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Tail Event Driven ASset allocation: evidence from equity and mutual funds' markets

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Abstract

Classical asset allocation methods have assumed that the distribution of asset returns is smooth, well behaved with stable statistical moments over time. The distribution is assumed to have constant moments with e.g., Gaussian distribution that can be conveniently parameterised by the first two moments. However, with market volatility increasing over time and after recent crises, asset allocators have cast doubts on the usefulness of such static methods that registered large drawdown of the portfolio. Others have suggested dynamic or synthetic strategies as alternatives, which have proven to be costly to implement. The authors propose and apply a method that focuses on the left tail of the distribution and does not require the knowledge of the entire distribution, and may be less costly to implement. The recently introduced TEDAS -Tail Event Driven ASset allocation approach determines the dependence between assets at tail measures. TEDAS uses adaptive Lasso based quantile regression in order to determine an active set of portfolio elements with negative non-zero coefficients. Based on these active risk factors, an adjustment for intertemporal dependency is made. The authors extend TEDAS methodology to three gestalts differing in allocation weights' determination: a Cornish-Fisher Value-at-Risk minimization,

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Markowitz diversification rule and naive equal weighting. TEDAS strategies significantly outperform other widely used allocation approaches on two asset markets: German equity and Global mutual funds.

Key words: adaptive lasso, portfolio optimisation, quantile regression, Value-at-Risk, tail events

JEL Classification: C00, C14, C50, C58

Portfolio allocation and selection go hand in hand with risk management, and are not only important concepts in quantitative finance and applied statistics, but are important determinants for long term portfolio returns for large funds. Over the past 60 years, several long-term asset allocation methods have been implemented. With each crisis occurring, more advanced methods were proposed after previous techniques failed to deliver. Notable approaches are the traditional 60/40-portfolio investment adopted by pension funds, Transparent Beta Base Model adopted by the Norwegian Sovereign Wealth Fund (NSWF), the Endowment Model popularised by University Endowments, the Core-Satellite Strategy introduced in the early 2000's , Risk Parity Model originated from the fund management firm Bridgewater, Factor Models/ Insurance and Option Overlay studied by academics and adopted by practitioners and insurers, Value and Focus Investing Model by Warren Buffett and other value investors, and ad-hoc Family Office/Real Estate Model that, however, has a notable bias of real estate in the portfolio although favoured by Asian tycoons, see Swensen [2009].

Absence of significant correlation among various asset classes is the essential motivation for traditional portfolio allocation. In reality, some strategies contradicted this principle, such as the traditional 60 equity/40 bond portfolio approach: the correlation between the bond market and the stock market was 0.98 in the last 15 years (Geczy [2014]). During the Global Financial Crisis the Endowment Model underperformed due to increased correlation across assets, Swensen [2009]. The Risk Parity strategy recommended a significant allocation to bonds amidst the implementation of quantitative easing and performed poorly because of interest rate volatility (Kazemi [2012] and Nathan [2013]). The Norwegian SWF model, strongly relied on the CAPM beta, which itself was unclear (Klarman [1991]). Performance of other models varied among investors, e.g., Factor Models that employed single or multiple factors, for instance, macroeconomic, risk or market factors, which were difficult to interpret; the Value Investing Model/ Warren Buffett that underperformed in recent years, and the Family Office Model that performed well during real asset bubble, Hamilton [2002].

A pillar in portfolio theory, mean-variance (MV) portfolio optimisation by Markowitz [1952] proposed to study semi-variance even though the optimisation was not straightforward given the low computation power at that time. As the computing capacities increased, later models incorporated optimisation involving higher and time varying moments. The mean-variance and subsequent refined models did not perform well during volatile periods and there were technical problems that were not addressed adequately. When the number of assets (p) is larger than the number of observations (n), there is a statistical problem, Bai et al. [2009] proved that the asset return estimate given by the Markowitz MV model was always larger than the theoretical return and the rate of the difference was related to p/n, the ratio of the dimension to the sample size. Jobson et al. [1979] and Jobson and Korkie [1980] showed that the Markowitz mean-variance efficient portfolios were highly sensitive to p/n. They suggested to shrink the number of estimators or assets. From this point of view, the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani [1996]) may provide a feasible solution.

According to Lee et al. [2006], the inclusion of assets with returns that are skewed and leptokurtic in the portfolio will enhance returns. These assets provide the opportunity of downside protection especially during periods of high volatility. Härdle et al. [2014] introduce a new asset allocation strategy Tail Event Driven Asset Allocation (TEDAS), which exploits negative co-movement of alternative assets in the tail to hedge for downside risk. The subset of alternative or satellite assets performs the role of downside protection. Successful protection of the portfolio by limiting the downside risk during volatile periods allows the portfolio returns to recover sooner. It is not surprising that TEDAS, with smaller drawdowns, outperforms more traditional methods that suffer larger drawdowns during extreme events. Given that a subset of alternative or satellite assets is chosen from a larger universe of assets, TEDAS can also be viewed as an application of the Core-Satellite model. For big data, where the number of possible alternatives is larger than the number of observations, the Adaptive LASSO quantile regression (ALQR) is introduced to address this issue and is used to simultaneously pursue variable selection and measure relations between variables at tail quantiles. In order to deal with changing volatility and correlation structure problem and to better match the higher moments of the portfolio distribution, one applies Cornish-Fisher VaR (Value-at Risk) model with Dynamic Conditional Correlation (DCC) and higher moments, such as skewness and kurtosis, can be used to obtain optimal asset weights among chosen products. Here, we extend TEDAS by introducing three modifications, which we call *"TEDAS gestalts"*: *TEDAS basic*, *TEDAS naive*, which places equal weights on every satellite asset, and *TEDAS hybrid*, which uses the most common Markowitz variance-covariance rule to select the weights.

In addition, we apply the TEDAS methods to global mutual fund and German stock market data. First, TEDAS yields robust and consistent results, with various assets,time periods, parameter frequencies, and in big and small data. Secondly, we show results that compare different TEDAS methods. Finally, the results are presented with transaction costs incorporated into our portfolio rebalancing.

The rest of the paper is organised as follows. In section 2, we introduce the framework of TEDAS. In section 3 and 4, we apply the methods to different markets and compare the performance between different models. Section 5 will present the conclusion and discussion. All codes and datasets are available as Quantlets on Quantnet (Borke and Härdle [2015]) .

TEDAS - Tail Event Driven Portfolio Allocation

The basic elements of TEDAS are presented in Härdle et al. [2014]. The proposed tool set has important implications for portfolio risk management and asset allocation decisions. Along with the basic setup we propose two modifications: *TEDAS naive* and *TEDAS hybrid*.

The TEDAS strategy is based on a simple idea widely used in core-satellite approach. The core asset is chosen to be e.g., the DAX index or S&P 500. The strategy is to select satellite assets to complement the core portfolio. The core portfolio is chosen by the fund manager and the satellite assets are chosen by TEDAS to limit the downside of the core portfolio during extreme events.

The second step is a selection of satellite portfolio constituents. In TEDAS the Adaptive Lasso Quantile Regression (ALQR) is applied to pick assets for a new portfolio Zheng et al. [2013]. This technique allows to simultaneously solve two challenges for portfolio managers. It shrinks the high dimensional universe of satellite assets to potential candidates for portfolio's constituents. ALQR also provides the information concerning the dependence between core portfolio and satellites at different quantiles (for various tail events). TEDAS employs 5%, 10%, 25%, 35% and 50% tail events. Assets with negative ALQR coefficients, i.e. assets adversely moving with the core for chosen level of a tail event, are constituents of a new rebalanced portfolio. For the case with only positive ALQR coefficients received, it is supposed, the value of the portfolio does not change in comparison with the previous period (a portfolio manager keeps a so-called "stay-in-cash" position). Technical details for the ALQR are provided in appendix.

The third step is a determination of portfolio weights for assets selected on the second step. TEDAS proposes three alternative ways to solve this task, we refer to them as TEDAS gestalts, which is originally a german word to indicate an organised whole that is perceived as more than the sum of its parts and literally can be translated as "form, shape" (Oxford Dictionary of English [2010]). Depending on a volatility-modeling method and the portfolio weights' optimisation rule three TEDAS gestalts can be applied. The *TEDAS basic* gestalt employs the dynamic conditional correlation model (DCC) is used (Engle [2002], Franke et al. [2015]) to account for time-varying covariance structure and correlation shifts in returns' covariance. The weights of satellites are defined based on the Cornish-Fischer Value-at-Risk (VaR) minimization rule, Favre and Galeano [2002] (Technical details are included in appendix).

The *TEDAS naive* gestalt assigns to every satellite asset the same portfolio weight.

The *TEDAS hybrid* after LASSO selection employs the simplest approach to estimate the covariance structure of assets' returns, the historical covariance matrix; portfolio weights are calculated according to classical mean-variance optimisation procedure (Markowitz diversification rule), Markowitz [1952].

The choice of satellite assets and data description

Small and mid-cap stocks

Banz [1981] found smaller firms (small caps) have had higher risk-adjusted returns, on average, than larger firms. Reinganum [1981] observed portfolios based on firm size or earnings/price ratios experienced average returns systematically different from those predicted by the CAPM. Since these pioneer papers the effect of relation between size and expected return attracted a significant attention of academics and practitioners. Research in this area is often referred to as "small cap premium", "size premium", or "size anomaly" literature. The size premium effect was preserved even after controlling for market factor and the value effect Fama and French [1993] , the momentum effect Jegadeesh and Titman [1993] and Carhart [1997], liquidity effects Pastor and Stambaugh [2003] and Ibbotson et al. [2013], industry factors as well as high leverage, low liquidity, Menchero et al. [2008]. Moreover, studies of stock returns across many separate countries and regions also confirmed the size phenomenon, Rizova [2006] summarised the academic evidence on the international existence of the size effect.

What is the source of the size premium? The traditional theory claimed that firm size was a proxy for systematic risk, small cap stocks were riskier than large cap stocks, and, therefore, market forced exert downward pressure on the prices of small cap stocks to provide investors with higher returns, Fama and French [1993]. Subsequent researchers explored the underlying sources of such risk, but the results were controversial. For example, Amihud and Mendelson [1986] proposed to link the size effect with liquidity risk, measured as bid-ask spread, and their results demonstrated the size premium effect was mostly a liquidity driven. Amihud [2002] found that smaller firms' returns were more sensitive to market illiquidity and that small cap stocks had more liquidity risk than large caps stocks, Liu [2006] also argued that small caps required higher returns for accepting liquidity risk. Zhang [2006] proposed another source of risk, namely 'information uncertainty', which linked small caps to law quality of the information disclosure and information about a firms' volatile fundamentals. Chan and Chen [1991] and Dichev [1998] suggested that size served as a proxy for financial distress, Vassalou and Xing [2004] stated the size effect was a default effect and together with value (the book-to-market) effect existed only in market segments with high default risk. Overall, this group of literature explored reasons, why higher risks were linked to small and mid caps. Lakonishok et al. [1994] proposed an alternative explanation and proved that small caps were mispriced by investors due to behavioural biases and not because these types of assets were fundamentally riskier.

After first discovering and documentation of size premium in Banz [1981], Fama and French [1993] also observed a premium of 0.27% per month in the US over the period 1963 to 1991. However, more recent studies documented the size anomaly disappeared (see, e.g., Amihud [2002] , Dichev [1998]) since 1980 in the US. Furthermore, Fama and French [2012] observed no size effect across 23 countries from November 1990 to September 2010. At the same time Hou and Dijk [2010] argued that U.S. stocks of smaller firms had not had higher returns since the early 1980s because of firm profitability "shocks": smaller firms had negative earnings surprises and larger firms had positive earnings surprises during this time. Based on this argument, they claimed that the size effect still existed even it was not so obvious (see also Crain [2011]). Three studies on the size anomaly in Germany provided inconsistent results. Namely, Stehle [1992] found some evidence of a size effect in Germany, especially in January, whereas Schlag and Wohlschieß [1992] obtained very low t-statistics for size as an explanatory variable for mean returns. Sauer [1994] too did not detect a size related anomaly for stock returns in Germany. For an extensive literature review concerning a size effect we refer to e.g., Crain [2011]. It can be summarised, that the size effect has been challenged along many fronts. Over the last decade, however, global small caps and mid caps have been relatively strong again and outperformed large caps (Figure 1). The existence of size effect as well as the benefits of diversification (see, e.g., Bender et al. [2012]) strongly motivates inclusion of small and mid cap stocks into allocation strategies. In our research we utilise small and mid cap stocks as satellite assets for the TEDAS strategy.

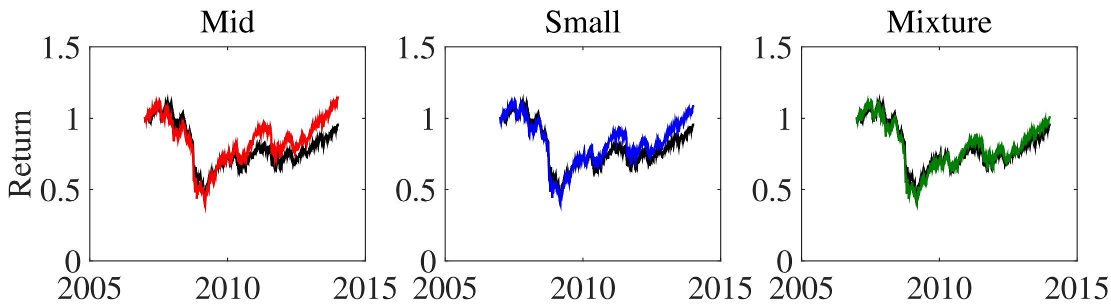

Figure 1: Daily cumulative returns of MSCI World Large Cap index (black) from 1 Jan 2007 to 31 Dec 2014 against MSCI World Mid Cap index (red), MSCI World Small Cap index (blue) and MSCI World Small and Mid Cap / mixture index (green)

The empirical analysis of TEDAS application to equity market focuses on the German stock market. As the core-asset DAX index is employed and 125 constituents of indices SDAX, MDAX and TecDAX construct the universe of hedging assets – small and mid-cap stocks. The collected data cover the time period from 21 Dec 2012 to

27 Nov 2014 (Source: *Datastream*). The performance of TEDAS strategy for German equity market was analysed on 41 sixty-weeks moving windows.

Mutual funds

The role of Mutual Funds in world economy has increased in the 20 years or so due to their fast growth (from 52 746 in 1999 they of Mutual Finds has reached 76 200 by 2013) (Figure 2). The US economy is the market that accounts for about half of the global mutual fund market of $30 trillion which underlines its importance in the US economy. In addition mutual fund investment companies account for 88 percent of investment companies in total. The popularity of mutual funds is due to their perceived safety compared to alternatives, notably stocks. This perception has resulted in a situation where almost half specifically, 46.3 percent of US households have participated in such funds. All this underlines the sheer size and the importance of the US mutual find market which, therefore, should provide us with an important test case for the evaluation of the performance of TEDAS strategy and would show whether TEDAS can handle cases of big data.

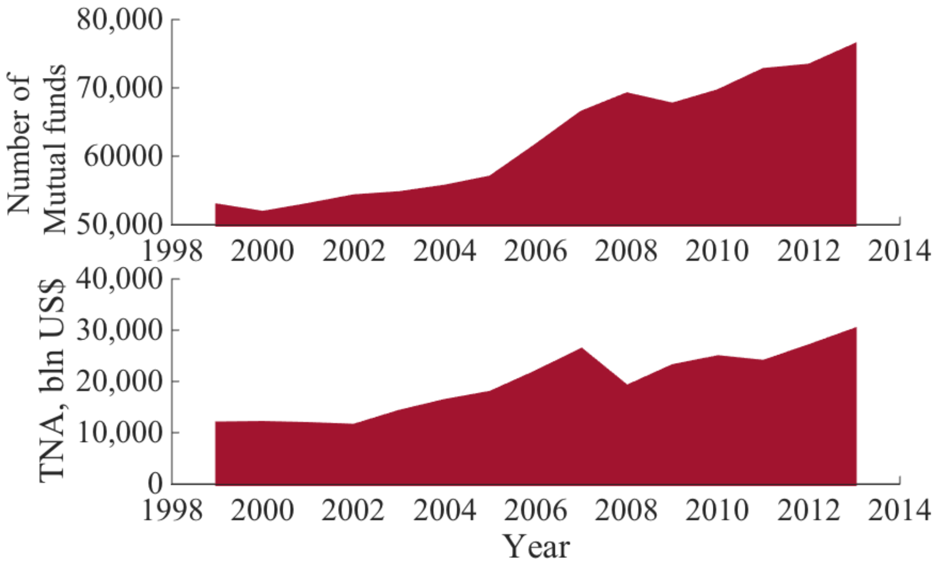

Figure 2: Number (upper graph) and Total net Assets (lower graph) of Worldwide Mutual Funds from 1999 to 2013

The potential of diversification, a major determinant for asset allocation, is a major and very attractive characteristic of mutual funds. In the 2013 US market, 38 percent of all industry assets were held by domestic equity funds and an additional 14 percent by world equity funds. Moreover, it is pointed out that the percentage of mutual fund assets that were in the form of bond funds is at 22 percent, whereas money market funds covered 18 percent and 8 percent, the remaining, was accounted by hybrid funds. Finally, it has been observed that in the US there has been a tendency towards equity mutual funds regarding portfolio diversification, which means increased investment rates in foreign (non-US) markets.

The data for this study come from Datastream and represent the period from January 1998 to December 2013, i.e. a period of 192 months. The classification of the data was performed on the basis of three locations in which they originated: United States, Singapore and the World. At first hand, cross-sectional data from 2616 funds were retrieved, but only that from funds that had had a life of at least 10 years. Not surprisingly, the US market had the largest representation in the data set with 2347 cases of mutual funds, whereas Singapore had only 13 and the other markets 256. To simplify the processing of the data some further reduction of the data set was applied: inactive cases – the ones which showed no price change for 3 months – were excluded resulting to a total of 583 remaining cases which provided the dataset for our calculations. S&P 500 provided the core asset, whereas Bloomberg was the source of the data from the same time space.

Empirical results

Results for German equity market

The comparison of the three TEDAS gestalts with the core DAX30 index is given on Figure 3. As is seen, all three TEDAS strategies demonstrate almost equal results in terms of cumulative return. At the end of the analysed timespan these strategies yield 41-42 % of cumulative return taking into account 1% of transaction fees (The cumulative returns reach even 60 % - 70 % without the transaction costs). The asset allocation decision is twofold: one has to define which assets to buy and which proportions to use to construct the portfolio (solution of weights' optimisation problem). One observes though the main driving factor of the overperformance for TEDAS strategy comes from the portfolio assets' selection and not really from weights' optimisation. A conducted sign test confirms the absence of difference in medians of returns for the three TEDAS gestalts (on 5% significance level).

TEDAS needs to be benchmarked with three alternative widely used strategies: Risk-Parity portfolio (Equal risk contribution portfolio), OGARCH mean-variance strategy, 60/40 portfolio. The mean-variance (MV) portfolio selection has been widely used by the financial community and is the common benchmark for every newly introduced asset allocation strategy. The traditional Markowitz portfolio optimisation approach as has been shown in previous literature has some drawbacks especially for the case when $p>n$. The portfolio formed by using the classical mean-variance approach

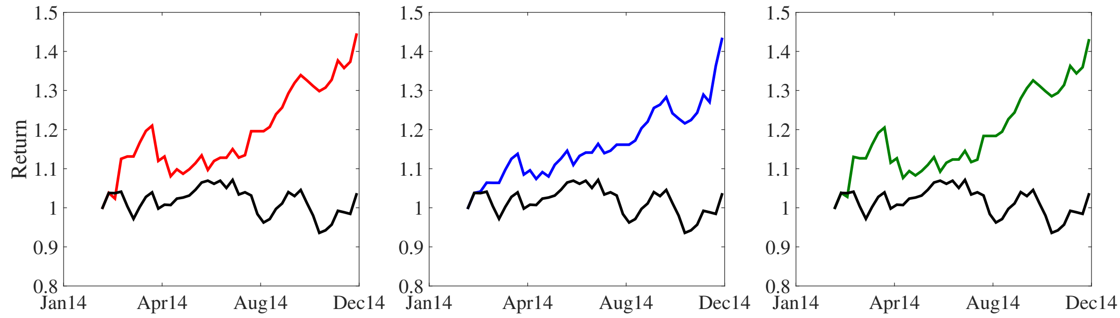

Figure 3: Weekly cumulative returns of DAX30 index (black) from 21 Dec 2012 to 27 Nov 2014 against TEDAS basic (red), TEDAS naive (blue) and TEDAS hybrid (green) strategies applied to German stocks

TEDAS_gestalts

always results in extreme portfolio weights Jorion [1985], that fluctuate substantially over time and perform poorly in the sample estimation (for example, Frankfurter et al. [1971], Simaan [1997], Kan and Zhou [2007]) as well as in the out-of-sample forecasting.

Different studies provide different observations and suggestions to investigate the reasons, why the MV optimisation estimate is so far away from its theoretic counterpart. So far, all believe that the reason behind this outcome is that the "optimal" return is formed by a combination of returns from an extremely large number of assets (see McNamara [1998]). Use of Markowitz optimisation procedure efficiently depends on whether the expected return and the covariance matrix can be estimated accurately. Many studies have improved the estimate of the classical Markowitz MV approach by using different approaches. For our comparative study, the conditional variance-covariance matrix was estimated with Orthogonal GARCH factors. In our study we use dynamic Markowitz risk-return optimisation with portfolio covariance matrix modelled by the basic orthogonal GARCH method. The Orthogonal GARCH model was first proposed in Alexander [2001], and is based on Principal Components Analysis (PCA).

60/40 portfolio allocation strategy implies the investing of 60% of the portfolio value in stocks (often via a broad index such as S& P500) and 40% in government or other high-quality bonds, with regular rebalancing to keep proportions steady. German market's 60/40 portfolio is constructed with DAX and RDAX indices.

Risk-parity portfolio-strategy is based on allocation by risk, not by capital. In this case, the portfolio manager defines a set of risk budgets and then computes the weights of the portfolio such that the risk contributions match the risk budgets (for details see Maillard et al. [2010]).

The comparison of cumulative returns achieved with *TEDAS hybrid* and alternative

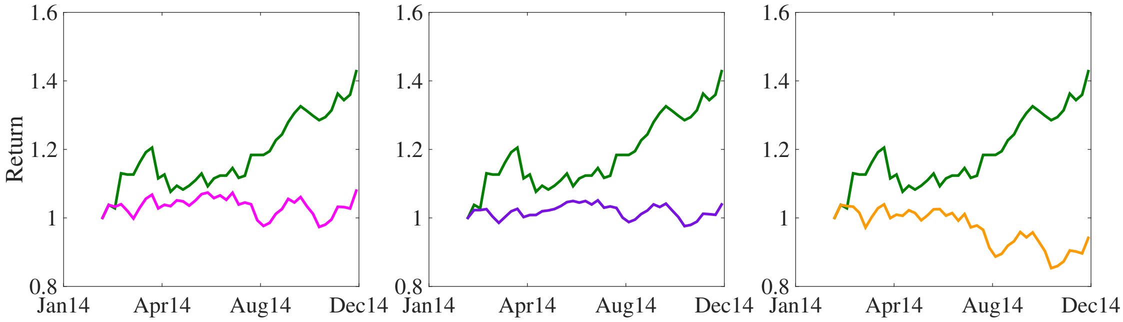

Figure 4: Weekly cumulative returns of TEDAS Hybrid (green) from 21 Dec 2012 to 27 Nov 2014 against MV OGARCH (magenta), 60/40-portfolio (purple) and Risk Parity (orange) strategies applied to German stocks

TEDAS_gestalts

strategies, demonstrated in Figure 4 , shows that TEDAS performs significantly better than other considered approaches.

Strategy	Cumulative return	Sharpe ratio	Maximum drawdown
TEDAS basic	143%	0.3184	0.1069
TEDAS naive	144%	0.3792	0.0564
TEDAS hybrid	143%	0.3079	0.1068
MV OGARCH	108%	0.0687	0.0934
Risk-Parity	95%	-0.0693	0.1792
60/40 portfolio	121%	0.0306	0.0718
DAX30	103%	0.0210	0.1264

Table 1: Strategies' performance overview: German stocks' sample

TEDAS_perform

The rebalancing of portfolio to hedge the core asset occurred 21 times out of 41 moving-window estimation periods. Table 1 summarises the performance of portfolio strategies in terms of cumulative returns as well as in terms of risk. We used two traditional measures to evaluate portfolios' risk-adjusted returns: Sharpe ratios and maximum drawdown. As it can be seen from the results, the most attractive strategy is *TEDAS basic*, which gives the highest excess return for the extra volatility. At the same time, *TEDAS naive* demonstrates the lowest financial risk, measured with maximum drawdown. In general we can conclude that TEDAS strategies show better risk-adjusted returns than all other analysed benchmarks and have comparatively the same level of risk.

Figure 5 shows the frequency of the number of selected variables for different quantiles. As can be noticed, the number of selected satellites in most of cases is

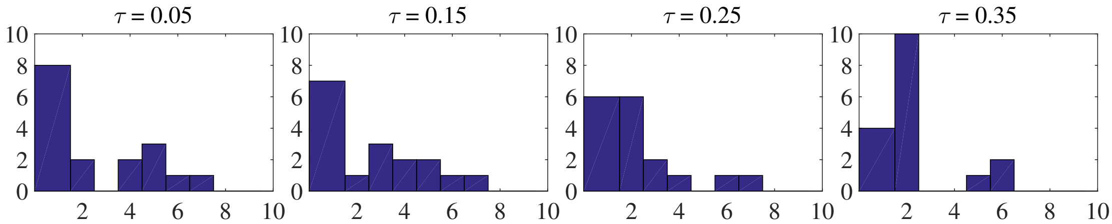

Figure 5: Frequency of the number of selected stocks for 4 different quantiles (German stocks' sample)

less than five, which is also indicative of this strategy and the simplicity of portfolio rebalancing. Furthermore, we analyze how frequently certain stocks were selected as satellites (i.e. how often they have significant ALQR non-positive coefficients) the results of which are given in figure 6. More frequently small stocks (first 50 stocks on the graph) and stocks of high-tech companies (last 30 stocks) hedge the core. This conclusion is also confirmed by table 2, which lists the most frequently used German stocks for 5 % quantile and most part of them operate in the high technology innovative industries.

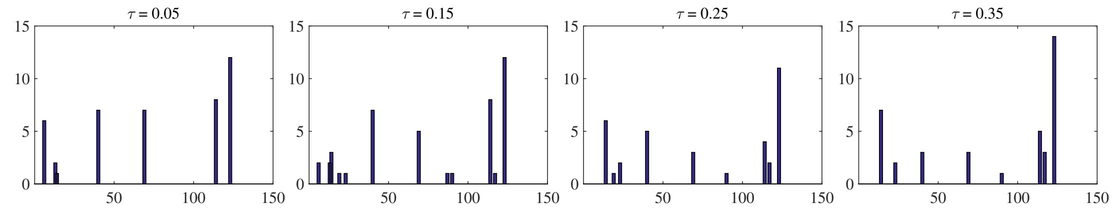

Figure 6: Frequency of selected stocks for 4 different quantiles (German stocks' sample)

Top 5 influential stocks	Frequency	Index	Industry
Sartorius Aktiengesellschaft	12	TecDAX	Provision of laboratory and process technologies and equipment
XING AG	8	TecDAX	Online business communication services
Surteco SE	7	SDAX	Household Goods & Home Construction
Kabel Deutschland Holding AG	7	MDAX	Cable-based telecommunication services
Biotest AG	6	SDAX	Producing biological medications

Table 2: The selected German Stocks for 5% quantile

All TEDAS gestalts applied to the universe of German stocks outperform both traditional benchmark strategies such as Markowitz rule or 60/40 and more sophisticated ones such as the risk-parity model. Our analysis leads us to believe that using the ALQR technique delivers good results in reducing the dimensionality of the asset universe for more effective portfolio allocation.

Results for global mutual funds

Since the number of satellites after filtering (p=583) is very large, the moving window for Mutual funds' sample is adjusted to 120. We assume in December 2007 one starts to allocate 1 unit of money using each strategy and calculated the 73 monthly cumulative returns until Dec 2013.

Similar to the previous analysis, the outcomes of the three TEDAS strategies are compared. From 2007 to the end of 2013, the *TEDAS Naive* yields the highest return, 454%. *TEDAS Hybrid* and *TEDAS Basic* setups show similar returns of 433% and 421% respectively (Figure7).

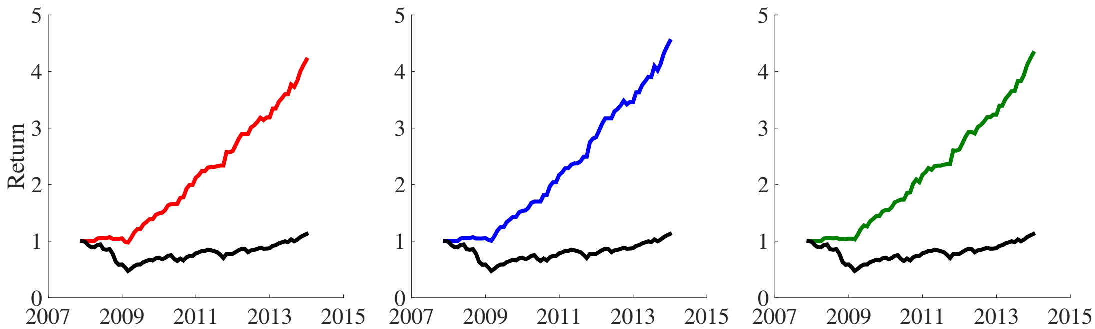

Figure 7: Monthly cumulative returns of S&P 500 from Dec 2007 to Dec 2013 against TEDAS basic (red), TEDAS naive (blue) and TEDAS hybrid (green) strategies applied to Mutual funds

TEDAS_gestalts

In order to check whether TEDAS is significantly better than popular methods that have been applied in the past years, we employed the same four benchmarks in the case of German stocks. We constructed a 60/40 portfolio using NASDAQ composite and the Barclays US treasury index. For the base case, we buy and hold the core asset, S&P 500, during the whole period. By comparing the TEDAS hybrid and the benchmarks, we can tell that TEDAS is out-performed. 60/40 and Risk-Parity portfolios have high correlation with the S&P 500 and these three gave similar returns of around 125% (Figure 8). By Sign Test between *TEDAS Hybrid* and other four benchmarks, we could get the p-values, which are all smaller than 5% and therefore, we could conclude that the return of our strategy is statistically and significantly different from others.

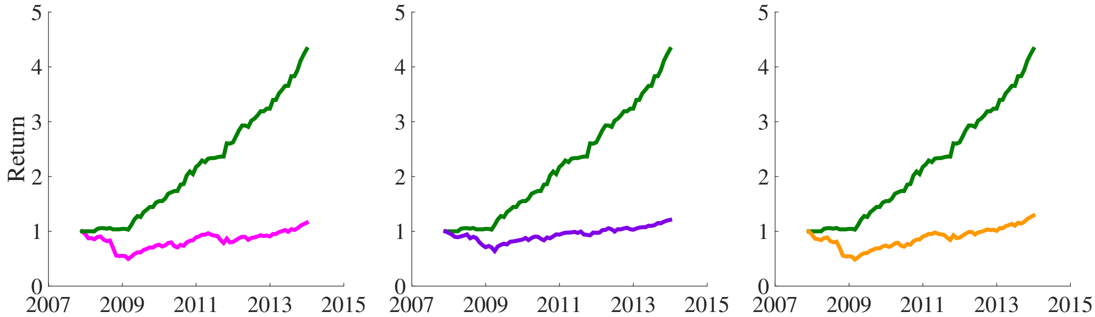

Figure 8: Monthly cumulative returns of TEDAS Hybrid (green) from Dec 2007 to Dec 2013 against MV OGARCH (magenta), 60/40-portfolio (purple) and Risk Parity (orange) strategies applied to Mutual funds

TEDAS_gestalts

Strategy	Cumulative return	Sharpe ratio	Maximum drawdown
TEDAS basic	421%	0.6393	0.0855
TEDAS naive	454%	0.6974	0.0583
TEDAS hybrid	433%	0.6740	0.0276
MV OGARCH	116%	0.0214	0.4772
Risk-Parity	129%	0.0487	0.4899
60/40 portfolio	121%	0.0252	0.3473
S&P500	113%	0.0132	0.5037

Table 3: Strategies' performance overview: Mutual funds' sample

TEDAS_perform

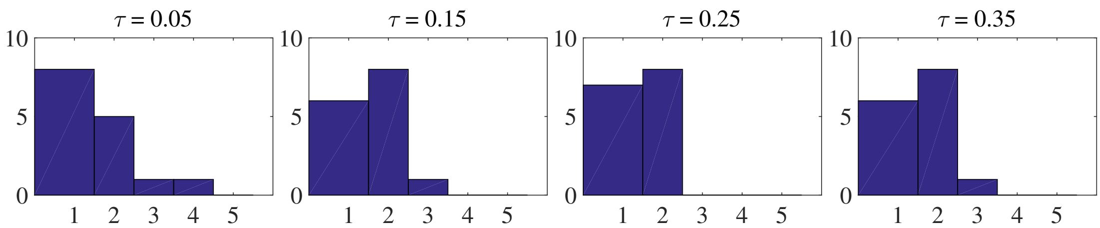

Figure 9: Frequency of the number of selected variables for 4 different quantiles (Mutual funds' sample)

Figure 9 shows the different frequencies of the number of selected variables from 4 quantiles (0.05, 0.15, 0.25 and 0.35). Unexpectedly, the number of selected satellites is all less than four in all cases, which is similar with the German Stock data. Compared with the number of selection pool (583 Mutual Funds), 4 is really small.

One explanation might be that even though Mutual Funds consist of combinations of many products (different kinds of bonds, domestic and international equities), and have many different investment ways, there is a huge part of the investment pool has been allocated into the U.S. stock markets or into related products. As a result of globalization, the U.S. market strongly affects other markets.

Influential Mutual Funds	Frequency	Market
Blackrock Eurofund Class I	12	U.S.
Pimco Funds Long Term United States Government Institutional Shares	8	U.S.
Prudential International Value Fund Class Z	4	U.S.
Artisan International Fund Investor Shares	3	U.S.
American Century 2OTH Century International Growth Investor Class	1	U.S.
First Eagle Overseas Fund Class A	1	U.S.

Table 4: The selected Mutual Funds for for 5% quantile

TEDAS does not select many different Mutual Funds, only 6 Mutual funds hedged the core in extreme events throughout the analysed period. From Table 4 we can see that all selected Mutual Funds exchanged in U.S. market, but most of them are related to the products outside the U.S. markets.

Conclusion and Discussion

Asset allocators have difficulties in constructing a portfolio that can sufficiently protect the downside with acceptable level of drawdown. Each crisis, previously adopted methods failed to limit the downside as suggested by empirical stress testing based on historical data. Here, we have proposed a method that focuses on the co-movement of the core and the universe of satellite assets during extreme events. The degree of extremeness is defined as the percentage of historical observations in the tail, also known as quantiles. By selecting and reducing the universe of satellite assets to a manageable subset and at the same time having the properties of negative or zero correlation with the core during extreme event is the innovation of this paper.

The main contribution of this paper is to demonstrate the practical significance of the TEDAS tool set for a wide range of both institutional and private investors in various settings. We conducted an empirical study on the performance of TEDAS strategy applied to a broad spectrum of core and satellite configurations. The testing of TEDAS strategy for Global Mutual funds and German equity data leads to conclusion TEDAS is meaningful for geographically different markets (global and Germany), using weekly and monthly returns as well as for different levels of dimensionality of the universe of potential portfolio constituents. This paper demonstrated the power of the TEDAS strategy for different asset markets, such as equity, Mutual funds and Hedge funds. Furthermore, compared with four conventional benchmark allocation approaches, TEDAS cumulative returns are significantly higher. Investigation of TEDAS outperformance in terms of risk measures, such as Sharpe ratio and maximal drawdown, also demonstrates better results than other benchmark strategies. Finally, when we relaxed the assumption of zero transaction fees TEDAS still demonstrates superior performance, significantly different from other traditional approaches.

There are many ways in which we envision the research reported here can be extended. The results of three modifications of TEDAS adopted in this study are robust. Theoretically speaking, *TEDAS basic*, which takes the third and fourth moments into account, should perform better than the other two. However, we do not observe it in our empirical study. There are some possible explanations and directions for further analysis. One is to solve the utility maximization problem with higher moments or to include time-varying modelling of higher portfolio moments as in Ghalanos et al. [2015].

Analysing the superior returns of TEDAS strategies, it is necessary to keep in mind all results were received based on realized returns and not on expected returns. Therefore, the possible direction for a further development of TEDAS strategy might be an incorporation of returns' forecasting and examining of out-of-sample performance. In conclusion, the results suggest that these TEDAS methods, while still relying on historical methods, are producing promising results. The caveat remains that history may not necessarily repeats itself and further studies are needed.

Appendix

Adaptive LASSO Quantile regression (ALQR)

Adaptive Lasso Procedure

Introduced in Bassett and Koenker [1978] quantile regression (QR) estimates conditional quantile functions–models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates (see Koenker and Hallock [2001]).

L_1 - penalty is considered to nullify "excessive" coefficients (Belloni and Chernozhukov [2011]). Simple lasso-penalized QR optimisation problem is:

$$\hat{\beta}_{\tau,\lambda} = \arg\min_{\beta\in\mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(Y_i - X_i^\top \beta) + \lambda\|\beta\|_1 \qquad (1)$$

The adaptive Lasso, Zou [2006], yields a sparser solution and is less biased. L_1 -

penalty is replaced by a re-weighted version:

$$\hat{\beta}^{\text{adapt}}_{\tau,\lambda_n} = \arg\min_{\beta\in\mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(Y_i - X_i^\top \beta) + \lambda_n \|\hat{\omega}^\top \beta\|_1 \tag{2}$$

here $\tau \in (0,1)$ is a quantile level, $\rho_\tau(u) = u\{\tau - \mathbf{I}(u<0)\}$ piecewise loss function, λ_n regularization parameter. Weights $\hat{\omega} = 1/|\hat{\beta}^{\text{init}}|$, $\hat{\beta}^{\text{init}}$ is obtained from (1). In TEDAS setup $Y \in \mathbb{R}^n$ represents core log-returns (DAX or S&P500 indices)and $X \in \mathbb{R}^{n\times p}$ – satellites' log-returns (German stocks or Mutual funds), $p > n$.

Algorithm for Adaptive Lasso Penalized QR

The optimisation for the adaptive Lasso can be re-formulated as a Lasso problem:

- the covariates are rescaled: $\tilde{X} = (X_1 \circ \hat{\beta}^{\text{init}}_1, \dots, X_p \circ \hat{\beta}^{\text{init}}_p)$;
- the lasso problem (1) is solved:

$$\hat{\hat{\beta}}_{\tau,\hat{\lambda}} = \arg\min_{\beta\in\mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(Y_i - \tilde{X}_i^\top \beta) + \lambda \|\beta\|_1 \tag{3}$$

- the coefficients are re-weighted as $\hat{\beta}^{\text{adapt}} = \hat{\hat{\beta}}_{\tau,\hat{\lambda}} \circ \hat{\beta}^{\text{init}}$

Cornish-Fisher VaR optimisation

A modification of VaR via the Cornish-Fisher (CF) expansion improves its precision adjusting estimated quantiles for non-normality. To obtain asset allocation weights the following VaR-minimization problem is solved (for details see Favre and Galeano [2002], Härdle et al. [2014]):

$$\begin{aligned} &\underset{w\in\mathbb{R}^d}{\text{minimize}} && W_t\{-q_\alpha(w_t)\cdot\sigma_p(w_t)\} \\ &\text{subject to} && w_t^\top\mu = \mu_p,\;\; w_t^\top 1 = 1,\;\; w_{t,i} \geq 0 \end{aligned} \tag{4}$$

here $W_t \overset{\text{def}}{=} W_0 \cdot \prod_{j=1}^{t-1} w_{t-j}^\top (1 + r_{t-j})$, $\tilde{w}$, W_0 initial wealth, $\sigma_p^2(w) \overset{\text{def}}{=} w_t^\top \Sigma_t w_t$,

$$q_\alpha(w_t) \overset{\text{def}}{=} z_\alpha + (z_\alpha^2 - 1)\frac{S_p(w_t)}{6} + (z_\alpha^3 - 3z_\alpha)\frac{K_p(w_t)}{24} - (2z_\alpha^3 - 5z_\alpha)\frac{S_p(w_t)^2}{36}, \tag{5}$$

here $S_p(w_t)$ skewness, $K_p(w_t)$ excess kurtosis, z_α is $\mathrm{N}(0,1)$ α-quantile. If $S_p(w_t)$, $K_p(w_t)$ are zero, then the problem reduces to the Markowitz case.

Mean-variance optimisation procedure (Markowitz diversification rule)

Mean-variance optimisation procedure is based on four inputs: the weights of total funds invested in each security w_i, $i = 1, \ldots, d$, the expected returns μ approximated as averages $\bar{r}$, volatilities (standard deviations) σ_i associated with each security and covariances σ_{ij}, $j = 1, \ldots, d; i \neq j$ between returns. Portfolio weights w_i are obtained from the quadratic optimisation problem, see Brandimarte [2006], p. 74

$$
\begin{aligned}
\underset{w \in \mathbb{R}^d}{\text{minimize}} \quad & \sigma_p^2(w_t) \stackrel{\text{def}}{=} w_t^\top \Sigma w_t \\
\text{subject to} \quad & w_t^\top \mu = r_T, \\
& \sum_{i=1}^{d} w_{i,t} = 1, \\
& w_{i,t} \geq 0
\end{aligned}
\tag{6}
$$

where $\Sigma \in \mathbb{R}^{d \times d}$ is the covariance matrix for d portfolio asset returns, r_T is the "target" return for the portfolio assigned by the investor. Markowitz optimisation procedure gives the same result as CF-VaR optimisation in case of skewness and excess kurtosis are zero (in excess of 3, which corresponds to a Gaussian distribution).

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