling.

The marginal distribution for the univariate randomness of each asset is modelled using the stable Paretian distribution type, in the following simply called stable distribution. Basically, the stable distributions generalize the normal distribution. While the normal or Gaussian distribution is determined by the two parameters location and dispersion, i.e. mean and standard deviation, the stable distributions are defined through four parameters.

First, the characteristic exponent ($0 < \alpha < 2$), called the index of stability or stable index, determines the weight of the distribution's tails. For lower values of α, the shape of the distribution is more peaked at the location parameter and exhibits fatter tails, parameter value 2 corresponds to the normal distribution. Second, the parameter β, which is bounded between -1 (skewed to the left) and +1 (skewed to the right) determines the distribution's skewness and is informative on whether the occurrence of returns is more probable for negative or positive realizations. Third, the parameter σ is scaling the distribution. Fourth, as for any other type of commonly used distributions, the location parameter is responsible for the shift of the distribution's peak to the left ($\mu < 0$) or to the right ($\mu > 0$).

The fact that stable distributions are described by four parameters and may take a large variety of shapes is an advantage over other distribution types, with the fact that asymmetric probability distributions and heavy tails are featured being very favourable. Especially when being compared to the normal distribution function, the stable models show up as being more in line with real market observations, as the probabilities of occurrence of extreme observations far away from the mean of a variable are heavily underestimated by the normal distribution.

More detailed discussions and overviews on the properties and applications of stable distributions in finance are provided in Mittnik and Rachev (1993), Samorodnitsky and Taqqu (1994), Rachev and Han (2000), Rachev and Mittnik (2000) and in Ortobelli et al. (2002 and 2003), while the stable property's importance for financial data has been initially discussed by Mandelbrot (1963).

4.3. Asymmetric t copula, heavy-tailed marginals and tail risk valuation; Example with FoF's Data

As the properties of both the interdependence and the univariate randomness are changing over time and therefore should be estimated on a regular basis, we use a short time span for the estimations in this study. Thus, the data set is chosen to reflect the very recent realizations of the variables under consideration, mirroring the need of up to date estimations that are crucial in financial market applications for which often only a limited data span is available. Using a window of 100 trading days that is rolled through the whole data sample is beneficial on the one hand as the estimations are always very focussed on recent realizations but is resulting in a small sample for each estimation on the other hand.

This classical trade off is losing its severity in our approach, as we reduce the dimension of the problem to a bivariate one. We use all available funds at each time point to build a synthetic equal-weighted FoF. If a fund dies, the allocation share of it is evenly distributed among all surviving funds in the next period and vice versa. We have therefore a time-series of an artificial FoF to estimate against the market index. In practice, FoF managers may of course use their own actual and current portfolio weights for the 100 day backward time-series generation. Investors to FoFs may use the actual time series of the FoF – thereby keeping in mind that it is an approximation due to allocation changes within the time period – or may go on with the equal-weighted approach as some FoFs may be approximated as equal-weight schemes of their fund universe.

With the bivariate approach, we obtain the dependence structure by fitting the asymmetric *t* copula to the two return series in any window, and then generate simulations of the FoF and the index using the stable distribution for the univariate randomness. One benefit of the bivariate approach is that we do not need to estimate a large number of parameters, a pre-requisite for a dynamic approach with only limited data input, as we have here with only 100 trading days. An estimation of the parameters for each fund in the respective time period would make the analysis far more complex and would demand more data and/or calculation steps. The return series entered the estimation process unfiltered, that is, no time-varying effects, volatility clustering or similar features have been modelled upfront as the aim is to show directly the dependence structure of the variables. The framework may as well be combined and used on pre-filtered data, for example on the innovations of a multivariate AR(I)MA/GARCH model between the FoF and the Index or on results of time-series analysis with a decaying time influence, but the input data set needs to be larger then.[19]

Our choice for the size of simulations was 1.000 simulations for each variable. This keeps the computational burden on a practical level that allows for daily application of the approach. In addition, for appropriate backtesting of the model over a considerable history the size of the simulations should be kept in a sensible range. Therefore, we are generating a 1.000 by 2 matrix of simulations for each estimation window, with the simulations on the one hand being based on the true dependence between

[19] See Sun et al. (2009) for a multivariate approach to estimating tail risks using the ARMA-GARCH methodology and the Student's *t* copula.

the FoF and the broad index as being estimated by the copula, and on the other hand mirroring the single return distributions adequately.

The resulting simulations may be used in a large variety of ways, for example for portfolio optimization or the calculation of risk measures. Moreover, the obtained results may be used by sector FoF managers or investors of sector FoFs to hedge their broad market exposure incurred by the sector investment when no industry-specific tools may be available. We track whether the model did adequately capture both the dependence structure and the structure of the single variables by comparing the simulations' properties with the actual properties of the FoF and the index. In addition, we compare the results obtained with other methods that were commonly used in financial markets and that were discussed above.

We have chosen the technology (tech) sector as an example in this study. The tech sector has undergone tremendous up-and-down phases in the late 1990s and the beginning of the new century, and the returns of tech stocks show high concentration in the tails that makes the need for application of sophisticated methods obvious. As a FoF analysis was done for measuring the dependence on broad market movements, the approach is interesting in light of diversification arguments too, as the benefit of diversification is an oft-heard argument by FoF proponents. In addition, the approach is straightforward, as an estimation of the dependence of each single fund on the index is not needed when considering a FoF that one is managing, neither is it possible to do so when one is invested in the FoF and is seeking to estimate the dependence of it on the market.

Selection of the funds and streaming of the total return series was done using Bloomberg[20] based on the following criteria. All funds included are mutual funds that are (1) listed in the Unites States, (2) have their investment focus on tech stocks of the domestic market, (3) are denominated in U.S. dollar, and (4) report daily net asset values. Fortunately, the resulting fund spectrum includes both dead and alive funds such that

[20] Datasource: Bloomberg Finance L.P.

even the last return of any fund before going out of business enters the analysis. Daily data were used for the 10 years ending April 2009. The resulting return matrix consists of 2.527 daily returns for each of the 255 funds included. Measuring the broad stock market was done using the S&P 500 for the respective time-period. The S&P 500 was selected because it is the index that is typically used for benchmarking by institutional investors and an indicative check of FoFs that satisfy our selection criteria strengthened this notion. Because we use an equal-weighted FoF construction, we have a 2.526 by 2 matrix of returns as our sample for the whole period, and 2.426 matrices of size 100 by 2 for the dynamic intertemporal estimations.

Concerning the measurement of risk for the index and the synthetic FoFs, we use the expected tail loss (ETL) which is the conditional value at risk (CVaR) for continuous distributions[21],

$$ETL_{1-\alpha}(r_a) = E\left(\max(-r_a, 0) \middle| -r_a > VaR_{1-\alpha}(r_a)\right)$$

with $ETL_{1-\alpha}(r_p)$ being the expected tail loss with tail probability α for asset returns r_a and VaR denoting the value at risk In accordance with common confidence levels for other risk measures such as VaR are 1% or 5% for α, corresponding to confidence levels of 99% and 95%, respectively. For any confidence level, ETL is higher than VaR as it measures the expected losses in the case of a tail event rather than measuring the loss not to be exceeded with the respective confidence[22]. Concerning the measurement of risk the choice of an appropriate measure is another way to omit erroneous estimations, as for example the VaR at 95% confidence of a normal distribution may be the same as the corresponding measure for a stable

[21] See Rachev et al. (2007) for discussions on risk, uncertainty and performance measures. The conditional value at risk (CVaR) corresponds to the average value at risk (AVaR), see Pflug and Romisch (2007) for example.

[22] See Sortino and Sachell (2001) and Rockafellar (2002) among others concerning VaR and CVaR / ETL.

distribution or a *t* distribution, but the ETLs or CVaRs (AVaRs) at 95% may be largely differing.

4.4. Empirical Results

Before we apply the rolling window approach for successive 100 trading day periods, we check the data's full sample characteristics. Looking at the return scatter plot of the index and the synthetic FoF as shown in Exhibit 4.1., the elliptical shape indicates significant dependence, showing the immediate need for detailed modelling of the dependence structure of the two series.

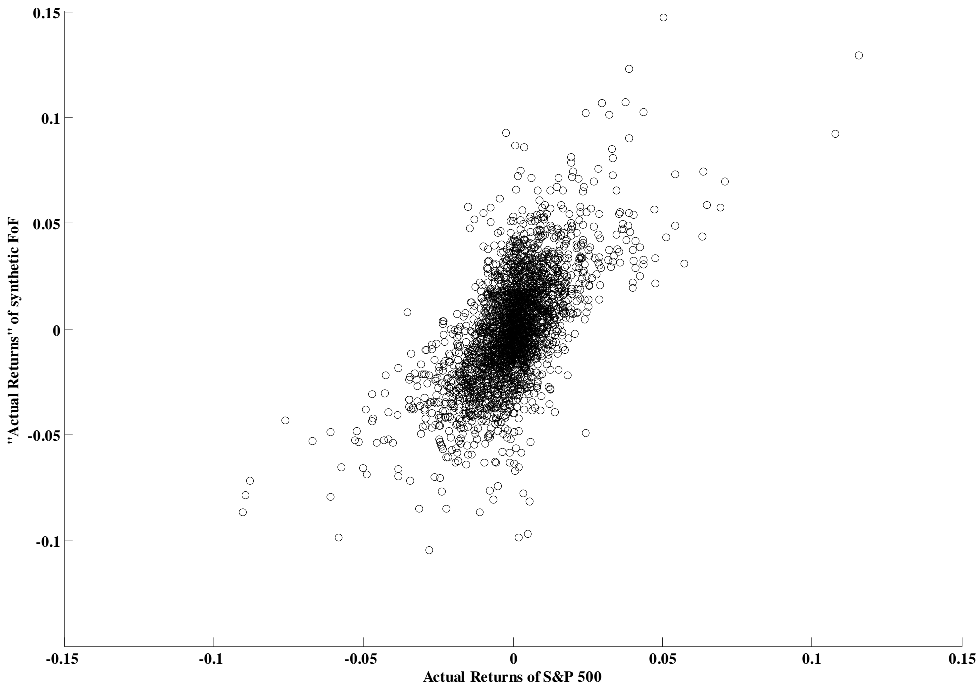

Exhibit 4.1. The return scatter plot of the synthetic tech FoF and the index for the whole sample period

In general, to check whether the pair of tools we favour adequately models both the dependence structure and the univariate randomness, we estimate the asymmetric *t* copula and generate simulations using the stable distributions from the entire sample of observations. The result is a 2.500 by 2 matrix with simulations for the FoF and the index. For comparison purposes, we used a number of simulations being approximately equal to the actual observation series. For comparability to other commonly used approaches, we have included the results of simulations using a normal copula and normal marginal distributions approach as well as the results of a directly applied multivariate *t* distribution (the distribution being applied on the returns rather than on the cumulative density function of the variables).

From Exhibit 4.2. it can be seen that the normal approach suffers from the fact that the normal copula cannot capture tail dependence and the marginal distribution does not account for univariate tail risks. The multivariate *t* distribution approach suffers from the fact that the dependence structure and the marginal distributions are not modelled separately, leading to a loss of information and a less detailed modelling. Therefore, a too radial and poor fitting shape is obtained. Increasing the number of simulations made this problem even more obvious when checking the approaches' behavior. In contrast, the simulations obtained from our approach with the asymmetric *t* copula and stable marginals appear to be a good tracking of the dependence structure of the FoF and the index.

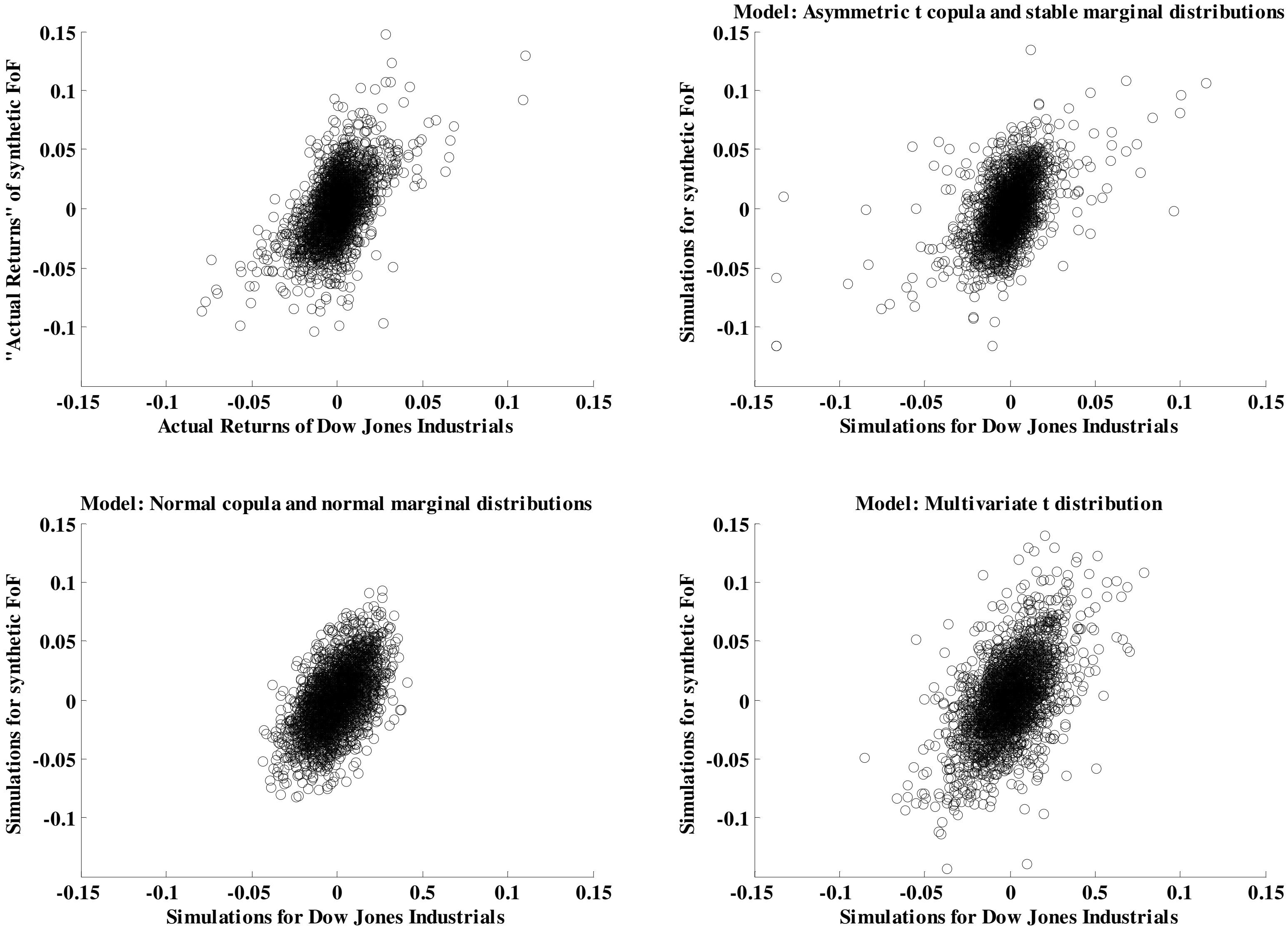

Exhibit 4.2. The simulations of the synthetic tech FoF and the index for several approaches for the whole sample period

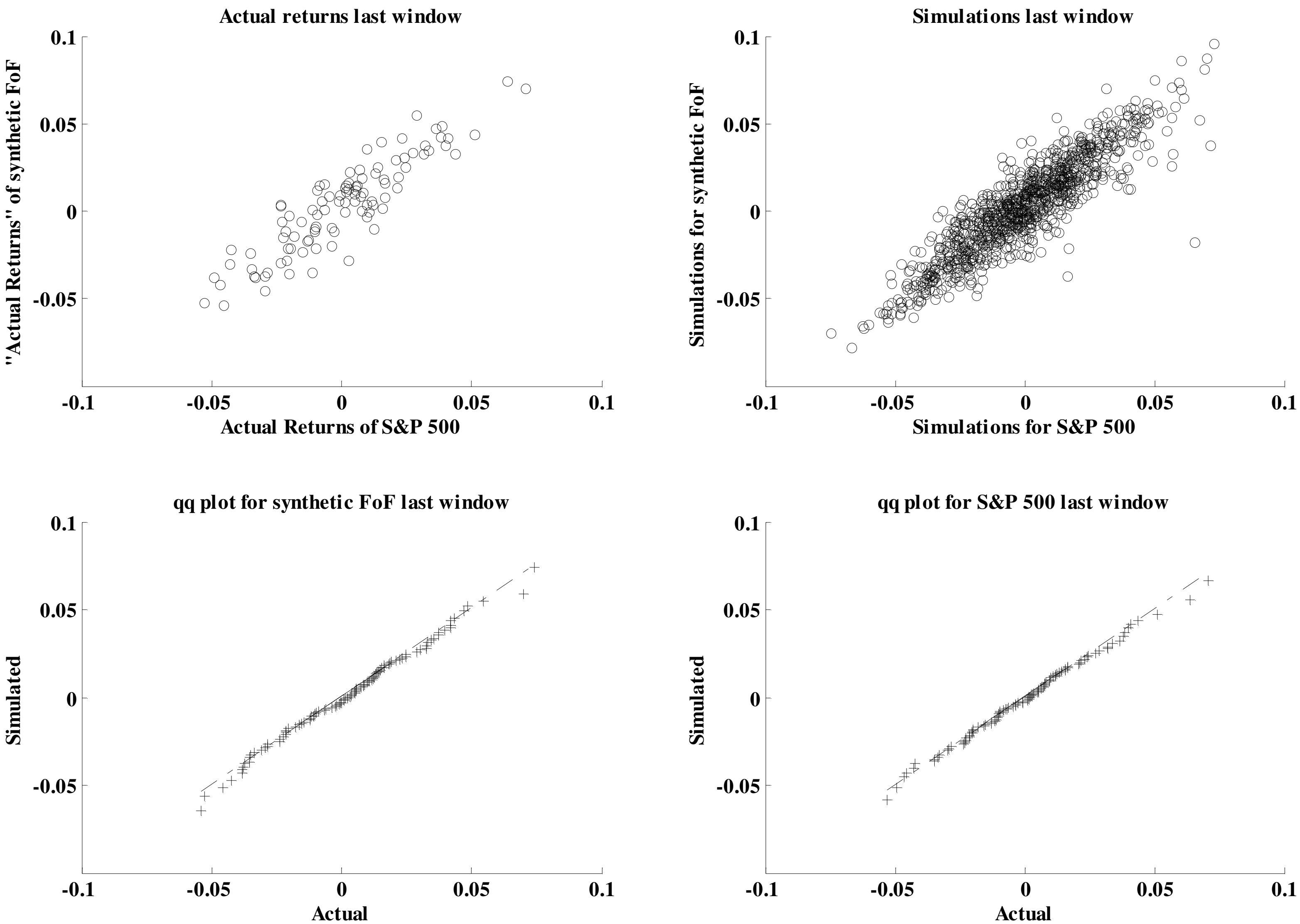

Exhibit 4.3. Example of last period estimations

Using the approach with rolling 100-day periods, we continued by modelling the bivariate set over time. When it comes to modelling the dependence structure over time, we need to check the ability of the approach to fit the data well even in the presence of a heavily reduced data set because only 100 days were selected as the time window in the example. Since we originally had 2.526 return observations, we have 2.426 windows for which we generated the simulations, Exhibit 4.3. shows the last period as an example. We checked the short sample properties of the other methods as well, and the deviations from the true data sets are even more severe than in the whole data sample, again strengthening the notion that the appropriate tools were chosen for the analysis.

As the simulations are of size 1.000 and the returns were 100 each, the scatter diagram of the simulations is of course more crowded than the one of the observations. In addition, the realizations on the tail sides seem to be more pronounced in the simulations. To see whether this is due to overestimation of the tails or to a small sample bias, the quantile-quantile (q-q) plots were checked for both the index and the synthetic FoF. From the q-q plots we can see that the simulations fit the data very well and that for both variables only two simulated realizations are somewhat deviating. Indicative checks of other periods did not give rise to doubts concerning the estimation and fitting performance for the problem at hand.

We can see from the calculations of the expected tail loss that it is good practice to model the broad market risk for the FoF in dynamic nature, as both the magnitude of the risk measure as well as the joint changes therein are heavily time-dependent, as can be seen in Exhibit 4.4.

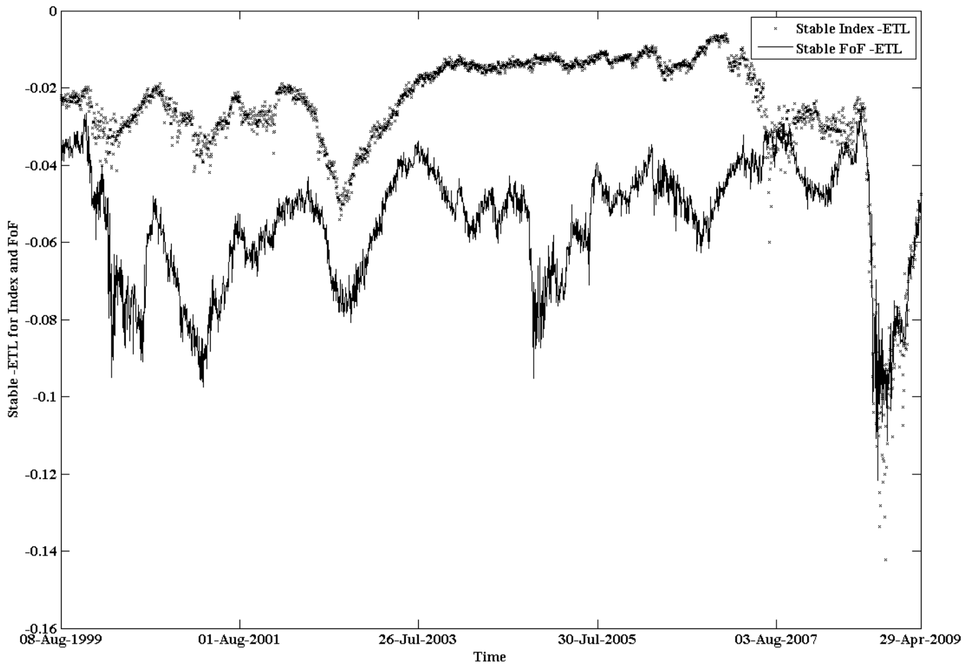

Exhibit 4.4. Stable negative expected tail losses over time

Note: The negative of the ETL is plotted, according to industry usage of the negative loss as risk measure.

With respect to the expected tail losses of the two variables, the fact that a large increase in the magnitude of this risk measure for the index leads to an increase of it for the FoF too, shows that the influence of the broad market risk on the FoF is substantial and modelled adequately. In addition, the tech sector had its own characteristic increases in the tail risk during drawdowns (besides more severe tail events throughout the sample) which did not appear in the broad market and did not affect the estimation results of the index expected tail loss. The latter fact is very favourable concerning the judgment of the measurement of dependence, showing that with the asymmetric *t* copula, increases in broad market risk lead to increases in sector FoF risk, but not the other way round and therefore no spurious causality seems to be generated during the asymmetric *t* copula fitting and simulation generating using the stable distributions.

4.5. Conclusion

The asymmetric *t* copula approach for the estimation of the dependence of a sector FoF on broad market risk captured the independence structure very well. Combined with the stable distribution we obtained well-fitting simulations for the synthetic FoF and the index for each estimation window. Being applied to a very short window of data of 100 trading days, the approach suits estimation needs concerning short term tracking of risks and risk dependencies and may be applied to problems with limited and small data sets in general. This is because the problem of measuring the interdependence is of the bivariate type and the estimation efficiency using the asymmetric *t* copula and the subsequent generation of simulations using the numeric solutions to the previous fitting.

As the procedure appears to generate well-fitting simulations, these may serve as input to a large variety of applications, from risk management and measurement, portfolio optimizations and scenario analyses to investment selection and hedging purposes as examples. It is critical to have an approach that identifies the joint risks of a sector FoF and the broad markets because for many industries or (sub) sectors no viable derivative market exists. The results obtained by using our approach may serve both FoF investors as well as FoF managers when it comes to not only measuring risks, but also isolating the sector portfolios from general market movements. Possible extensions or adjustments would be to take into account time-series effects such as volatility clustering and to combine the procedure with those, although this would demand more data points for each estimation, reducing the great benefit of a parsimonious approach as proposed in this chapter.

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5. Flow-Induced Redemption Costs in Funds of Funds

5.1. Introduction

The recent crisis has clearly demonstrated that the direction and magnitude of capital flows are crucial to the survivorship and performance of financial market assets. While the years following the dotcom crisis were characterized by very low costs of capital, the global economy and the financial markets were flooded with excess liquidity. Until the sub-prime mortgage crisis unfolded and triggered the worst economic slump since the Great Depression, along with the worst year for global stock market performance, capital was available in huge lot sizes and at both low borrowing costs and restrictions. As this ended and money was withdrawn from investments in unprecedented speed and strength, the problems surrounding cash-flows and liquidity management came back into the discussions in the financial world and academia.

As many fund management companies try to find ways to protect from renewed problems caused by capital flows, the appropriate handling of load fees, or redemption fees, is crucial for investors. Especially when investors to funds are themselves exposed to capital flows they cannot control, as are most FoFs, the holding of funds that may not be redeemed without costs calls for appropriate tracking of the cost that may be incurred when funds must be sold. In this chapter, we show how this may be done in two differing ways:

While a static view with calculating the costs to be incurred in the presence of a liquidity shock delivers insight on the span of possible costs at one point of time, a dynamic approach with path-dependent cost effects takes into account the possibility of successive periods of fund cash-flows and the resulting cost effects.

The chapter is organized as follows: In Section 5.2 we discuss fund (of fund) flows and the resulting problems for FoFs. Sections 5.3 and 5.4 show analyses for fund flows and resulting costs using a static and a dynamic framework, respectively. Our conclusions are summarized in Section 5.5.

5.2. Fund Flows, Liquidity Risk and Liquidity Costs in Funds (of Funds)

The topic of fund flows and liquidity risk has been researched in the past, with research concerning mutual fund flows by Ippolito (1992), Sirri and Tufano (1998), Hendricks et al. (1994), Warther (1995), Zheng (1999) and Greene et al. (2007) being important among others. Nanda et al. (2000) model the interaction of flows, performance, and load structure for mutual funds. Although the primary focus of many theoretical and empirical studies has been on determining factors driving fund flows and how investors are affected by the loads and fees that are charged by the respective mutual funds, the management of flow-induced liquidity and flow-induced selling of target investments on the fund side has been studied as well. While Edelen (1999) finds that flow-induced trades are lowering fund performances, Chan and Lakonishok (1997) and Keim and Madhavan (1997) focus on the fact that trading costs increase with the size of the trades that are necessary to meet unexpected redemptions.

The majority of studies focussed on funds however, rather than on funds of funds, which have sort of a special problem: As many FoFs invest at least part of their capital into funds that may not be redeemed at net asset value, they face the danger of performance losses when outflows occur and they have to sell off costly funds. The practical relevance of these problems is very high, and the lessons learned from the recent crisis are implying that this will be amplified in the future:

The problem in practice was that in the upswing of financial markets, the management of liquidity and the costs and risks that come along with it have been ignored or at least were at minor positions in the priorities of asset managers. Caused by steady and growing capital flows, the markets grew and prospered along with the ignorance of market players concerning the potential risks associated with leverage and consequences that would come should the funding sources run dry. The consequence was excessive leverage not only on the balance sheets of banks and households, but in asset management firms as well. Firms such as hedge funds and private equity funds that traditionally use large amounts of debt were heavily leveraged in the hunt for stellar returns and in a market that was pushed upward only with huge pressure on market participants not to fall behind their successful peers.

In what has become a downturn in financial markets called the sub-prime crisis and the following credit crunch, the globally increasing interest rates and the burst of the housing price bubble in the United States has ended the spree and money was withdrawn from all kinds of investments. Of course, this severely affected the asset management industry as well: A large number of funds had to close business or at least turned out to be unable to fulfil the redemption wishes of their investors and had to lock in those. “If everybody panics, panic first” was the phrase best describing the mood in the industry, with investors withdrawing huge amounts from investments that are or could be in any way be affected by the crisis.

The large outflows that the asset management world was facing were redemptions of shares by both retail investors and institutional investors. While the massive withdrawals of money took place in every kind of financial asset class, we will focus on the problems of FoFs in the presence of share redemptions. While funds investing into stocks or bonds for example may have the problem that their underlyings are turning illiquid or a high spread is charged, FoFs have to sell target funds and may face the problem of redemption costs or back end load fees. With many asset management companies now taking actions to prevent from problems induced by share redemptions, one can expect to see increased use of redemption fees, causing fund investors to be conscious on the possible cost consequences of their investments.

Of course, the discussion of flows in mutual funds and the fee structure of the funds with front-end and back-end load fees is highly relevant when it comes to investment and divestment decisions as well as concerning performance expectations. Among others, Ippolito (1989), Elton et al. (1993), Gruber (1996), Zheng (1999), Alves and Mendes (2007) investigate the performance differences between load and no-load funds, with the latter reporting the back-end load fees being influential on investor (non-)reaction to poor performance. Therefore, an assessment of the possible costs that are caused by an investment when being sold should be in line with the possible benefits of that particular investment when FoF managers select their target funds.

Generally, it has been the focus to assess the differences of funds with and without load fees, to investigate the differing performances, and how the flow-induced trading filters through to the funds. However, neither has there been a detailed analysis of the inside of the funds, that is, of how the flows and the costs incurred may be seen as a risk factor to the fund liquidity, nor has there been an analysis on how funds of funds may deal with load fees when faced with flows on their own side. Although the sub-prime crisis and the credit crunch have shown the immediate need of dealing with liquidity shocks, there appears to be a lack of approaches that enable portfolio managers to track the risks appropriately when being invested in fund shares that may not be redeemed at the book value. We will show in the next sections how different the effects of redemption fees can be with an example of time-dependent back-end load fees.

5.3. The Static Framework: Liquidity Shock Analysis

In this section, we show a slim approach that can be used by FoF managers to track the effects of their investments with respect to costs when needing liquidity and their own possible future cash flow pattern. We suggest FoF managers track their portfolio of investments according to time spans and fund volume spans as the baseline. This is straightforward, as some target funds held by FoFs can only be redeemed at a cost (for example back-end load fees), after lock-up periods or a combination of both (time-dependent discounts when redeeming shares). Of course, the costs to be incurred when reducing positions in the respective funds have changing magnitude with regard to the volume the FoF has when redeeming and with regard to the size of the redemption.

While borne out of practical considerations for FoFs facing redemption costs, the analysis of costs when facing capital outflows is crucial for other effects as well. For example during times where target funds turn illiquid and suspend the redemption of shares, FoF managers may be forced into secondary markets, where funds often are traded at discounts to their NAV, the discount being a result of the illiquidity and the expectation concerning the NAV at a future date when the fund shares may be redeemed at NAV. This holds true even for open-end funds, if those need to (temporarily) suspend the redemption of shares or introduce restrictions.

In this section, we consider a one-off redemption of shares to the FoF, and use an example to show how a FoF may be affected by costs that are caused by the forced selling to meet investors' demand for capital. Consider the following example:

A FoF currently has US $500 million of assets under management. The FoF has invested in several target funds with back-end load fees. To keep the analysis tractable and transparent, we set all funds with a back-end load fee to charge 5%, 3% and 1% for shares held less than 1 year, 2 years and 3 years, respectively. This means that for any time point after the first investment into a back-end load fee fund, we are able to calculate which costs at this point of time would have to be incurred depending on the amount of the redemption and the time held. Of course, these costs have direct impact on the FoF performance, with the magnitude depending on the size of the FoF at the time the shares are sold.

We now look at the investments done by a FoF in Exhibit 5.1. The example FoF has invested a total of US $100 million, or 20%, of the fund volume of US $500 million into funds that may charge a cost when positions are reduced, depending on the time of selling.

Investment Number	**Amount (in US $)**	**Date**	**Time passed (in years)**	**Cost (in US $)**	**Cost (in % of fund volume)**
1	20 million	1-Mar-2007	3,0	0	0,00%
2	10 million	1-Apr-2007	2,9	100.000	0,02%
3	10 million	1-Jun-2007	2,8	100.000	0,02%
4	5 million	1-Sep-2007	2,5	50.000	0,01%
5	10 million	1-Sep-2007	2,5	100.000	0,02%
6	5 million	1-Nov-2007	2,3	50.000	0,01%
7	5 million	1-Jan-2008	2,2	50.000	0,01%
8	20 million	1-Jan-2008	2,2	200.000	0,04%
9	10 million	1-Jul-2008	1,7	300.000	0,06%
10	5 million	1-Jan-2009	1,2	150.000	0,03%
Total	**100 million**				

We have chosen to set the date of observation to 1st of March 2010, when the first investment already may be redeemed without charge of costs as can be seen from the 2 columns on the right. However, it is even more interesting to see how these positions influence the potential costs over time and over different fund volumes. As the fund volume in the future is far from certain, one is best advised to calculate possible effects form redemption costs up front.

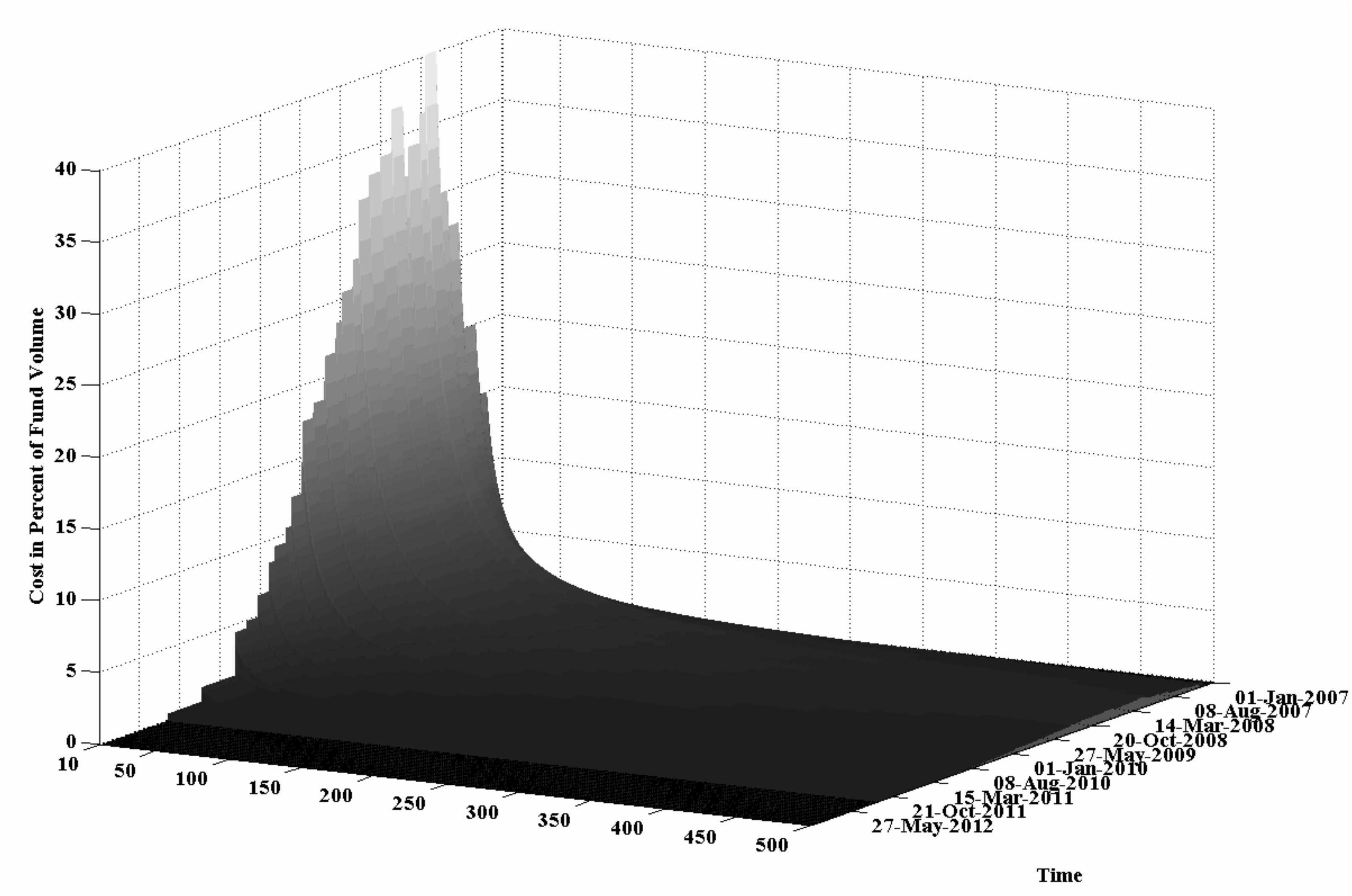

Exhibit 5.2. Costs of redemptions over time and fund volume spans

Notes: Assumption of redemption according to fund volume reduction (allocation neutral), i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold. Costs calculated into new fund volume, after outflows.

From Exhibit 5.2 we can see the time- and fund volume- dependent costs that would have to be incurred when being faced with redemptions, thereby assuming that the redemptions are made on an allocation neutral basis (for example an outflow of capital of 10% of the FoF volume would lead to a 10% reduction in the positions in funds that charge redemption fees).

It is obvious that the differing investment points are determining where the peaks in the possible costs from redeeming are, and that performance effects of over 5% are possible even though the maximum charged is 5%. This is due to the fact that a large outflow of capital that leads to a fund volume that is even smaller than the total share of capital allocated to funds with redemptions fees would leverage the costs on a relative basis. For example a reduction of 450 million US $ (90% of the original fund volume) would lead to a fund volume of 50 million US $, the redemptions of costly funds would be 90 million US $ (90% of the invested 100 million US $) and one would have to pay costs that will be calculated into the new fund volume of 50 million US $ in the next period. Admittedly, this is a strong scenario that there will be a hit in the fund with outflows of 90% of the fund volume, but this can be seen as a high stress-test level.

In addition, FoFs normally have notifications of redemptions and can sell off target funds before the outflows are booked, that is, the costs are calculated into the fund volume at the time the outflows occur, rather than afterwards. One the one hand, this is done to be able to serve all liquidity demands by FoF investors, on the other hand, waiting to sell assets and then pay the costs on the new fund volume is both more performance damaging and punishing remaining investors. How tremendous the influence of direct selling is, can be seen in Exhibit 5.3, where the dimension of resulting fund volume is irrelevant as costs have to be incurred by the fund volume of 500 million US $ when the liquidity shock occurs, as here the effects are less severe than in Exhibit 5.2.

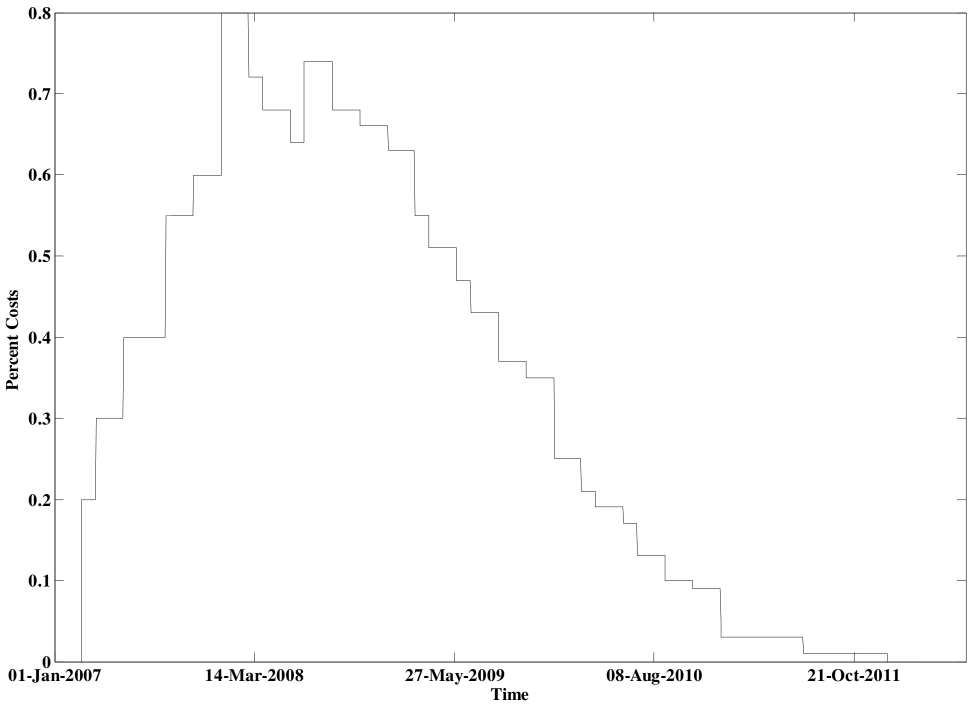

Exhibit 5.3. Costs of redemptions over time

Notes: Assumption of redemption according to fund volume reduction (allocation neutral), i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold. Costs calculated into old fund volume, i.e. 500 million US $.

Apart from the extreme events, the plane of costs over time and possible fund volumes (the line when selling directly) is informative on the potential costs that have to be incurred when liquidity is needed due to own outflows of capital. Please note that even the moderate share of 20% of assets invested into costly funds may lead to large costs (especially in the case of high outflows and when selling may be possible only after outflows occurred, as seen in Exhibit 5.2). However, the assumption underlying this kind of static overview is that there is a single hit at the specified time point. A more realistic view is to see how the costs would affect the portfolio when there are several periods of outflows, i.e. the fund volume changes from time to time and the FoF management must liquidate positions in target funds in tranches. This brings us to a path-dependent view of the liquidity costs, where the process of forced redemptions is gradual, rather than a one-hit event in the preceding baseline example.

5.4. The Dynamic Framework: Path-Dependent Analysis

In this section, we look at the path-dependent costs, thereby modelling the fund volume with Monte Carlo simulations for possible flow patterns.

For problems related to the analysis of liquidity and cash-flows, the modelling of cash-flows is crucial. While from a general view the modelling of the expected cash-flows seems to be highly desirable, the very nature of those makes it complicated to do so. Inflows and outflows into and from investments are caused by a large variety of factors. Not only do market (participant) expectations, general economic surroundings, historic performance and observable information heavily influence the cash flow patterns. With the institutionalization of the asset management industry, sales power, mutual agreements, contracting, communication and marketing, and executive decision making plays a major role when it comes to the direction and magnitude of fund flows. This makes an extrapolation of historic cash-flows inappropriate for the vast majority of investments, even if there is data available at all. If a fund or FoF is erased from a recommendation list of a wealth management company for example, or if a distribution arm is lost in the course of a restructuring process, any historic data becomes useless, as the state of the world is no more the same.

The choice of flow types, magnitudes and the statistical distribution type of flows is crucial to the outcomes of the analysis and any risk manager, portfolio manager or other to apply the analysis needs to select the distribution type that fits best the nature of the flows and/or the needs and aims of the analysis. We model daily flows with a chi squared distribution, using 1 and 3 degrees of freedom for the random number generation. To obtain both positive and negative flows, we multiply the number generated with the sign of a random number from a normal distribution. Flows are modelled on a daily basis and a time span of 1.000 trading days begins on the 1st of January 2009 when the last investment in shares charging costs was done. Of course, the path for the possible fund volumes over time may be largely differing. While the restrictions of holding period based redemption fees are generally based on calendar days rather than trading days, we left out the weekend days following 5 trading days. Of course, the choice of the appropriate frequency is left to managers and should be done in accordance to the respective product structures. For redemptions, we use a first in-first out premise, an assumption that is not very strong as we model the funds to be equal. In practice, one would simply adjust for first in- first out for each of the respective funds.

Our approach yields a considerable large span of possible outcomes, with the paths to the final outcomes being heavily differing as well as the final volume of the simulated FoF.

We employ two different strategies: One is a conservative strategy, where inflows do not lead to successive investments into the funds with redemption fees; this means that the management successively reduces the cost-prone investments when there are outflows but does not buy shares when there are inflows.

The second strategy is an allocation neutral strategy, such that if there is a decrease in capital, the respective share is divested and if there is an increase, the additional capital is invested proportionally into "costly funds", this means that the 20% share is maintained throughout the analysis.

Strategy 1: The Conservative Strategy

The rationale behind the conservative strategy in the presence of flow-forced adjustment may be for example a FoF whose management is expecting that there will be more outflows than inflows in the future and therefore the positions in cost-prone investments are passively reduced in inflow times.

In this section we show the results that were obtained from the path-dependent analysis using the conservative approach, where inflows are not invested into funds that charge back-end load fees but for each outflow, the same proportion of “costly” target funds is redeemed. As this means that over time the allocation into such funds is decreasing due to a pessimistic outlook, we can expect that the relative performance effects from redemption costs that have to be incurred decrease because of two facts: First, the holdings are decreased successively, and second, increasing amounts of shares may be sold at no cost after minimum holding periods have expired.

We need to keep in mind that even when there is a fund volume of for example 2 billion US $, an outflow of x % of the total volume leads to a reduction in the respective costly positions of x % as well, a very pessimistic approach. However, this is in line with several policies, guidelines, and management rules that have been implemented throughout the industry, to face the redemption and liquidity risks, especially during the recent crisis. First, this is to ensure that all investors are treated equal, i.e. to prevent from the problem of the losses being loaded on remaining investors only and second, to prevent from to high relative costs to be incurred when selling off at reduced fund volumes later on.

Exhibit 5.4 shows the example for 5 of the 10.000 simulated paths. As expected, the different paths lead to very different costs that have to be incurred over time. The earlier outflows occur, the higher are the fees that have to be paid, and if large outflows occur at the end of the 1.000 day analysis, the additional costs are only marginal or tend to zero.

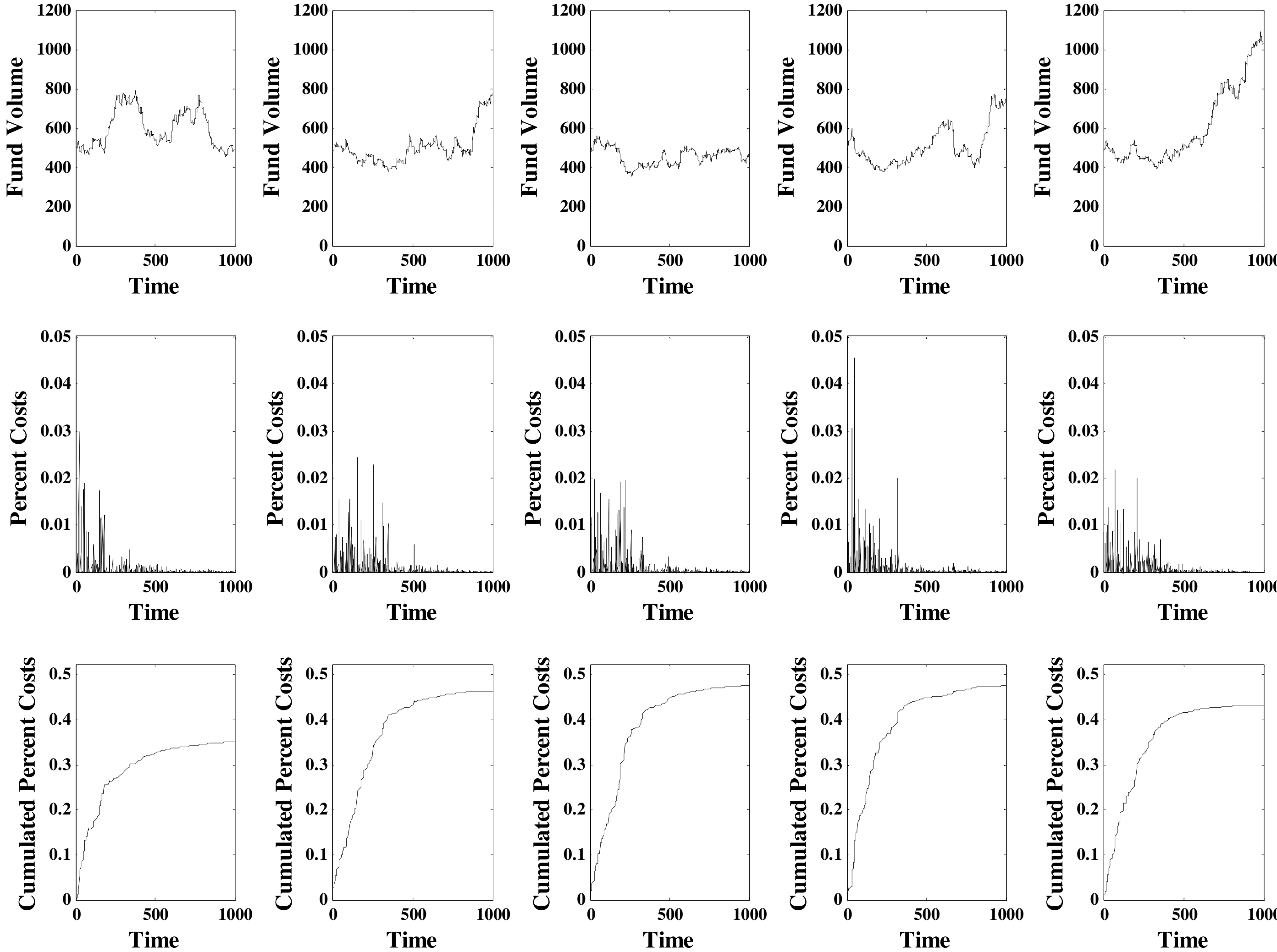

Exhibit 5.4. Fund volume paths and resulting costs of redemptions over time (conservative strategy, 1 degree of freedom)

Notes: Assumption of redemption according to outflows, no new investments in inflow periods, i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold, an inflow of 10% does not lead to buying. 5 examples from 10.000 simulations.

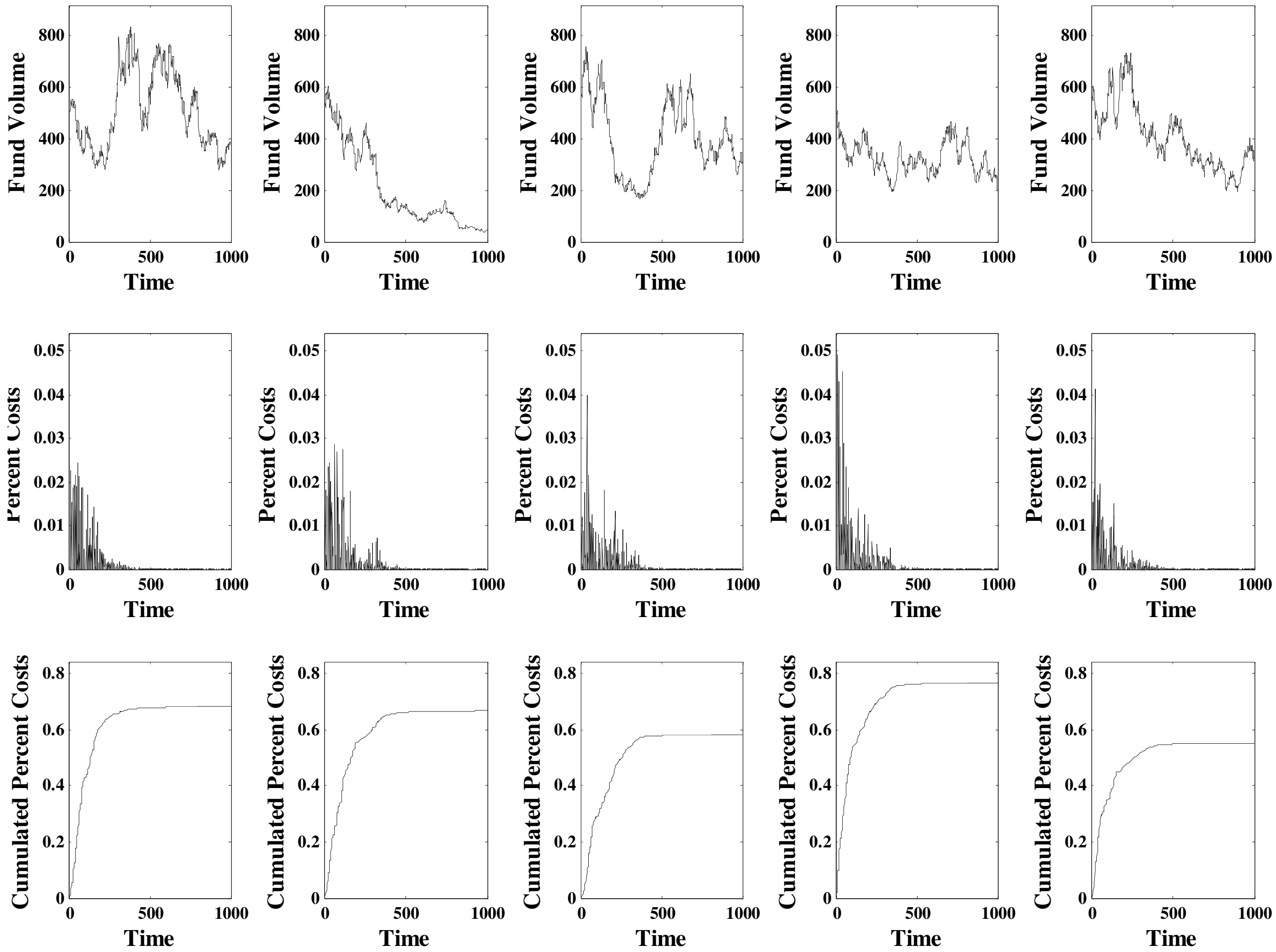

Exhibit 5.5. Fund volume paths and resulting costs of redemptions over time (conservative strategy, 3 degrees of freedom)

Notes: Assumption of redemption according to outflows, no new investments in inflow periods, i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold, an inflow of 10% does not lead to buying. 5 examples from 10.000 simulations.

As we can see from Exhibit 5.8 in the top left graph, the distribution of the total percentage costs, i.e. performance effects, while being diverse regarding the magnitude, no path did lead to total costs of even 1 percent with the used parameters. The performance effects therefore are considerable small for little over 2 and a half years, meaning that less than about a third of one percent point is lost per year.

How influential the pessimistic or conservative strategy is on the costs to be incurred can be seen in Exhibit 5.5 and in the bottom left graph of Exhibit 5.8: Although the magnitude of the flows is greatly enlarged, the strategy of selling proportionally but not re-investing when receiving inflows of capital is limiting the performance effects such that still over 90% of the paths do not lead to total costs of one percent or above for the 1.000 day period. This has strong implications for the selection of investments into cost-prone target funds, as the 20% share has an implied outperformance requirement of less than one percent over about 2 and a half years to justify its selection with respect to additional gains for additional (possible) costs.

Strategy 2: The Allocation Neutral Strategy

The rationale behind an allocation neutral strategy in the presence of flow-forced rebalancing may be for example a FoF product structure that needs to be maintained, when product characteristics of target funds with and without redemption fees may be different.

In this section, we show the results that were obtained from the path-dependent analysis using the allocation neutral approach, where inflows are invested into funds that charge back-end load fees as for each outflow the same proportion of "costly" target funds is redeemed. Therefore, a constant proportion of 20% of costly funds is maintained, regardless the fund volume. This means that over time, we can expect that the relative performance effects from redemption costs that have to be incurred over time remain fairly stable apart from some steps due to expiration of holding periods from the initially invested tranches of larger lot sizes and the first in-first out assumption.

Exhibit 5.6 shows the example for five of the 10.000 simulated paths. As in the conservative framework, the different paths lead to very different costs that have to be incurred over time. However, as expected the timing of the flows is not as influential as in the previous analysis, because inflows are invested into cost-prone funds and therefore costs when facing outflows have to be incurred even in later stages of the analysis.

Of course, the allocation neutral strategy results in considerably higher total costs over the simulation span, with the majority of the total percentage effects being between 2,5% and 4%, as seen in the top right graph of Exhibit 5.8. This implies that any of the invested shares of back-end load fee funds should annually yield about over 1% more than other funds to justify the investment. Naturally, the magnitude of the costs to be paid is larger for the analysis using 3 degrees of freedom (Exhibit 5.7), with the majority of the simulation paths resulting in 9% to 12% performance losses as can bee seen on the bottom right of Exhibit 5.8, where the implied required outperformance of the restricted funds versus other funds is becoming vast.

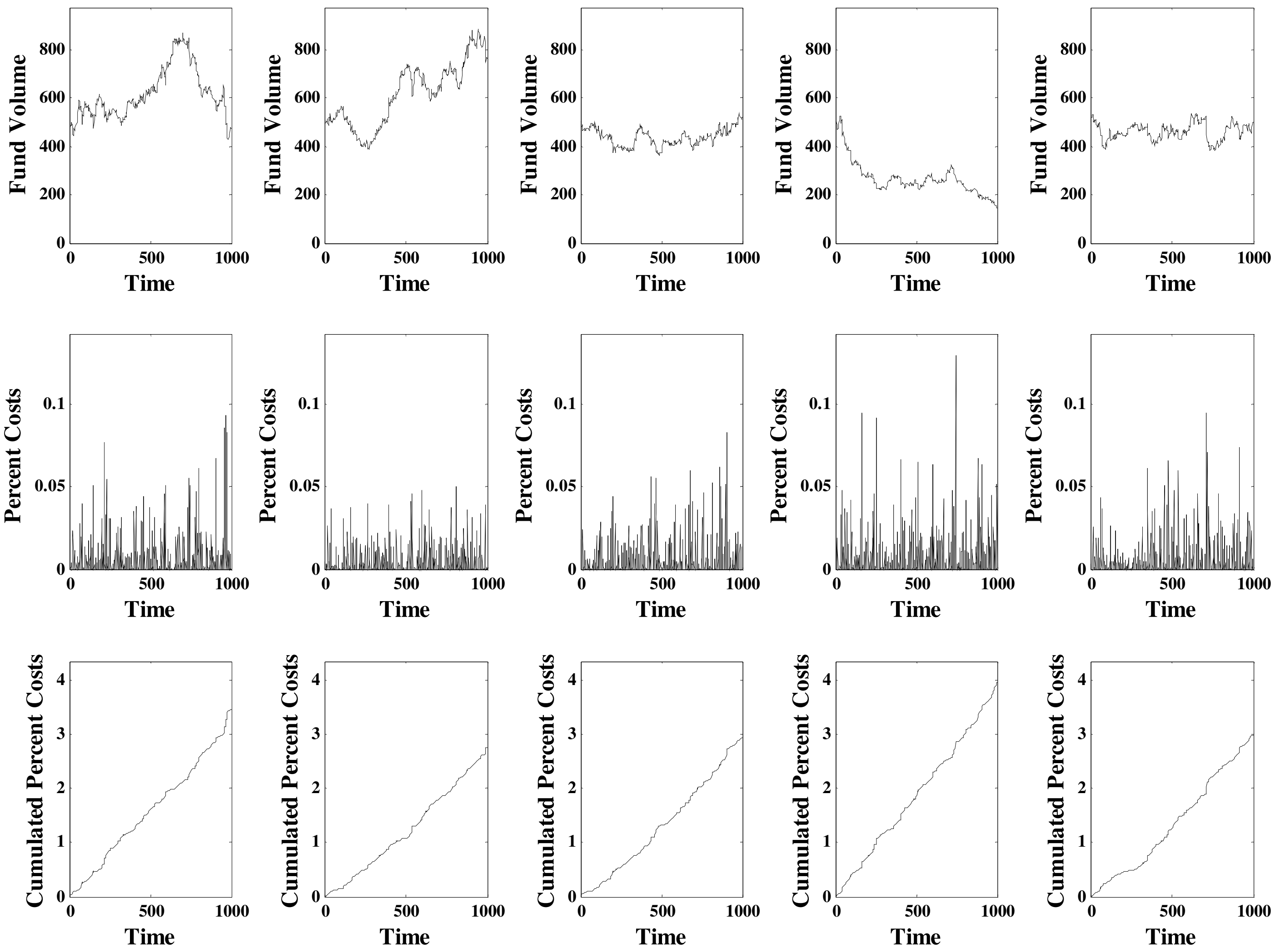

Exhibit 5.6. Fund volume paths and resulting costs of redemptions over time (allocation neutral strategy, 1 degree of freedom)

Notes: Assumption of redemption according to outflows and new investments in inflow periods, i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold, an inflow of 10% leads to buying. 5 examples from 10.000 simulations.

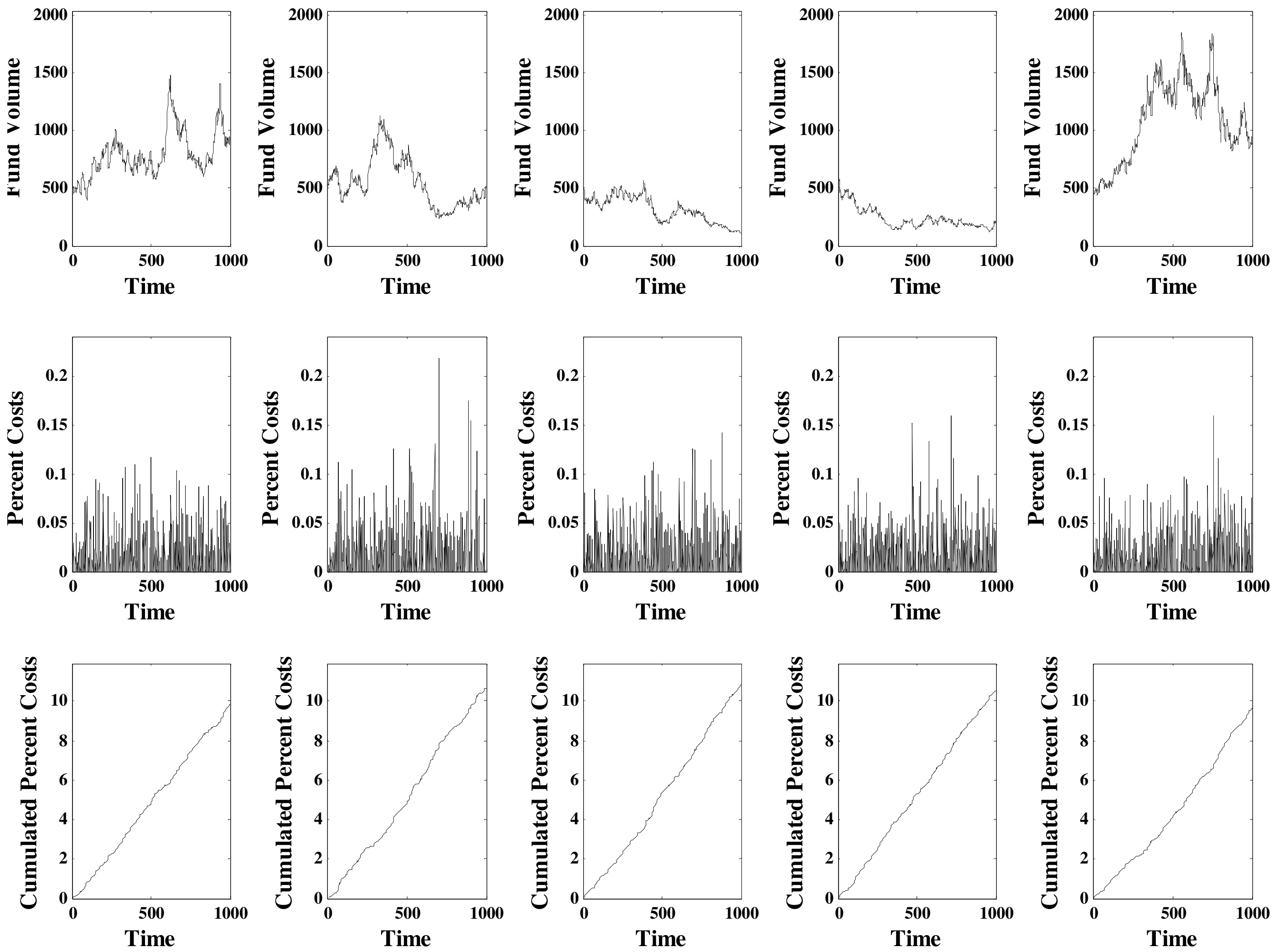

Exhibit 5.7. Fund volume paths and resulting costs of redemptions over time (allocation neutral strategy, 3 degrees of freedom)

Notes: Assumption of redemption according to outflows and new investments in inflow periods, i.e. if the FoF has outflows of 10%, the respective share of 10% of funds with redemption fees is sold, an inflow of 10% leads to buying. 5 examples from 10.000 simulations.

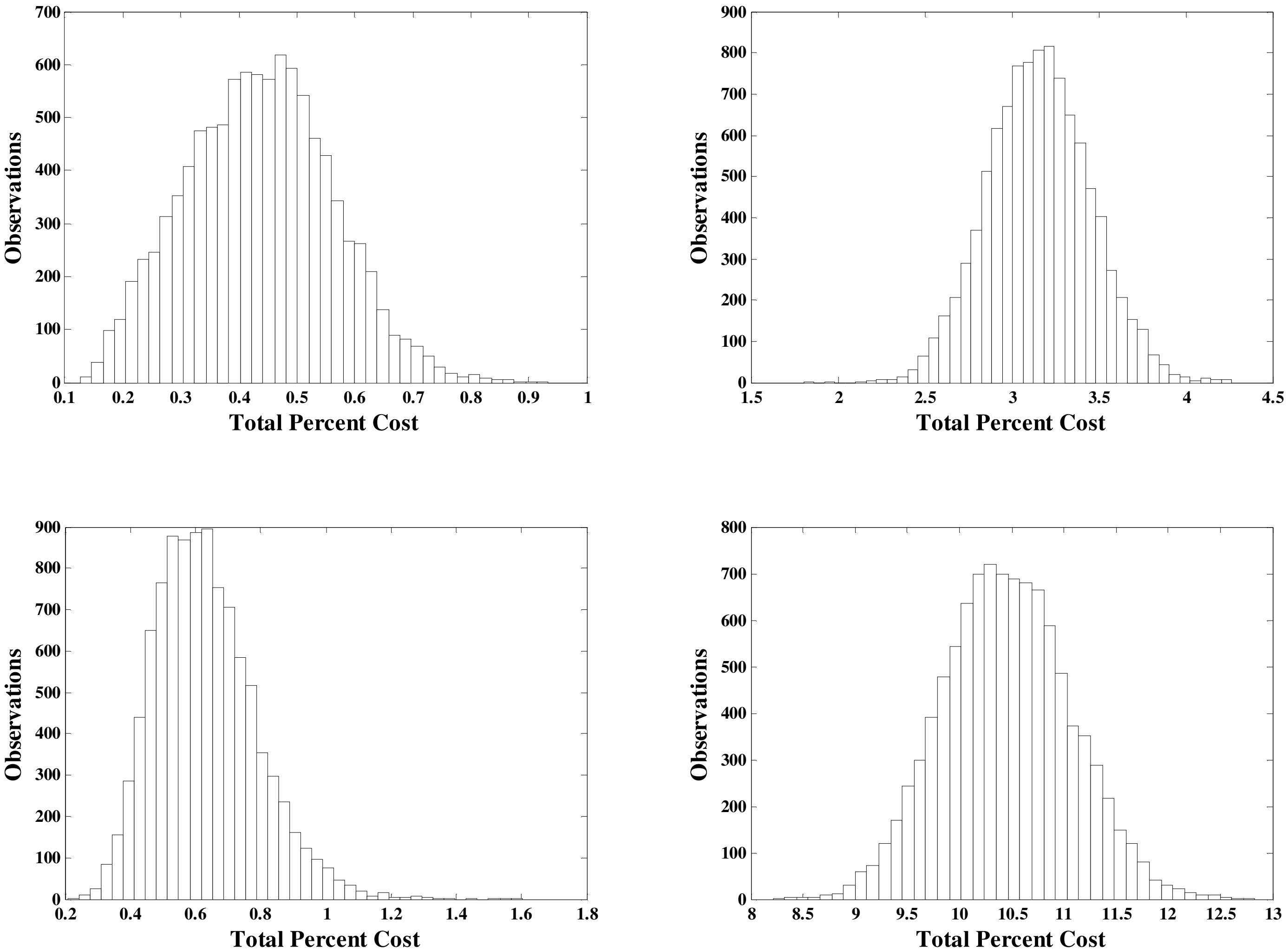

Exhibit 5.8. Total percent costs of redemptions over time, distribution comparison

Notes: Histograms of total costs of 10.000 simulations. Conservative strategy on the left, allocation neutral strategy at the right. Simulations with 1 degree of freedom on top, results using 3 degrees at the bottom.

5.5. Conclusion

FoF managers that invest into funds that may charge redemption fees are in the need of appropriately tracking the costs that may be incurred when target funds need to be sold. This is necessary both for existing positions as well as for new investments to be done. Especially in times of strong outflows of capital, the effects from flow-induced redemptions of target funds may be severe for a fund portfolio. We therefore suggest that FoF managers adequately mirror their risks over time and over possible fund volumes.

Our analysis using the static approach yields insight into how a FoF is affected by a liquidity shock due to a large outflow of capital and delivers direct information on how severe performance effects may be in the future. This information may be best processed as part of a risk analysis, as well as part of investment selection, with the possible cost-induced performance drain implying how large the outperformance of cost-prone investments versus other holdings should be for an investment to be justified.

The dynamic, path dependent analysis of the influence of flows on the costs that have to be incurred by a FoF investing into funds with time-dependent redemption fees, has shown that a very conservative strategy leads to considerable small performance effects, even in the presence of large changes in the fund volume. However, if a pessimistic approach is not demanded, for example due to additional gains to be expected from the back-end load fee funds if they are differing in nature from the other funds, the (possible) costs are heavily increasing in an allocation neutral approach. Therefore, both FoF managers and risk managers are best advised to closely model the possible performance effects of investments and holdings of cost-prone target funds over time.

5.6. References

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6. Conclusion and Outlook

In the studies for this thesis, several concepts and statistical methods were applied to problems that one faces when managing a FoF. As FoFs may pose special problems for which appropriate and practical tools are needed, we used both existent methods and new concepts to address this.

Laying the focus on the direct solutions to FoF specific problems, we mainly omitted discussions on FoF concepts themselves, but concentrated on the management aspects and challenges that one faces in FoF management. One chapter however had a relation to discussions of FoF concepts and their (dis) advantages, as Chapter 2 dealt with the comparison of value, growth and neutral style FoFs, in a transmission of the ever-young discussion surrounding styles to the FoF world.

While the study concerning the style-neutral FoFs used a standard approach of equal-weighted portfolios, we introduced a post-modern method to determine optimal portfolio weights in Chapter 3. In practice, it is especially the task of mixing very heterogeneous funds, which makes FoF management so challenging. Using the simulation of the return series with appropriate methods and solving the tricky computational burden when dealing with reward-to-risk measures in portfolio optimization suited us very well in that task.

Chapter 4 turned the focus away from an isolated view of the funds to be chosen by a FoF manager, with the study of broad market influences on sector FoFs highlighting the problems and solutions concerning the measurement of market dependencies. In contrast to the reward-to-risk measures used for the determination of optimal portfolios in Chapter 3, we employed a risk measurement framework, as is increasingly demanded by fast-moving markets and by regulations and practices addressing those.

Finally, in Chapter 5 we show how FoF managers may be affected by flows of money into and out of their portfolio when being invested in target funds charging fees. We employed a straightforward representation of the fee effects in FoFs that is both flow-dependent and time-dependent. Such representations and the incorporation and consideration of such effects into investment decisions are increasingly called for by recent market developments and industry changes.

As a large variety of aspects of FoF management are covered and addressed using statistical and mathematical methods in all chapters of this thesis, it becomes clear how important it is to have the right tools to properly manage FoFs and to achieve the best risk-adjusted returns for the portfolio. Therefore, only when using modern and flawless methods, FoF managers may be able to deal appropriately with the special issues posed by managing a fund portfolio.