Master Thesis
Department of Finance
Fall 2017

DO THEY ALWAYS HEDGE?

Applications of quantile regressions to risk measurement across hedge fund strategies

Gustaf Sävendahl
22950@student.hhs.se

Oleg Pavlovskyy
41152@student.hhs.se

Abstract. Extending previous work on quantile regression analysis of hedge fund returns, this thesis explores risk factor exposures across performance quantiles of 22 hedge fund strategies from 1994 to 2016. Specific characteristics of hedge funds are taken into consideration. Factor exposures are found to vary considerably across performance quantiles, implying that common conditional mean regression models fail to capture factor dependencies across hedge fund performance periods. Potential applications of quantile regression analysis to risk measurement and management are illustrated with two examples of conditional quantiles and conditional stress tests.

Keywords: hedge funds, investment strategies, quantile regressions, factor exposures, risk

Tutor: Michael Halling

Thesis seminar: December 18, 2017

Acknowledgements: We would like to express our sincere appreciation and gratitude to our tutor, Associate Professor of Finance at the Stockholm School of Economics, Michael Halling, for his valuable support during the development of this thesis.

This page intentionally left blank

Contents

List of Figures

List of Tables

1 Introduction

Less than 25 years ago the hedge fund industry started to emerge as a specialized player within the global financial market. Hedge funds differ from plain vanilla long only mutual funds in the sense that the nature of their exposures are unconventional and sometimes involve more dynamic strategies. Three common aspects that differentiate hedge funds from mutual funds are that managers often use leverage, short sales and can place their trading ideas in many ways such as with derivatives. This lays the foundation for potentially non-linear exposures, i.e. more option resembling payoffs from hedge funds. These features lead to atypical return distributions which need to be accounted for when one assesses risk characteristics of hedge funds.

Hedge funds have been attracting the investment community by marketing three main alleged benefits - that investors may access abnormal performance associated with hedge fund alphas, that hedge funds may meet investors' quest for alternative beta exposures, and that hedge funds add significant value to investors' portfolios regarding risk management and diversification. This study touches upon the latter two claimed advantages through a detailed analysis of hedge fund risk exposures with arising ramifications for measured betas and risk characteristics.

With the increased demand from investors and regulators following the 2007-2008 financial crisis, hedge funds have come under elevated pressure to measure, manage and monitor their risks more efficiently and transparently. In addition, the importance of hedge fund risk management can be related to the increased scrutiny of active portfolio management performance in relation to risk taking (SvD, 2017). This has made the investor spectra to an extent move capital to passively managed funds assumed to be far less risky. For instance, Lamm (2013) showed that the Sharpe ratios delivered by funds of hedge funds deteriorated substantially after the crisis compared to a simple 60% stock / 40% bond portfolio. Moreover, higher fees (management and incentive), lock-up periods during which investment withdrawals are forbidden altogether, gate provisions which limit the maximum amount of redemptions for the current period, and side pockets which are used to separate liquid and illiquid holdings comprise an additional burden compared to passive investments.

Thus, hedge funds that want to attract additional capital have to improve transparency regarding their risk profiles. There are numerous approaches to evaluate the risk profiles of the hedge fund strategies, proposed by academic literature and practitioners. However, one should proceed with caution when evaluating hedge fund risk profiles as hedge funds may exhibit several properties which violate the assumptions commonly made, e.g. normal distribution assumption and no autocorrelation assumption. Specifically, as hedge funds often hold illiquid positions which are difficult to value on a monthly basis and due to the intentional smoothing arising from lower degrees of transparency, hedge fund returns usually exhibit some degree of autocorrelation. Moreover, in many cases the return distribution is leptokurtic and asymmetric, i.e. has negative skewness and positive excess kurtosis. Furthermore, if one is to identify risk factor exposures of hedge fund strategies, for instance, to make an evaluation of "what-if" scenarios, one can put into contrast the risk exposures identified with quantile regressions versus the ones identified with simple mean linear regressions, in light of unorthodox properties influencing beta estimations.

Therefore, this topic is important mainly to institutional investors in hedge funds and funds of hedge funds that have an interest in evaluating the exposure of hedge fund strategies in a more robust way and building worst case scenarios of their risky investments to complement standard risk measures. The topic is also of interest to hedge fund managers that want to assess and / or market to investors their risk profiles and factor exposures in different performance states.

2 Previous literature

In the academic hedge fund literature that can be related to the topic of this thesis, six sub-areas are identified. First, there is wide contribution to the research area of exploring risk-adjusted performance measures concerning hedge funds (Kaplan and Knowles, 2004; Carretta and Mattarocci, 2013). These papers propose and discuss performance metrics more suitable in case of non-normality in return distributions, i.e. with skewed and / or kurtic characteristics. The evaluation of a given investment strategy can change depending on the risk metric chosen, partially due to sensitivity to distributional characteristics, which leads to an impact on optimal investment decisions. This thesis makes further use of these risk metrics by, first, elaborating on the relationships between implications that can be made from these metrics and specific features of hedge funds across investment strategies, taking orders of shape into consideration, and, second, by contrasting these metrics with the metrics suggested by this thesis, argued to offer a more comprehensive risk assessment of hedge fund strategies.

Second, many authors focus specifically on the tail and downside risk of hedge funds. Liang and Park (2010) construct downside risk metrics that account for higher return moments, i.e. semideviation, Value at Risk, expected shortfall with the Cornish-Fisher expansion and tail risk, in order to predict hedge fund failure. Bollen (2013) finds that diversified portfolios of zero-Rˆ2 funds, given regression models on best subsets of factors identified with stepwise regressions, still exhibit volatility levels which suggest that these do not offer purely idiosyncratic returns and are exposed to more systematic risks. Thus, semblant market neutrality of a huge number of hedge funds as captured by explanatory power measures may tempt investors to think they are less risky, hiding the significant systematic downside risk. He also shows that zero-Rˆ2 funds exhibit a higher probability to fail. Agarwal et al (2017) construct a systematic tail risk measure for equity hedge funds, which captures the joint probability of hedge fund return being in the tail of its distribution, simultaneously with market return being in the tail of its corresponding distribution, adjusted for the severity (magnitude) of hedge fund returns. This thesis extends this literature by offering the risk proxies obtained by applying conditional quantile and conditional stress testing methodologies, conceptually allowing to incorporate multivariate risk factor exposure in the downside state into risk assessment.

Third, another direction of research in the hedge fund literature is identifying and examining the risk factors that the hedge fund industry is exposed to (Fung and Hsieh, 1997, 2001, 2002, 2004; Sadka, 2010; Bali et al, 2014; Buraschi et al, 2014; Agarwal et al, 2017), namely equity market, size spread, interest rates, credit spread, trend following, market liquidity, macroeconomic uncertainty, correlation risk and volatility of volatilities. This thesis contributes to these papers, first, by analyzing the exposure of hedge funds to risk factors across investment strategies, second, by noting the impact of risk factors not only on the conditional expectation of the hedge fund strategy return, but also on the full distribution of returns, and, third, by incorporating relationships between risk factors and risk measurement techniques.

Fourth, many academics and practitioners have been researching the specific features of hedge funds. For example, Getmansky et al (2004) explain autocorrelation found in hedge fund returns by smoothing patterns resulting from illiquidity. Further, Bollen and Pool (2008) using a conditional framework, divide these smoothing patterns into intentional return variability dampening and general hedge fund holding illiquidity. They also construct a statistical screen to help identify suspicious smoothing activity. As another example, Avramov et al (2013) research the return predictability issues in the hedge fund industry, accounting for illiquidity, and find that in sample and out of sample the return predictability is widespread, which may be explained by differences in key hedge fund characteristics such as leverage or capacity constraints. This thesis accounts for the feature of smoothing in hedge fund returns. However, this adjustment is used to compare and contrast risk exposures of hedge fund strategies with and without unsmoothing adjustment. It is also used to contrast the impact of smoothing on OLS regression estimates compared to tail factor exposures.

Fifth, literature applying quantile regressions to hedge fund returns is somewhat sparse. Meligkotsidou et al (2009) is the closest work in spirit to this thesis. They introduce the suggestion to apply quantile regressions across hedge fund strategies to capture differences in risk factor exposures across performance quantiles. They find that these exposures vary substantially along quantiles. Moreover, they use information criteria and the Bayesian framework to select a subset of risk factors which are most relevant for each performance quantile. In addition, Vrontos (2015) applies quantile regressions to assess managerial skill (alpha) and discovers that estimates of managerial skill are superior when one uses the quantile regression framework. This thesis extends these works by first, analyzing specific factor exposure differences across hedge fund investment strategies, second, incorporating specific hedge fund features (i.e. smoothing) in quantile regression analysis and third, by applying quantile regression results to risk measurement, as suggested as a potential further research opportunity by Meligkotsidou et al (2009).

Finally, in light of limitations posed by limited data samples and too strong normal approximation assumption, Chernozhukov et al (2017) propose a method, called extremal quantile regressions, to focus on the tails of the distribution. They set forth the method in univariate and multivariate cases and apply it on the financial time series of individual stocks to estimate Conditional Value at Risk. Since limited data samples and issues with normal approximation assumption are known to be perturbing in the hedge fund industry, this thesis makes use of the extremal quantile regressions method. This contributes, first, to normal quantile regression analysis by modifying standard errors, second, to tail exposure analysis by allowing to evaluate extreme tail exposures with extrapolation, third, to risk measurement, allowing to make inferences across various hedge fund strategies. This in turn reveals whether the extremal quantile regression method adds value in assessing tail exposure and tail risk of hedge fund strategies.

3 Data

3.1 Hedge fund data

Obtaining accurate data that provide a faithful representation of hedge fund strategies is of extreme significance to researchers in the hedge fund industry. There are several commercial databases available that provide hedge fund data (e.g. Hedge Fund Research, Lipper TASS, BarclayHedge, EurekaHedge). These database vendors collect and assimilate fund-level data to then publish hedge fund strategy indices that may be used in the analysis of hedge fund strategies. However, hedge fund managers report their performance to the databases on a voluntary basis. Deliberate reporting implies two potential consequences for the constructed indices. First, unaudited and subjective definitions of hedge fund investment strategies bring about uncertainties in assigning a fund to a particular strategy since several fund managers may define the strategy differently or may pursue various investment strategies within the fund. Second, the whole hedge fund universe within the strategy at any time point cannot be covered by a database and is thus not observable. The second issue leads to a variety of data biases pertinent to hedge fund databases which may result in incomplete statistics and misleading results. As a result, it is useful to be aware of these potential biases and account for them while choosing the dataset for subsequent research. Major hedge fund database biases include the following (Ackerman et al, 1999):

1) Survivorship bias. One should make a distinction between funds that continue reporting to the database (live), funds that have stopped reporting to the database (defunct), and funds that have stopped their operations due to liquidation or bankruptcy (dead). Several databases include information exclusively on operating funds, leaving out defunct funds, which leads to the bias. This bias is relevant to this study as live funds and defunct funds may have different risk characteristics and factor exposures. The fact that live funds and defunct funds (including dead funds) have different characteristics is well documented in the hedge fund literature (Liang, 2000; Lhabitant, 2008; Agarwal and Jorion, 2010; Xu et al, 2011). Thus, implications from this thesis can be affected by the survivorship bias in case the index chosen does not contain data on defunct funds.

2) Liquidation / participation bias. Hedge funds may stop reporting to the database before their final liquidation when they put their efforts into closing the remaining operations, leading to the liquidation bias. On the contrary, after proving their quality with successful performance to the investment community and attracting large inflows of asset under management which may create size constraints, several managers may close their funds to outside investors and cease reporting to the database, leading to the participation bias. Both issues are relevant to this study as they may cause an unjustifiable picture of defunct fund true risk exposures. Again, conclusions drawn from

this thesis can be hurt if the index chosen does not contain accurate and timely data on defunct funds.

3) Self-selection bias. Since reporting to commercial databases is voluntary, hedge fund managers have the possibility to choose whether they wish to report to the database. Indeed, several managers report to the database when their results are positive and avoid reporting when their results are negative (Fung and Hsieh, 2004). It would be equally justified if managers chose to report when the perceived riskiness of their fund was low and declined to report when it was high. On the other hand, managers may also avoid reporting if they want to keep their investment strategies protected. The funds run by these managers may also have uncommon risk levels or factor exposures. This issue is likely to remain unsolved regardless of the index chosen in this thesis as no commercial database is able to require funds to report since inception up until liquidation.

4) Instant history (backfill) bias. During the initial incubation period, managers are mainly provided with the initial (seed) capital to run their hedge funds. If the manager's strategy fails and / or is too risky, the fund is usually liquidated, never showing up in the database. However, if the hedge fund proves its quality with positive performance, it usually proceeds to reporting to the database in order to attract capital when it becomes publicly offered. The database vendor, in turn, may backfill the historic performance of this more successful fund, introducing the instant history bias. This bias is relevant to this study as intentional smoothing may be even a more aggravated concern for backfilled historical returns, resulting in distorted risk metrics. Unless the index without backfilled data is chosen, conclusions from this thesis may be less reliable.

Moreover, it may well be that the impact of the aforementioned biases across hedge fund strategies is different, as pointed out by Liang (2000) and Edwards and Caglayan (2001), which may lead to imprecisions not only in absolute values of risk metrics and exposures, but also in relative rankings of strategies. Thus, the choice of the database used in this thesis is made to account for the existence of these biases. This thesis uses the hedge fund strategy index data obtained from Hedge Fund Research (HFR). First, HFR takes care of the survivorship bias because it includes the track record of the defunct funds that remain in the index for perpetuity. Second, HFR mitigates the liquidation / participation bias by actively contacting funds which stopped reporting returns in order to obtain the data. If the contacting efforts are not successful, HFR seeks to get the needed data from investors. Finally, HFR tracks information about the date when hedge funds joined the database so as to allow them to start reporting only beginning from the month after they are admitted to the index, solving the instant history bias. One should be cautious, however, since even with such efforts it is not possible to completely eliminate data biases as shown by underperformance of investable hedge fund indices compared to their non-investable counterparts. As an evidence, the main investable HFRX Global Hedge Fund Index, which is free of biases by its very nature, underperformed the non-investable HFRI Fund Weighted Composite Index by 5.6% on average per annum from 2003 to 2011 (Financial Times, 2011).

This study uses HFRI indices downloaded from HFR. HFRI are monthly equally-weighted indices established to capture the performance across investment styles as well as geographies and serve as industry benchmarks. HFRI indices are commonly known as hedge fund industry standards. As HFRI indices are equally-weighted, the strategy performance is not skewed towards larger funds. Indices are updated 3 times per month. To be included in the HFRI index, the fund has to fulfill several criteria, i.e. report monthly returns net of fees and in USD as well as have at least $50m AUM or have been actively trading for at least 12 months. HFR seeks to collect fund performance data that would be experienced by a typical investor. In case a fund manager reports data on mirror-performance funds, HFR only includes the fund with the larger AUM. In addition, funds can contribute data to more than one index. However, constituent funds may be included in only 1 index at the sub-strategy-level. For example, an equity market neutral hedge fund focused on investments in Brazilian equities will be included in Equity Hedge Total strategy index, Equity Market Neutral sub-strategy index, Emerging Markets Total strategy index, Latin America sub-strategy index and Fund Weighted Composite index. As noted above, HFRI indices are non-investable and thus to some extent contain hedge fund data biases. Nevertheless, this thesis prioritizes larger hedge fund constituent universe, longer historical data and greater variety of strategies, characteristic of HFRI indices. HFRI index values and returns are collected every month, net of fees, with asset values reported in USD. The dataset used in this thesis includes 276 observations of monthly returns of 22 hedge fund strategy indices over the period January 1994 - December 2016.

Similar to the methodology employed by HFR, hedge fund strategy indices are further classified as follows:

1) Equity Hedge strategies: Equity Market Neutral, Quantitative Directional, Short Bias, Equity Hedge Total.

2) Event Driven strategies: Distressed / Restructuring, Merger Arbitrage, Event-Driven Total.

3) Macro strategies: Macro Total, Macro Systematic Diversified.

4) Relative Value strategies: Relative Value Total, Fixed Income-Asset Backed, Fixed Income-Convertible Arbitrage, Fixed Income-Corporate, Multi-Strategy, Yield Alternatives.

5) Fund Of Hedge Funds strategies: Conservative, Diversified, Market Defensive, Strategic, Fund of Funds Composite.

Additionally, Fund Weighted Composite Index will act as a benchmark for hedge fund industry performance whereas Emerging Markets Total will reveal features of funds with the regional focus targeted at emerging markets. Detailed strategy descriptions are presented in Appendix 1.

3.2 Summary statistics

Appendix 2 provides summary statistics of hedge fund returns across investment strategies. The short bias strategy is the only one with a negative mean. Over the analyzed period there were more upward market movements than downward movements which explains the negative mean return for the strategy that maintains net short exposure. In addition, since funds of hedge funds impose an additional layer of fees, their net-of-fees performance is worse than that of hedge funds.

The short bias strategy shows the highest monthly volatility. This can be related to its consistent short exposure which may probably be regarded as a riskier "bet" than a long position since if the manager is wrong, the downside is unlimited. Also, the emerging markets strategy shows a high volatility which can be explained by investments often exposed to very risky assets. The equity market neutral strategy turned out to be the least volatile strategy, possibly thanks to its low net long or short exposure as well as neutrality to market factors. Besides, maximum drawdown estimates are used to complement volatilities in this thesis. This measure is the maximum negative drop during the negative period and is commonly used in practice as it is not connected to investor's structure of preference (Cogneau et al, 2013). The short bias strategy also experienced the highest maximum drawdown, in line with the highest volatility.

Since most hedge fund strategies are to a large extent related to the equity market which has negative skewness as well as exhibit non-linearities using the dynamic trading strategies, one could expect hedge fund returns to exhibit negative skewness. Indeed, hedge fund returns show negative skewness except for the short bias (mirroring the market with their short exposure), market defensive (investing in short strategies) and macro (trading on movements in macroeconomic variables rather than equities) strategies. Relative value strategies exhibit the most negative skewness. These funds identify security mispricings and place bets on differences in prices between related securities. In most cases these bets will succeed but in the case of a failure will result in large losses.

As hedge funds invest vastly in equity markets, employ leverage, and possess inherent non-linearities, most hedge fund returns are leptokurtic. The macro strategies exhibit lower kurtosis as these strategies follow macro factors carefully and adjust the exposure thereafter, producing an insurance effect mitigating the kurtosis of the return distribution.

Bera-Jarque tests for non-normality depict that most hedge fund strategy return time series do not satisfy the normal distribution assumption. In most cases these non-normal distributions are caused by negative skewness and fat tails, undesirable for hedge fund investors as a rational investor would prefer positive odd moments such as mean and skewness and avoid positive even moments such as variance and excess kurtosis (Siragusa, 2013). The only exceptions are market defensive and macro systematic diversified strategies which both have jointly insignificant skewness and excess kurtosis. Generally speaking, descriptive statistics in this study resemble results from Meligkotsidou et al (2009).

The results of augmented Dickey-Fuller tests for a unit root in a univariate time series of each strategy returns, indicate that these tests reject the null hypothesis of a unit root, i.e. the series are stationary. Thus, hedge fund strategy returns are used in the subsequent analysis.

It is important to identify the dates of worst historical returns for hedge funds to make inferences about the nature of unfavorable events and possible magnitudes of negative returns. As shown in Appendix 3, the worst hedge fund industry return was observed in August 1998, associated with the fall of LTCM which shook financial markets. This month was also the worst for most hedge fund strategies. Several strategies, on the other hand, suffered the most in September - November 2008. This period relates to the critical stage of the subprime mortgage crisis with vanished liquidity, Fannie Mae and Freddie Mac under conservatorship and the Lehman bankruptcy. However, there are a few notable exceptions. First, the worst month for the macro strategy was February 1994. In February 1994 interest rates were increased unexpectedly by 25 bps, resulting in major losses for several global macro funds (Sokolowska, 2015). This proves the effect of unexpected macroeconomic policy changes on this strategy. Second, November 2007 was the worst period for the macro systematic diversified strategy. The month evidenced reversals in currency, oil and equity markets (Eurekahedge, 2007). As there are more funds within this strategy which use the trend following style than reversing style, these reversals hurt strategy performance. Magnitudes of worst performances also vary by strategy. The worst return for the hedge fund industry was -8.7%. Milder failures are associated with more defensive strategies, e.g. equity market neutral, macro and market defensive funds of funds strategies. More disastrous months can be found for emerging markets, short bias and convertible arbitrage strategies that are typically known to be riskier.

3.3 Standard risk metrics in hedge fund industry

The academic literature that constructs and compares risk metrics in the hedge fund industry is extensive. Risk proxies have evolved from standard Gaussian volatility measures to more complex metrics as required by the sophisticated investment community in the non-Gaussian world. Risk metrics are generally found in denominators of risk-adjusted performance measures profoundly studied in the literature (Kaplan and Knowles, 2004; Carretta and Mattarocci, 2013). An overview of a selection of these measures is presented in Appendix 4 (denominators only).

If hedge fund strategies considered had been well described by the normal distribution, the standard deviation would have been an adequate measure to evaluate riskiness. However, given the general nature of hedge fund strategy returns, the Gaussian distribution is far from suitable. This can lead to invalid conclusions when only taking the standard deviation into consideration. Higher order moments have a material impact on standard risk metrics used in the hedge fund industry (Appendix 5). As illustrated by Figure 1 and Figure 2, third and fourth order kappa metrics for all strategies exceed corresponding second order kappa measures as second order metrics are amplified by the higher power by definition. It is of higher interest to evaluate the relevance of risk metrics of different order for strategies based on distributional characteristics. The third order kappa risk metric considers skewness while the fourth order metric considers kurtosis

(Kaplan and Knowles 2004). When analyzing strategies of similar second order kappa metrics, it appears that the ones with more extreme skewness are subject to a more extreme amplification of the third order metric. The fixed income-corporate and macro systematic diversified strategies are, for example, judged similarly by the second order kappa metric. However, the more extremely skewed fixed income-corporate strategy is more risky considering the third order kappa metric. Similarly, whereas conservative funds of funds and fixed income-asset backed strategies exhibit comparable second order kappa metrics, the first one with skewness of -1.70 has lower third order kappa, the second one with skewness of -3.42 has a higher third order kappa.

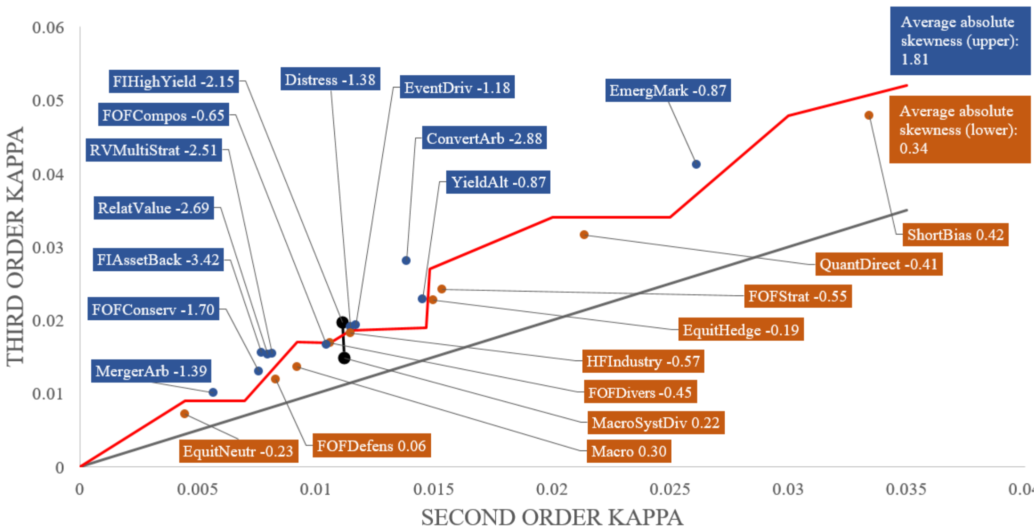


Figure 1: Second and third order kappa metrics. Data points represent a third order kappa metric (y-axis) and a second order kappa metric (x-axis), with corresponding labels of strategy name and skewness. Dark gray line is a reference 45 degree line showing equal third and second order kappas, highlighting the magnitude between third and second order kappas. Red line splits the strategies that are relatively more skewed (blue) from ones that have relatively less skewed (orange). Average absolute skewness is presented for both the strategies above (blue) and below (orange) the red line. Average absolute skewness is used since deviations from zero are characterizing non-normality. Strategies connected by a black line are an example of two strategies with similar second order kappa, as discussed further in the text.

The same applies to the fourth order kappa metric where higher kurtosis amplifies the fourth order metric compared to the second order kappa. For instance, the fixed income-corporate strategy is more extreme in terms of excess kurtosis than the macro systematic diversified strategy and is hence also judged riskier than the macro systematic diversified strategy by the fourth order kappa metric. In addition, while the conservative fund of funds and fixed income asset-backed strategies have similar values of second order kappa metrics, the conservative funds of funds with excess kurtosis of 7.57 has lower fourth order kappa than the fixed income asset-backed with excess kurtosis of 24.11.

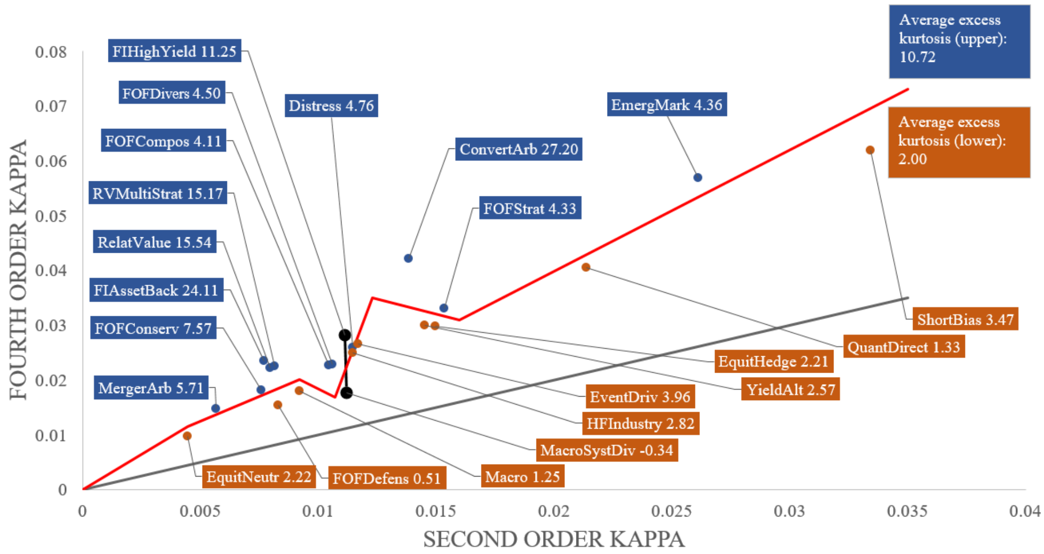


Figure 2: Second and fourth order kappa metrics. Data points represent a fourth order kappa metric (y-axis) and a second order kappa metric (x-axis), with corresponding labels of strategy name and excess kurtosis. Dark gray line is a reference 45 degree line showing equal fourth and second order kappas, highlighting the magnitude between fourth and second order kappas. Red line splits the strategies that have relatively higher excess kurtosis (blue) from strategies with lower excess kurtosis (orange). Average excess kurtosis is presented for both the strategies above (blue) and below (orange) the red line. Strategies connected by a black line are an example of two strategies with similar second order kappa, as discussed further in the text.

These patterns are consistent across hedge fund strategies. It is thus inferred that, first, strategies with more prominently skewed returns are judged more risky by the third order kappa metric and, second, strategies possessing a more leptokurtic nature of returns are judged more risky by the fourth order kappa metric.

Additionally, Value at Risk and Conditional Value at Risk are estimated based on the simple historical simulation. Historical simulations are based on the comprehensive search stress testing method which compiles all historical returns of the hedge fund strategy, i.e. approximates the empirical distribution of the hedge fund strategy returns using historical data, and computes the 5% and the 1% percentile of the obtained distribution in order to estimate Value at Risk. The 5% percentile is commonly used in the evaluation of the hedge fund industry (Guizot, 2007). In addition, the 1% percentile is used in order to gauge the extreme riskiness of hedge fund strategies. Then all historical observations for which the hedge fund strategy return is lower than the Value at Risk threshold are averaged to obtain Conditional Value at Risk, i.e. the expected tail loss.

5% and 1% historical Value at Risk estimates (Appendix 6) show that magnitudes of losses at the respective percentile thresholds are widely different across strategies. For example, the equity market neutral strategy has the lowest historical Value at Risk of 0.94% for the 5% threshold and 2.53% for the 1% threshold. The short bias strategy is in the opposite end of the spectra with a 5% Value at Risk of 7.38% and a 1% Value at Risk of 12.30%. The patterns are similar when comparing historical Value at Risk thresholds with standard deviations where the short bias strategy is the most risky while the equity market neutral strategy is the least.

It is interesting to highlight differences between Value at Risk and Conditional Value at Risk measures. For example, while the Value at Risk is higher for the macro investment strategy than for the convertible arbitrage strategy, the relationship is reversed for the expected tail loss, which is higher for the convertible arbitrage strategy. This indicates that once ending up in the tail observing extreme returns, the outcome will on average be worse for the convertible arbitrage strategy. Hence, for this strategy beyond the threshold outlier observations are further away from the threshold. In fact, when convertible arbitrage trades fail, they are known to produce extreme losses. For macro strategies, expected tail losses are low compared to threshold Value at Risk values, meaning that extreme losses on average were of relatively low magnitude.

One should note that 1% tail Value at Risk and Conditional Value at Risk values are highly dependent on the nature of the lowest few values of return distributions because of data scarcity. One should therefore use caution when drawing conclusions from 1% Value at Risk and Conditional Value at Risk measures.

3.4 Factor description and construction

The literature examining risk factors that are able to explain hedge fund returns is vast. Choosing the set of adequate risk factors for the regression model is a concern of growing discussion in the hedge fund literature. Developing a complete set of risk factors that explain hedge fund returns is a Sisyphean task and thus it is important to use the most relevant factors as proposed by the literature. This thesis uses various risk factors put forward by Fung and Hsieh (2004), namely equity market risk factor, size spread risk factor, trend-following risk-factor, bond risk factor, credit spread risk factor, as well as liquidity risk factor investigated by Sadka (2010) and volatility of aggregate volatility risk factor discovered by Agarwal et al (2017). However, rather than studying the impact of these factors on the cross-sectional differences in fund returns, the focus of this thesis is put on the differences of risk exposures across strategies and the corresponding risk management implications.

Most hedge fund strategies have equity exposure, i.e. stock market exposure (Fung and Hsieh, 2004). Therefore, this thesis uses the equity market factor, which corresponds to monthly S&P 500 index total returns. Additionally, many strategies are found to exhibit size spread exposure. For instance, equity long-short funds are prone to have long exposure to small capital stocks and short exposure to large capital stock (Fung and Hsieh, 2004). Thus, this thesis uses the size spread factor, which corresponds to the spread between monthly Russell 2000 index total returns (small cap proxy) and S&P 500 index total returns (large cap proxy). Total return indices are obtained from Datastream, in order to calculate two risk factor realizations at each month.

Commonly, several fixed income hedge fund strategies buy illiquid bonds of lower credit rating and then hedge the interest rate risk with short positions in treasury bonds that are of higher credit rating as well as liquidity level (Fung and Hsieh, 2004). The credit spread would be the corresponding difference between the yields of the two bonds.

Furthermore, the credit spread comes into play when taking into consideration the often highly levered positions of, for instance, fixed income arbitrage funds (Fung and Hsieh, 2004). Thus, this thesis uses the credit spread factor, which is defined as the change in the spread between the Moody's Investors Service Baa yield (high credit risk proxy) and the constant 10-year maturity treasury bond yield (low credit risk proxy). In addition, fixed income hedge fund strategies commonly have exposure to interest rate movements. Therefore, this thesis uses the bond factor, which corresponds to the change in the constant 10-year maturity treasury bond yield. Bond yields are retrieved from the Federal Reserve Board and the Federal Reserve Bank of St. Louis, in order to calculate two risk factor realizations at each month.

Trend-following funds typically found in macro hedge fund strategies have trend following exposure (Fung and Hsieh, 1997, 2001, 2004). Therefore, this thesis uses common trend following factors, which correspond to option lookback straddle returns. Lookback straddles imitate the perfect trend follower, i.e. one that buys at the minimum price and sells at the maximum price during a given horizon. In short, the common description of the trend following strategy is "buying breakouts and selling breakdowns". Fung and Hsieh (1997, 2001) found lookback straddles on bonds, currencies and commodities to be statistically significant factors. Trend following risk factors on bonds, currencies and commodities are retrieved from David A. Hsieh's data library and averaged to get one risk factor representing trend following style.

Hedge funds are found to be generally negatively exposed to uncertainty in stock market volatility (Agarwal et al, 2017). Swings in volatilities are typically unfavorable for hedge funds. Agarwal et al (2017) construct the volatility of aggregate volatility risk factor, which is composed of monthly returns on lookback straddles on the volatility index (VIX). The volatility of volatilities straddle offers its holder the benefit from significant deviations in the fear index VIX and, similarly to the Fung and Hsieh (1997, 2001) lookback options, provides a payoff corresponding to the range of the VIX during the option lifetime. Agarwal et al (2017) proved that the exposure to this factor has significant explanatory value for hedge fund returns. As data to construct lookback straddles on VIX are difficult to obtain, this thesis uses the statistical proxy for these straddles (monthly VIX range). Agarwal et al (2017) outlined that the usage of this proxy is warranted since monthly VIX range is highly correlated with lookback straddle returns on VIX. VIX data are downloaded from CBOE, in order to calculate monthly VIX ranges at each month.

Typically, hedge funds experience hard times in periods of market liquidity drying up (Sadka, 2010). Therefore, this thesis uses the systematic risk factor in the form of market-wide liquidity. The factor used is described by Pastor and Stambaugh (2003) as the monthly measure of market liquidity, which is equal to the equally weighted liquidities of individual stocks traded on the NYSE. Liquidity measures are based on the return effects from reversing a stock position and thus captures the magnitude of order flows of individual stocks. The liquidity risk factor is obtained from Lubos Pastor's Chicago Booth webpage.

4 Methodology

4.1 Return unsmoothing

Hedge fund return time series possess several properties that may distort inferences made with different types of statistical analyses. Serial correlation in hedge fund returns is one of these undesirable properties. The fact that there is autocorrelation in returns of several hedge fund strategies is well documented in the literature (Brooks and Kat, 2002). Since hedge fund strategy index data are used in this thesis, it is worth noting that aggregation of funds with autocorrelated returns to an index level will generally result in an index with autocorrelated returns, too, whereas several funds within the strategy may be free of autocorrelation even when the strategy index exhibits autocorrelation (Getmansky et al, 2004). Thus, while the primary focus of this thesis is to identify patterns on a strategy level, it is possible that several funds within the particular strategy show a different autocorrelation behavior.

Sources of autocorrelation include, among others, time-varying leverage, time-varying expected returns, incentive fee structure with high watermarks, illiquid holdings of hedge funds and intentional performance smoothing, with the last two being the two major reasons since the serial collection of the magnitudes found in the hedge fund industry cannot be explained by the first three factors, all of which may cause serial correlation but of a much milder level (Getmansky et al, 2004). Some researchers, who concentrate mainly on illiquid holdings (Getmansky et al, 2004), assert that illiquidity may stem from the non-synchronous trading effects, from marking holdings to linearly extrapolated transaction prices when these holdings were not traded on the market and thus market prices were stale, i.e. not readily available, from trading limitations enforced by control positions and various regulatory requirements, and from averaging quotes obtained from brokers who may in turn use linear extrapolations in the absence of market prices. Moreover, Semmler et al (2013) claim that these illiquid holdings can be explained by lock-in periods and other restrictions which allow hedge fund managers, unlike mutual fund managers, to invest in more illiquid assets. Worth noting, these types of illiquidity relate to asset specific illiquidity, rather than market illiquidity described in Section 3.3. Others, who analyze purposeful return smoothing (Bollen and Pool, 2008), suggest that due to the incentive structures for hedge fund managers as well as the general competitive pressure in the industry, managers may be inclined to smooth returns to reduce the apparent volatility and the perceived riskiness of their strategy, which may also result in fraud cases. Nevertheless, although one might think the autocorrelation derives from performance persistence rather than illiquid holdings and return smoothing, it is shown in the literature (Agarwal and Naik, 2000, Brown et al, 1999) that winners repeat only at short-term frequencies, with no evidence of long-term performance persistence.

Several types of autocorrelation analysis are performed in this thesis. First, autocorrelation (ACF) and partial autocorrelation (PACF) functions are carefully inspected for each strategy to visually identify whether the times series of hedge fund strategy returns are autocorrelated. Second, in order to use a more formal test, Ljung-Box test p-values up to lag five (representing autocorrelations up to fifth month back in time) are plotted against the specified threshold of 5%, commonly used for such tests.

Autocorrelation in hedge fund returns leads to undesirable statistical, economic and econometric properties. First, it creates a downward bias of the computed return volatility. Thus, hedge fund strategies which exhibit serial correlation in their returns would tend to underestimate their inherent riskiness and would hence wrongfully appear more attractive to investors. Second, it pushes market betas of serially correlated strategy returns towards zero, creating an illusion that the strategy is market neutral whereas in reality it may still be highly dependent on the market factor. However, in regressions this dependence would manifest in betas on lagged market factors (which are rarely included in the analysis in practice), rather than on contemporaneous market factors. That may be the reason why lagged market returns often exhibit significance in explaining current returns of supposedly market-neutral strategies (Asness et al, 2001). Third, the coefficient estimates obtained using regression analysis tools (such as OLS) become inefficient, i.e. these estimates do not have the lowest variance anymore, standard error estimates become wrong, impacting the factor statistical significance tests, and explanatory power of the regression becomes incorrectly estimated since the true error variance is different (Brooks, 2014).

There are several ways to account for serial correlation in hedge fund returns, with lagged market factor adjustments (Asness et al, 2001; Malkiel and Saha, 2005), with the autoregressive approach (Okunev and White, 2003) and the moving approach (Getmansky et al, 2004) being the most widely used in the hedge fund literature. The method based on lagged market factor adjustments may be counter-intuitive for hedge fund strategies that are less dependent on the equity market. Hence, it is argued that since the market factor may not be the most appropriate one for certain strategies and styles (e.g. non-equity-oriented strategies), adjusting regressions with a lagged market factor might not fully account for the effect of illiquidity and return smoothing (Getmansky et al, 2004). On the other hand, the results obtained while using both autoregressive and moving average approaches are similar (Cavenaile et al, 2011). For this reason, in this thesis only one (the moving average) approach is used. According to this approach, the information set which impacts the hedge fund's return in period t may not be fully reflected in the current observed return but will be partly reflected in the current observed return and partly in the observed returns of the next periods, where the number of such periods depends on the number of lags. It means that the impact of some information is delayed to the next periods. The approach is intuitive for two reasons. First, even extremely illiquid holdings eventually end up in the market when the cumulative information set finally gets reflected in the market price and in the return. Second, purposeful performance smoothing is not eternal due to strict supervision by regulators, investors and auditors, especially following the great recession.

Econometrically, the assumption is that the observed hedge fund returns represent a weighted average of past and current "true" unobservable independent and identically distributed returns:

$$(Eq.1.1): \ r_t^0 = \theta_0 \cdot \eta_t + \theta_1 \cdot \eta_{t-1} + ... + \theta_q \cdot \eta_{q-1}$$

where r_t^0 - observed return, η - "true" unobservable return, θ - weight coefficient

Such that

$$(Eq.1.2) : \theta_j \in [0,1], j = 0, ..., q$$
$$(Eq.1.3) : \theta_0 + \theta_1 + ... + \theta_q = 1$$

Essentially, after the procedure of de-meaning the observed returns, one gets a moving average process:

$$(Eq.1.4) : \ X_t = r_t^o - \bar{r^o}$$

where X_t - de-meaned observed return, $\bar{r^o}$ - mean of observed returns

$$(Eq.1.5) : \ X_t = \theta_0 \cdot e_t + \theta_1 \cdot e_{t-1} + ... + \theta_q \cdot e_{q-1}$$

where e - de-meaned "true" unobservable return, θ - moving average process MA(q) coefficient

In order to objectively choose the actual lag length of the moving average process for each strategy return time series, information criteria are used. The number of lags is chosen so as to minimize the information criterion value. The intuition behind using this method is that adding a new lag decreases the residual sum of squares of the model but at the same time introduces a penalty for the loss of the degrees of freedom due to adding extra parameters. It is argued in the literature that there are three information criteria that are the most widely used - the Akaike information criterion, the Schwarz-Bayesian information criterion and the Hannan-Quinn information criterion (Brooks, 2014). These three information criteria are computed for the different sets of moving average models up to five lags. The results obtained with information criteria are compared with the graphical analysis of ACFs and PACFs to determine the criterion used in this thesis.

Having chosen the optimal number of lags, according to the approach, the condition that the moving average coefficients should sum up to one (instead of the normalization that $\theta_0 = 1$) is imposed, which is reasonable as it means that smoothing only happens over the most recent periods and all information is reflected in those periods. For that reason the more standard moving average coefficients with the normalization that $\theta_0 = 1$ are transformed into the desired ones by dividing each standardly estimated coefficient by the sum of standardly estimated coefficients. It is also ensured the maximum likelihood estimates yield an invertible moving average process.

The "true" demeaned unobserved returns are estimated as follows, for example, for the

MA(2) process, which is the process found to be the best in hedge fund return unsmoothing (Getmansky et al, 2004). The process has the following general form:

$$(Eq.2.1): \; X_t = \theta_0 \cdot e_t + \theta_1 \cdot e_{t-1} + \theta_2 \cdot e_{t-2}$$

The first unsmoothed "true" demeaned return (the one in January 1994) is simply the first original observed demeaned return divided by θ_0, capturing the fact that the certain part of this first unsmoothed "true" demeaned return will be reflected in the next periods only:

$$(Eq.2.2): X_1 = \theta_0 \cdot e_t$$
$$(Eq.2.3): e_1 = \frac{X_1}{\theta_0}$$

The second unsmoothed "true" demeaned return (in February 1994) is estimated, using the information about the previous "true" demeaned return, the second original observed demeaned return and the moving average coefficient estimates:

$$(Eq.2.4): X_2 = \theta_0 \cdot e_2 + \theta_1 \cdot e_1$$
$$(Eq.2.5): \theta_0 \cdot e_2 = X_2 - \theta_1 \cdot e_1$$
$$(Eq.2.6): e_2 = \frac{(X_2 - \theta_1 \cdot e_1)}{\theta_0}$$

The third (in March 1994) and subsequent unsmoothed "true" demeaned return are calculated in the similar way, using all moving average coefficient estimates:

$$(Eq.2.7): X_3 = \theta_0 \cdot e_3 + \theta_1 \cdot e_2 + \theta_2 \cdot e_1$$
$$(Eq.2.8): \theta_0 \cdot e_3 = X_3 - \theta_1 \cdot e_2 - \theta_2 \cdot e_1$$
$$(Eq.2.9): e_3 = \frac{(X_3 - \theta_1 \cdot e_2 - \theta_2 \cdot e_1)}{\theta_0}$$

One should note that the model for unsmoothing used in this thesis is unconditional. Besides, one has to note that although the maximum likelihood estimator used to estimate the moving average process has desirable statistical properties in the sense that it is asymptotically efficient and consistent, it may not perform equally well in small samples. Since the hedge fund index data are monthly, the sample size is rather small. Additionally, the moving average process assumes that the "true" unobservable returns are normally distributed: e_t ~N(0,σ^2). However, hedge fund returns are shown to have non-normal distributions, often with negative skewness and positive excess kurtosis.

Furthermore, what is worth noting is that the literature asserts that the aggregation of a set of illiquid hedge funds on a strategy level will generally yield a strategy index which will be illiquid as well (smoothed returns), the opposite might not always be true so that if the index returns are found to be smoothed, it need not imply all hedge funds pursuing the strategy are illiquid (Getmansky et al, 2004). Since this thesis uses the data on a strategy (index) level, this caution is relevant.

4.2 Best subset regression

As noted in Section 3.4, academic researchers have identified numerous factors which are able to partly explain hedge fund returns. However, it should also be noted that hedge fund strategies are not homogeneous and differ heavily, for example, in focus on asset classes (equities, bonds, commodities, currencies), in trade idea generation method (bottom-up, top-down), in trading approach (systematic, discretionary), in style (event-driven, equity hedge, macro, relative value, multistrategy) etc. Hence, it may be reasonable that the set of factors affecting hedge fund returns is different across strategies. At the same time, in a lot of cases hedge fund strategy returns may be more parsimoniously explained by using only a subset of all available factors that impact this particular strategy. Furthermore, it is argued that it is undesirable to retain irrelevant explanatory variables in the final model specification as the resultant model loses explanatory power and becomes difficult to interpret meaningfully (Wu and Liu, 2009). There are two primary methods to select a subset of factors, namely the best subset regression method and the stepwise regression method (Liang, 1999; Agarwal and Naik, 2004; Titman and Tiu, 2011; Bollen, 2013). This thesis uses the best subset regression method to identify these subsets of factors for each strategy thanks to its straightforwardness.

Since the total number of factors used in this thesis is seven and multicollinearity is not a characteristic feature of these factors, the branch-and-bound combinatorial algorithm is used in this thesis. The branch-and-bound method is applied to identify the model with the minimized residual sum of squares (Land and Doig, 1960). The branch-and-bound algorithm is implemented in many statistical programming languages.

In order to choose the best subset regression, 252 monthly observations are used for model estimation and 24 observations are kept for testing the models and computing residual sums of squares. This specific choice is made to account for the trade-off between the statistical need to have as many observations for modelling as possible and the need to leave a meaningful number of observations for the test so that the testing results are not severely impacted by the particular period of the test. The maximum number of factors for each strategy is constrained to three to have a balance between a parsimonious model and a high explanatory power and to be in line with previous literature (Titman and Tiu, 2011; Bollen, 2013).

One has to note though that the limitation of this method is the normal distribution assumption. As discussed previously, this assumption is inappropriate in the context of hedge funds returns.

4.3 OLS regression analysis

Hedge fund investors continuously gauge the exposure of various hedge fund strategies to market risk factors. The basic method to analyze the relationship between hedge fund strategy returns and explanatory factors is the ordinary least square regression (OLS). The essence of the classical linear regression OLS method is to minimize the sum of squared residuals in order to estimate the conditional mean of the returns. The conditional mean is modelled by specifying:

$$(Eq.3.1): \ E[y|x] = \alpha + \beta \cdot x_i$$

where y - hedge fund strategy return, β - risk factor exposure, x - risk factor

To get the unconditional population beta coefficient, squared differences are minimized:

$$(Eq.3.2): \hat{\beta} = \arg \underset{\beta}{min} \sum_{i=1}^{n} (y_i - x_i \cdot \beta)^2$$

where $\hat{\beta}$ - OLS risk factor exposure

4.3.1 OLS criticism

While the OLS method is usually the preferred one in practice thanks to its simplicity and straightforward intuition, it describes exclusively the conditional mean of the underlying hedge fund strategy return distribution and is susceptible to several assumptions.

First, the OLS method models the average relationship between hedge fund returns and risk factors. The average exposure tells the investor "the average body temperature across the hospital, which can be perfect (36.6), where one patient can have 30.0 degrees celsius while another 43.2 degrees celsius". However, one might be interested in modelling the impact of risk factors on the entire return distribution, rather than on its mean. This is particularly useful since hedge fund returns deviate largely from the normal distribution. In the presence of these non-normalities, the OLS method might provide estimates which would would not be robust for the entire return distribution (Meligkotsidou et al, 2009). The intuition is that the linear OLS method is fragile when one or more outliers are present in the data. As hedge fund strategies have experienced both extreme positive and negative returns over their history, outliers in their distributions are common.

Second, for risk management purposes, one might be primarily interested in the tail relationship between hedge fund returns and risk factors. Whereas the strategy may be mildly exposed to risk factors on average, in the tail it may hugely exposed to these risk factors, leading to the patterns which shock the investors. It may thus be undesirable to focus solely on the average relationships provided by the OLS method.

Third, the OLS method rests on econometric assumptions that may not be validated by the data. For instance, one of the OLS assumptions is the assumption of homoscedasticity. It means that the variance of the regression errors is assumed to be constant over time. However, this strong assumption may be violated for the regressions of hedge funds returns on risk factors, possibly due to the dynamic nature of the trading strategies. If the assumption of homoscedasticity is violated, the OLS estimator is no longer efficient (Brooks, 2014). One method to account for heteroscedasticity is to use "sandwich" (heteroscedasticity-robust) standard errors. This method is used in this thesis to make inferences about the statistical significance of factor betas. Another method is to use another approach which accounts for heteroscedasticity by definition, presented in Section 4.4.

4.4 Quantile regression analysis

In light of the deficiencies highlighted in Section 4.3 the quantile regression analysis (Koenker and Bassett, 1978) serves as a useful tool to remedy the OLS drawbacks. The quantile regression method assists in uncovering differences in factor exposures across the entire distribution of hedge fund strategy returns (Meligkotsidou et al, 2009). It provides a more comprehensive and sophisticated picture because one is able to focus on the quantiles of interest and draw conclusions about factor exposures in more negative, median and more positive hedge fund return quantiles. The mechanism of the quantile regression method minimizes the asymmetric loss function (symmetric for the median case) to determine the sample quantile of interest. The conditional quantiles are modelled by specifying:

$$(Eq.4.1): \ Q_\tau[y|x] = \alpha(\tau) + \beta_\tau \cdot x_i$$

where $\alpha(\tau)$ - intercepts (alphas) across performance quantiles for τ between 0 and 1, β_τ - risk factor exposures across performance quantiles, x_i - risk factors

The quantile regression method allows to estimate factor exposures across quantiles (the quantile regression estimator), using the quantile regression loss function and minimizing the following objective function:

$$(Eq.4.2): \ Q(\beta_\tau) = \sum_{i:y_1 \geq x_i \cdot \beta}^{N} \tau|y_i - x_i \cdot \beta_\tau| \quad + \sum_{i:y_1 < x_i \cdot \beta}^{N} (1-\tau)|y_i - x_i \cdot \beta_\tau|$$

One shall note that there are multiple ways to choose a subset of risk factors for quantile regressions. For instance, Meligkotsidou et al (2009) propose to use the Akaike information criterion, the Schwarz-Bayesian information and the Bayesian framework to identify a subset of factors for each analyzed quantile. In this thesis, however, a simpler best subset regression method applied to the OLS framework is carried over to identify a subset of factors used subsequently in both OLS and quantile regression analysis. In this way, having the same subset of factors, a direct comparison in risk factor exposures will be possible and the risk measurement framework will be more consistent. The alternative option to include all risk factors for the quantile regression method ("kitchen sink" regression) is inspected in the robustness checks.

There are several options to choose from regarding standard errors of the quantile regression coefficient estimates - rank standard errors (with independently and identically distributed (i.i.d.) or non-i.i.d. errors), i.i.d. standard errors, Hendricks-Koenker "sandwich" standard errors, Powell "sandwich" standard errors. Rank standard errors produce confidence bounds by inverting a rank test. I.i.d. standard errors come from an estimation of the asymptotic variance-covariance matrix assuming that errors are i.i.d. Hendricks-Koenker "sandwich" standard errors assume conditional quantiles of dependent variables given independent variables are linear at quantiles around tau. Powell "sandwich" standard errors are based on the kernel estimator (Powell, 1991). Powell "sandwich" standard errors are used in this thesis. Alternative standard error choices are inspected in the robustness checks.

Compared to the OLS method, the quantile regression method is more robust. First, by definition it partly accounts for non-normalities and outliers found in the hedge fund strategy returns by modelling more extreme quantiles along with more centered quantiles. It is argued therefore that quantile estimators are less impacted by outlying observations in returns conditional on the explanatory covariates. Second, it is useful for risk management purposes (Allen et al, 2013) as modeling lower tails quantifies the tail risk. By specifying the extreme negative quantile of interest, one is able to directly observe the relationships between hedge fund returns and risk factors in this particular quantile. Finally, the quantile regression method is robust to heteroscedasticity as covariates are allowed to exert an effect both on the dispersion of returns and their location. On the other hand, there still are several issues with the approach carried over from the OLS method. For instance, the assumption of the correctly specified model is made, which is a very strong assumption in a hedge fund context.

4.4.1 Extremal quantile regressions

Despite having several advantages over the more traditional OLS method, the quantile regression estimators may still be inaccurate when analyzing extreme tails if the sample size is too small and if one uses Gaussian laws as distributional approximations at the tails (Chernozhukov et al, 2017).

In order to evaluate the quality of the normal approximation at the tails, it is important to define the order of the sample tau-T quantile. As this thesis uses 276 observations of monthly returns and for risk measurement purposes the 5% quantile is deemed to be the most appropriate for comparison purposes, this order is equal to 14 (rounded to next integer value). However, it should be noted that the normal approximation requires this order to approach infinity (Chernozhukov et al, 2017). Thus, the normal approximation might perform poorly in this case. The number of observations is limited by the limited history of hedge fund returns and risk factors whereas the less extreme quantiles (10%, 20%) may be less relevant for risk measurement and management purposes. Additionally, since in this thesis regressions of hedge fund strategy returns on risk factors are performed, one also has to account for the dimension of the independent variables. Since a constant and three risk factors (at maximum) are used in this thesis, the dimension of the independent variables is 4. Thus, the dimension-adjusted order is 3.5, which is significantly lower than the target 30 for the normal inference (Chernozhukov et al, 2017).

Therefore, to evaluate quantile regression coefficient confidence intervals, this thesis uses extremal quantile regressions which apply extreme value laws to the tails of the return distribution. The method of extremal quantile regressions is based on the extreme value theory that analyzes the tails of the underlying distributions (Gnedenko, 1943). The extreme value theory rests upon the assumption that the underlying distributions have Pareto-type tails, which implies that the tails exhibit approximately a power-function decay. The advantage of this assumption is the broad scope of tail behaviors covered by Pareto-type tails. For example, it is noted in the literature that Pareto-type tails support distribution with both thick and thin tails (Chernozhukov et al, 2017), which is relevant in this thesis since the distributions of interest are often thick tailed. The condition of Pareto-type tails only affects the far quantiles of the distribution, thus allowing for the different effect of risk factors on the extremal and more central quantiles (Chernozhukov et al, 2017). It should be noted that it is valuable to use both extreme value and normal types of inference to capture the extreme situations when these types of inference provide different results.

Moreover, as it is not possible to perform normal quantile regression analysis on the 1% tail, using Powell "sandwich" standard errors, due to small sample size and multiple risk factors, extrapolated estimators for "very extreme" quantiles are used as outlined by Chernozhukov et al (2017). Extrapolated estimators should be used when the dimension-adjusted order of the sample tau-T quantile is less than 1 (Chernozhukov et al, 2017). Since for the 1% tail the dimension-adjusted order is 0.7, extrapolation is a proper method to estimate 1% tail coefficients. Extrapolation estimators use the extremal assumptions on tail behaviors. In this thesis, the base for extrapolation is the 5% tail as it is the closest tail quantile to the desired 1% tail.

Extrapolated coefficients are found by applying the following formula (Chernozhukov et al, 2017):

$$(Eq.5.1) : \tilde{\beta}(\tau_T) = \hat{\beta}(\tilde{\tau}_T) + \frac{(\tau_T/\tilde{\tau}_T)^{-\hat{\xi}} - 1}{2^{-\hat{\xi}} - 1}\left[\hat{\beta}(2\tilde{\tau}_T) - \hat{\beta}(\tilde{\tau}_T)\right]$$

where $\tilde{\beta}(\tau_T)$ - extrapolated coefficient estimates at the 1% quantile, $\hat{\beta}(\tilde{\tau}_T)$ - quantile regression coefficient estimates at the 5% quantile, τ_T - 1% quantile, $\tilde{\tau}_T$ - 5% quantile, $\hat{\xi}$ - Pickands or Hill estimator of extreme value (EV) / tail index

4.5 Choice and description of risk metric construction methodologies

4.5.1 Conditional quantiles

Factor exposures of the hedge fund strategies computed with the methods described in Section 4.4 allow to estimate the values of the return distribution quantile conditional on risk factor realizations. Indeed, this method is a variation of the conditional Value at Risk approach and is used in the literature to predict the Value at Risk of a stock (Chernozhukov et al, 2017). In essence, factor exposures in the tail of interest are applied to factor realizations to estimate the conditional value of the return realization.

Y is a continous response variable with distribution function $F_Y(y) = P(Y \leq y)$ The conditional τ-quantile is the left inverse of $y \rightarrow F_Y(y)$ at tau, i.e. for $\tau \in (0, 1)$.

As described in Section 4.4, the τ-quantile regression estimator for the conditional τ-quantile is:

$$(Eq.6.1): \ \hat{Q}_Y(\tau|x) = x_i \cdot \hat{\beta}(\tau)$$

where $\hat{\beta}(\tau)$ - quantile regression risk factor exposures across performance quantiles

In this thesis conditional quantiles are estimated for the 1% and 5% tails. First, for the 5% tail the conditional quantile is estimated by applying standard quantile regression 5% tail coefficients to risk factor realizations at each month. The coefficients applied are estimated using the full sample method. Thus, the coefficients used are the same for each month. It is important to note that, for instance, the information available in January 2007 included hedge fund returns and risk factor realizations up to January 2007. However, the coefficients applied are estimated with the information up to December 2016, creating an information mismatch. It is crucial to mention that in January 2007 the global financial crisis which conveys important tail information has not happened yet. Nevertheless, it is argued that using full sample estimates is valid because of data scarcity. For instance, in January 2007 only 156 observations were available, making proper estimation of quantile regression coefficients difficult. However, the information mismatch problem is slightly mitigated by beginning conditional quantile estimation from January 2004. Second, for the 1% tail the conditional quantile is estimated with extrapolated estimates for the 1% tail from the 5% tail, as discussed in Section 4.4.1, and risk factor realizations at each month. Extrapolated coefficients are also estimated using the full sample.

Quality of conditional quantile estimates are assessed with Kupiec tests (Kupiec, 1995). Kupiec tests attempt to evaluate model performance by calculating the number of exceptions one could expect the model to throw and comparing it to the actual number of exceptions the model produces. Technically, it is a likelihood ratio test which counter balances type 1 and type 2 errors.

Kupiec tests have two important characteristics. First, it involves hypothesis testing and thus has statistical grounds. The null hypothesis of Kupiec tests is that the assumed tail probability is equal to the actual exception probability. The test statistic follows a chi-squared distribution with 1 degree of freedom since there is only one restriction, i.e. that the assumed threshold equals the actual exception probability. Second, the test is two-tailed, meaning that it will reject a model which has either too many exceptions (aggressive model) or too few exceptions (conservative model).

4.5.2 Conditional stress testing

In light of the limitations associated with using more standard Value at Risk measures for hedge funds, it is argued that investors should perform stress tests to capture extreme losses in adverse circumstances in a more robust way (Allen et al, 2013). Given the availability of risk factors and the analysis performed to measure the relationships between risk factors and hedge fund strategy returns, it is reasonable to analyze "what if" scenarios (Fung and Hsieh, 2002). Stress testing comprises stressing individual risk factors, followed by using the correlation information to determine the corresponding expected values of other (secondary) risk factors. The advantages of conditional stress testing include, among others, flexibility of the framework, accounting for the correlation structure and the possibility to stress the most impactful risk factor with any arbitrary shock based on any theoretical considerations. The methodology also enables to make a more qualitative assessment of risks beyond the quantitative measure (Fung and Hsieh, 2002). Furthermore, conditional stress testing is a forward-looking, rather than a history-focused metric. The drawbacks include, for example, the ad-hoc nature of the method and its limited usefulness in case the explanatory power of the risk factors is too low.

The procedure of conditional stress testing is defined as follows. The first methodology is to apply the specific shock to the stressed risk variable which corresponds to the 5%-percentile of the historical distribution of the risk variable time series in case this factor has a positive effect on hedge fund returns and the 95%-percentile in case this factor has a negative effect. The idea is to find an extreme shock to the risk factor which has already happened historically. The next step is estimating, given the full-sample correlation structure, the expected value of other risk factors affecting the hedge fund strategy returns based on the risk factor set obtained with the best subset regression method described in Section 4.2. A linear relationship (correlation) between risk factors is assumed:

$$(Eq.7.1) : \frac{y_t - \mu_y}{\sigma_y} = \rho \cdot \left(\frac{x_t - \mu_x}{\sigma_x}\right) + \sqrt{1-\rho^2 \epsilon_t}$$

where y_t - modelled realization of non-lead factor, μ_y - mean of non-lead factor, σ_y - standard deviation of non-lead factor, ρ - correlation coefficient between lead and non-lead factor, x_t - simulated realization of lead factor, μ_x - mean of lead factor, σ_x - standard deviation of lead factor, e_t - error term

The error term is assumed to be standard normally distributed. It follows that the corresponding conditional expectation is:

$$(Eq.7.2): E[y_t|x_t] = \mu_y - \left(\frac{\rho \cdot \sigma_y}{\sigma_x}\right) \cdot \mu_x + \left(\frac{\rho \cdot \sigma_y}{\sigma_x}\right) \cdot x_t$$

The final step is to calculate the implied hedge fund strategy return associated with the given risk factor values. This is achieved by using coefficient estimates from the simple linear (OLS) regression. The procedure is then repeated as many times as there are risk factors in the best subset regression by putting a new risk factor into the main (stressed) place.

The second methodology is to initially cut the time series used in conditional stress testing based on the 20% quantile of the hedge fund return distribution. After that the corresponding risk factor realizations at the corresponding dates are collected. Then the primary shock, which corresponds to the 25%-percentile of the historical distribution of the risk variable time series in case this factor has a positive effect on hedge fund returns and the 75%-percentile in case this factor has a negative effect, is applied. Other (secondary) shocks are estimated using the correlation structure within the 20% quantile of the hedge fund return distribution. The motivation to use this setup is to capture the relationships closer to the tails of the hedge fund return distribution specifically. The 20% quantile cutoff is used in order to balance the proximity to the tail and the number of data points left beyond this threshold.

Implied hedge fund strategy returns are calculated by using two approaches. The first approach is to use coefficient estimates from the normal quantile regression in the 5% tail of hedge fund strategy return distributions. The thought is to apply coefficients that correspond to the first desired tail, i.e. 5% tail. The second one is to use coefficient estimates in the 1% tail of hedge fund strategy return distributions, extrapolated based on the 5% tail and the extremal quantile regression approach. The idea is to apply coefficients that correspond to the second desired tail, i.e. 1% tail.

It is important to note that conditional stress testing approach employs the similar idea behind risk measurement as conditional quantile approach. Risk factor realizations and exposures are used to come up with a risk estimate. However, whereas conditional quantiles are more backward-looking, i.e. explanatory, because historical returns are attempted to be explained by risk factor realizations which were unknown yet during a particular month and became known at a month end, conditional stress tests are more forward-looking, i.e. providing grounds for forward-looking risk management, because risk factor realization scenarios are created to evaluate what might happen in the upcoming month, taking into account not only how factors relate to strategies, but also how they relate to each other.

5 Results

5.1 Identification of illiquid strategies and return unsmoothing

In order to identify returns of which strategies are required to be unsmoothed to proceed with further analysis, as noted in Section 4.1, hedge fund returns across investment strategies should be first checked for autocorrelation. For this purpose, ACF and PACF graphs as well as Ljung-Box test p-values up to lag five against the threshold of 5% are plotted (Appendix 7 - Appendix 9). To illustrate the inherent differences in autocorrelation patterns across strategies, three cases are analyzed, namely for the hedge fund industry and two extreme cases which are fixed income-convertible arbitrage and macro systematic diversified strategies. First, for the hedge fund industry there is a significant positive spike both in ACF and PACF at the first lag, meaning that the return of the previous month positively impacts the return of the current month. The spike is enough to drive Ljung-Box test p-values below the threshold for all joint lags up to lag five. Based on the graphical analysis, the MA(1) process would be the most appropriate out of all possible moving average specifications. Second, for the fixed income-convertible arbitrage strategy spikes at the first lag are higher, implying higher dependence of current returns on previous month returns. In addition, one can observe significant spikes in ACF at second and third lags, implying that an autoregressive AR(1) process could be more appropriate in this case from an econometric point of view. However, AR(p) models are fundamentally different in that they imply that observed hedge fund returns depend on "true" unobservable returns this month and lagged observed returns (Okunev and White, 2003). MA(q) models, proposed by Getmansky et al (2004), primarily used in the literature and used in this thesis, imply that observed hedge fund returns only depend on a sequence of most recent "true" unobservable returns, leaving other observed and thus smoothed returns out of the equation. Hence, MA(q) models suggest that hedge funds smooth returns based on "true" returns, regardless of what was observed. Thus, to follow the most used method in terms of the logic behind smoothing, the moving average process is used. Based on the graphical analysis, the MA(2) process would be the most appropriate for this strategy. Finally, for the macro systematic diversified strategy there are no spikes in autocorrelation or partial autocorrelation coefficients above the confidence bounds, resulting also in Ljung-Box test p-values being comfortably above the 5% threshold. Based on the graphical analysis, returns for this strategy may be regarded as non-autocorrelated and thus do not require any unsmoothing procedure.

Regarding more quantitative information criteria (Appendix 10), the Akaike criterion puts forward larger order models, the Hannan-Quinn criterion suggests intermediate order models whereas the Schwarz's Bayesian criterion offers more restrictive processes, in line with Brooks (2014). However, it is the Schwarz's Bayesian criterion that suggests results which are closest to the graphical analysis results. It is reasonable since preference is expressed towards more parsimonious models to avoid overfitting. Therefore, this criterion is used in this thesis to decide on the order of MA(q) processes.

As hedge fund returns across most strategies are found to be autocorrelated, they need to be unsmoothed according to the procedure described in Section 4.1. Results of the unsmoothing procedure are presented in Table 1. What is key to note is that hedge fund strategies exhibit great variability in degrees of illiquidity. Both macro strategies are found to be liquid. Macro-oriented hedge funds are primarily invested in liquid markets where prices are readily available at practically any time, consistent with Bollen and Pool (2008) who primarily relate the absence of illiquidity to the liquid nature of the securities traded by macro funds. Another related argument is that securities held by macro funds have well-established marks which are not easy to manipulate (Getmansky et al, 2004). For equity hedge strategies the degree of illiquidity (smoothing) is comparatively low as 83%-86% of current period observed returns are derived from the current period information about actual returns. A significantly higher level of illiquidity is observed for event driven strategies. This illiquidity might stem from the lag in marking prices to market in the transactions. It can also derive from the illiquidity of the underlying assets (Bollen and Pool, 2008). The emerging market hedge fund strategy is also found to be quite illiquid. It may stem from from the fact that emerging markets securities are generally less liquid and less covered by market participants. Researchers connect illiquidity found for the emerging markets strategy to the less frequent trading and the naïve nature of the methods (e.g. linear extrapolation from old transaction prices) used to determine fair values (Getmansky et al, 2004). Relative value strategies are ones of the most illiquid as 54-63% of the hedge fund strategy return is reported in the current period while the remaining 37-46% is distributed over the next 2 months. Securities held by relative value funds are generally less commonly traded, e.g. convertible bonds, corporate obligations, asset-backed securities. It also backs findings by Getmansky et al (2004) that relative value hedge funds which often hold assets that trade less frequently, such as real estate, asset-backed securities, restricted securities, are in turn less liquid.

There are several exceptional patterns within categories of strategies. For instance, there is one liquid strategy within the equity hedge category, i.e. the short bias strategy. Short selling is allowed more often in liquid securities and usually banned in illiquid securities and it is rather natural for short sellers to prefer trading liquid securities to be able to wind up their positions before they skyrocket. The prices of securities traded by short sellers are therefore available at higher frequencies and thus do not set grounds for illiquidity patterns. This finding confirms results obtained in the previous research, showing that dedicated short-seller funds have quite a low first-order autocorrelation coefficient that captures the high degree of liquidity inherent in the strategy as the ability to short a stock in the first place implies a certain level of its liquidity (Getmansky et al, 2004). Moreover, funds of funds demonstrate the most considerable variation in illiquidity patterns across categories. In this regard, conservative funds are the most illiquid as they invest in equity market neutral, fixed income arbitrage and convertible arbitrage strategies that are in turn rather illiquid. Strategic funds are also quite illiquid due to their investments in equity hedge and emerging market strategies. Illiquidity of the majority of fund of fund strategies may be explained by the fact that managers of these structures select individual hedge funds with rather low levels of liquidity, which may be influenced by their high reported Sharpe ratios (Bollen and Pool, 2008).

Table 1: Unsmoothing results across hedge fund strategies. First four columns present MA(q) model coefficients, normalized to sum up to 1. Mean(unsm) - arithmetic average of unsmoothed returns, annualized by multiplying monthly unsmoothed means by 12. Std(unsm) - sample standard deviation of unsmoothed returns, annualized by multiplying monthly unsmoothed sample standard deviations by $\sqrt{12}$. Std change - percentage increase in sample standard deviation as measured by unsmoothed returns compared to smoothed (observed) returns

Strategy	MA(0)	MA(1)	MA(2)	MA(3)	Mean(unsm)	Std(unsm)	Δ Std
Distressed	0.596	0.289	0.114	0	8.54%	8.99%	45.8%
MergerArb	0.645	0.152	0.098	0.105	7.01%	5.08%	47.3%
EquitNeutral	0.856	0.144	0	0	5.23%	3.50%	15.8%
QuantDirect	0.831	0.169	0	0	9.29%	13.90%	18.0%
ShortBias	0	0	0	0	-0.80%	17.20%	0
EmergMark	0.765	0.235	0	0	7.96%	16.40%	24.1%
EquitHedge	0.825	0.175	0	0	9.21%	10.50%	18.1%
EventDriv	0.749	0.251	0	0	9.15%	8.19%	25.2%
FOFConserv	0.545	0.224	0.142	0.089	4.73%	6.21%	61.1%
FOFDivers	0.757	0.243	0	0	4.68%	7.15%	24.4%
FOFDefens	0	0	0	0	5.69%	5.34%	0
FOFStrat	0.698	0.205	0.096	0	5.45%	11.00%	35.9%
FOFCompos	0.685	0.221	0.094	0	4.93%	7.70%	36.7%
HFIndustry	0.804	0.196	0	0	7.92%	8.05%	20.2%
Macro	0	0	0	0	6.80%	6.24%	0
MacroSystDiv	0	0	0	0	8.17%	7.58%	0
RelatValue	0.613	0.284	0.103	0	7.62%	5.90%	44.1%
FIAssetBack	0.635	0.241	0.124	0	8.69%	5.56%	42.1%
ConvertArb	0.541	0.337	0.122	0	7.28%	10.10%	52.2%
FIHighYield	0.613	0.273	0.114	0	5.99%	7.85%	45.0%
RVMultiStrat	0.612	0.290	0.098	0	6.28%	5.95%	44.5%
YieldAlt	0.856	0.144	0	0	7.76%	9.00%	15.1%

The only liquid fund of fund strategy is the market defensive strategy, which is reasonable considering that funds of funds in this strategy tend to invest in short-biased hedge funds and managed futures funds which are in turn very liquid. These results are directly relatable to Bessler and Kurmann (2013) findings that conservative funds of funds are the most illiquid due to their portfolio holdings while market defensive funds are the most liquid.

Hence, since the chosen order of MA(q) processes and magnitudes of order coefficients vary, inherent illiquidity is substantially different across investment strategies. Thus, unlike previous research which assumes the same order MA(2) model for all hedge fund strategies following findings by Getmansky et al (2004), this thesis accounts for intrinsic differences in how investment strategies operate and what kind of assets they hold. It is important in subsequent analysis in order to, first, identify excessively illiquid strategies for which the second order process is not enough and, second, avoid overfitting for more liquid strategies.

Figure 3 presents a plot of original and unsmoothed returns over time for the hedge fund industry. As one can conclude, the unsmoothing procedure generally exacerbates the magnitude of a return in most months, adding a certain portion to the original return. Looking from another angle, Table 1 shows that return means stay the same after the unsmoothing procedure whereas volatilities for illiquid strategies increase as the idea behind smoothing is to make returns be perceived as less risky by neutralizing return fluctuations, consistent with Getmansky et al (2004). The higher the degree of illiquidity, the more prominent the jump in volatilities. For instance, for the hedge fund industry annualized volatilities jump from 6.70% estimated from the raw (smoothed) data to 8.05% estimated from the unsmoothed data, or by 20%. For more illiquid strategies though, volatilities increase by as much as 61%. Thus, first, even most standard risk metrics such as standard deviation largely underestimate the actual return volatility. As the focus of this thesis is on measuring hedge fund strategy risk exposures and estimating risk measures, it is important to use unsmoothed returns that are free of illiquidity features. Second, the impact across strategies is variable, justifying the approach to use differing order models for individual investment strategies.

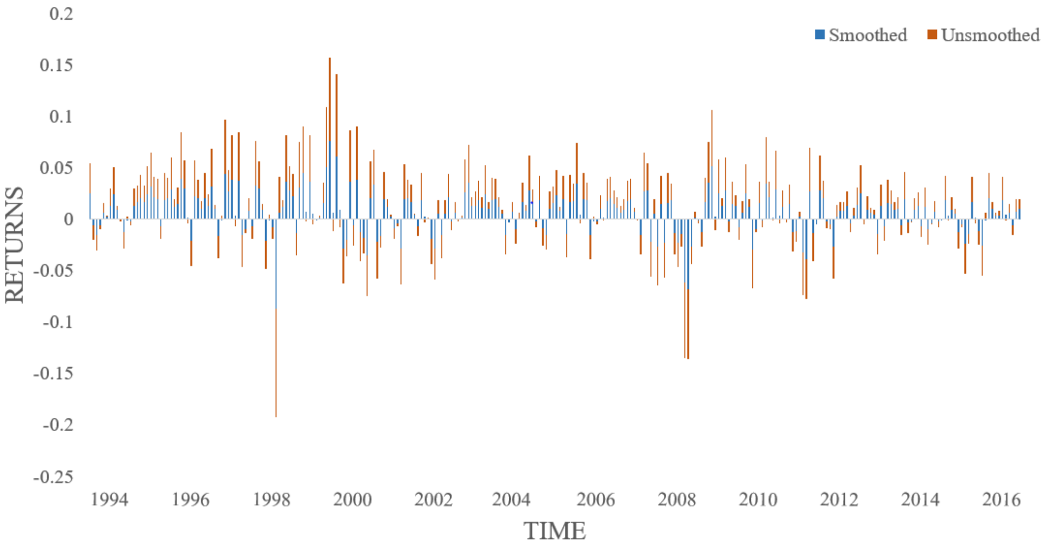


Figure 3: Original returns and exacerbated returns after the unsmoothing procedure

One should note that MA(q) model residuals, i.e. unsmoothed returns, do not become white noise after the unsmoothing procedure, with some evidence of persistent booms and contractions over time (Appendix 11). However, ACF graphs show no prominently significant autocorrelation spikes up to 5 lags. The interpretation is that there seems to be no serial correlation of the residuals. By performing Ljung Box-tests on the residuals and then estimating the p-values, null hypotheses of no joint autocorrelation up to 5 lags cannot be rejected at the 5% significance level. Hence, relying on economic and econometric benefits described above, this thesis uses unsmoothed return data to gauge riskiness of hedge fund strategies more accurately.

5.2 Selecting subsets of factors with best subset regressions

Obtained unsmoothed returns are first used in order to estimate factor exposures of hedge fund strategies. To begin with, the best subset regression method as described in Section 4.2 chooses risk factors which are to a large extent in line with previous literature findings. As an example, the method chooses the market factor to contribute to the explanation of returns across all hedge fund strategies except for the fixed income-asset backed strategy, which is reasonable given the exposure of most strategies to equity markets and the impact of equity markets on overall financial markets. The fixed income-asset backed strategy involves trading in fixed income instruments backed by specific physical collaterals (e.g. machinery, real estate) or financial obligations (e.g. loans, credit cards) other than the obligations of a specific firm. The equity market performance might thus be less relevant for this particular strategy. As another example, the credit spread factor contributes to explaining all relative value strategy returns, which is reasonable as the success of relative value trades depends on the credit quality. Credit / yield spread has been long known to impact fixed-income hedge funds (Fung and Hsieh, 2002) as these funds typically invest in riskier securities, hedging the interest rate risk out with government bonds, still being exposed to the credit risk.

5.3 OLS regressions

As a reference point to quantile regressions, obtained unsmoothed returns are regressed on chosen risk factors with the OLS method as discussed in Section 4.3. Table 2 presents OLS coefficient estimates for each hedge fund strategy. Most hedge fund strategies are positively exposed to the market factor. The economic significance is the strongest for the quantitative directional strategy and the emerging markets strategy. 1% market return implies 0.71%-0.72% return for these strategies. This magnitude is reasonable for emerging markets funds as managers within the strategy are primarily long emerging market equities that tend to move in part in line with global equity markets. However, the high market beta for quantitative directional funds is an unexpected observation. Quantitative directional funds use factor-based investment methods, supposed to deliver "smart" betas, and statistical arbitrage / trading techniques, supposed to be largely market-neutral. They also maintain varying levels of exposure over bull or bear market cycles. Thus, one could have expected these funds to be less exposed to the market factor than they are. The economic significance is the weakest for the equity market neutral strategy and the market defensive funds of funds strategy, consistent with their natures and in line with the literature (Foerster, 2006; Meligkotsidou et al, 2009) that found market neutral strategies to be imperfectly neutral in reality. Partly for this reason Fung and Hsieh (2004) argue that positive market exposures undermine equity hedge funds as an alternative investment for portfolio managers with significant current equity exposure. Positive equity exposure of intermediate economic magnitudes is found for macro, event driven and relative value funds. Regarding macro funds, the equity market is one of the main trading platforms for these funds. Furthermore, event driven and relative value funds rely on opportunistic transactions and mispricings which are more abundant to rip the benefits in bull markets than in tighter conditions. The only strategy which is negatively exposed to the equity market is the short bias strategy, which can be explained by the short market nature, as also argued by Meligkotsidou et al (2009).

Table 2: OLS coefficient estimates of regressions of hedge fund strategy unsmoothed returns on the subset of risk factors chosen by the best subset regression method. Intercept represents hedge fund strategy index alpha. LIQ - liquidity factor. TF - trend-following factor. BND - government bond factor. CRSPR - credit spread factor. VOV - volatility of aggregate volatility factor. MKT - market factor. SZSPR - size spread factor. Rˆ2 - adjusted Rˆ2 of OLS regressions. *** - coefficient significant at the 10% level. ** - coefficient significant at the 5% level. * - coefficient significant at the 1% level

Strategy	Intercept	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR	Rˆ2
Distressed	0.004*	NA	NA	NA	-3.101*	NA	0.330*	0.186*	56%
MergerArb	0.008*	NA	NA	NA	NA	-0.013**	0.176*	0.096*	37%
EquitNeutral	0.007*	NA	NA	NA	NA	-0.010**	0.062*	NA	10%
QuantDirect	0.002	NA	NA	NA	NA	NA	0.717*	0.448*	75%
ShortBias	0.006*	NA	NA	NA	NA	NA	-0.788*	-0.600*	65%
EmergMark	-0.000	0.184***	NA	NA	NA	NA	0.706*	0.258*	50%
EquitHedge	0.009*	NA	NA	NA	NA	-0.018*	0.505*	0.349*	73%
EventDriv	0.013*	NA	NA	NA	NA	-0.029*	0.375*	0.228*	69%
FOFConserv	0.010*	NA	NA	NA	-2.073*	-0.024*	0.192*	NA	46%
FOFDivers	0.011*	NA	NA	NA	NA	-0.031*	0.253*	0.160*	47%
FOFDefens	0.014*	NA	0.048*	NA	NA	-0.030*	0.058**	NA	17%
FOFStrat	0.011*	NA	NA	NA	NA	-0.035*	0.454*	0.295*	57%
FOFCompos	0.011*	NA	NA	NA	NA	-0.031*	0.300*	0.167*	51%
HFIndustry	0.010*	NA	NA	NA	NA	-0.021*	0.386*	0.234*	72%
Macro	0.015*	NA	0.051*	NA	NA	-0.034*	0.142*	NA	23%
MacroSystDiv	0.006*	NA	0.063*	NA	NA	NA	0.225*	NA	22%
RelatValue	0.005*	NA	NA	-1.390*	-3.609*	NA	0.188*	NA	49%
FIAssetBack	0.007*	NA	NA	NA	-3.161*	NA	NA	NA	17%
ConvertArb	0.004**	NA	NA	-2.904*	-7.087*	NA	0.219*	NA	39%
FIHighYield	0.003*	NA	NA	-1.938*	-5.940*	NA	0.230*	NA	57%
RVMultiStrat	0.004*	NA	NA	-1.601*	-4.499*	NA	0.157*	NA	51%
YieldAlt	0.004*	NA	NA	NA	-2.781*	NA	0.270*	NA	32%

As for other risk factors, exposures are tougher to compare across categories since different risk factors tend to be included in regressions by the best subset method. Nevertheless, one can note risk exposures within categories. First, the size spread factor is found to impact equity hedge and event driven strategies. Within equity hedge, it has a positive sign for quantitative directional and equity hedge total funds and negative for short bias funds, supporting research findings (Fung and Hsieh, 2002). The economic significance in this category is strong, as evidenced by, for example, short bias funds that produce negative 0.6% return when the size spread returns 1%. Within event driven, the distressed / restructuring strategy has a positive exposure as they invest more in smaller firms, prone to ending up in distress more than larger firms. The merger arbitrage strategy also has a positive size spread coefficient since merger arbitrageurs are long target companies which are usually smaller and short (in case of stock-for-stock mergers) acquiring companies which are larger. However, event driven funds exhibit coefficients of smaller magnitudes since they are less exposed to equity market features. Second, the liquidity factor is found to positively impact the emerging markets strategy exclusively. Emerging markets are more vulnerable than developed markets to fluctuations in overall market liquidity levels. Third, macro strategies have positive exposure to the trend following factor which implies that macro hedge funds commonly use trend following in their styles. Fourth, the credit spread factor negatively impacts relative value strategies. When credit spread widens, relative value strategies underperform because it implies lower credit quality that might make relative mispricings persist and even widen, rather than be temporary and converge as bet by relative value managers. Economically, when credit spread widens by 1 percentage point, relative value strategies return negative 2.78%-7.09%. The distressed / restructuring strategy also has a negative credit spread coefficient, in line with Fung and Hsieh (2002). As funds in this strategy focus on corporate fixed income instruments to a major extent, it is reasonable that there is exposure to the credit spread factor because widening credit spread implies lower values of corporate debt instruments. Fifth, the bond factor which represents treasury interest rate movements has a negative effect on multiple relative value strategies. Many managers within the category hedge their positions with interest rates and thus are hit when interest rates which they are short rise. Economically, rising interest rates by 1 percentage point implies negative 1.39%-2.90% return for relative value strategies. Sixth, the volatility of aggregate volatility factor is found to negatively impact several hedge fund strategies. This finding generally supports previous research conclusions (Agarwal et al, 2017). If volatilities wildly swing back and forth, hedge fund trades become more uncertain, manifesting in negative impacts on returns. However, one finding is different from Agarwal et al (2017) as the equity market neutral strategy is also found to be negatively exposed to volatility of volatilities. Finally, OLS coefficients for funds of funds strategies mirror coefficients across hedge fund strategies that the respective funds of funds strategy invests in.

What is a common feature is that most factors are statistically significant at the 1% level, which supports the use of the best subset method to predefine risk factors to be included in regressions. Explanatory values of OLS regressions tend to correlate substantially with absolute values of market betas. Indeed, for low-beta strategies (equity market neutral, market defensive funds of funds, macro strategies) the explanatory power ranges only from 10% to 23% whereas for higher-beta strategies it is in the 32%-75% range. Featuring exactly the same patterns as in Bollen (2013), equity market neutral and macro strategies exhibit the lowest explanatory power. As a big picture, it is important to mention that explanatory values of OLS regressions with constraints on the number of independent variables, as suggested by the best subset regression method, are compatible with explanatory values of “kitchen sink” regressions analyzed in the literature (Agarwal et al, 2017). One should also note statistically significant alphas estimated in OLS regressions across most strategies, which implies that despite observing quite a high explanatory power, a large part of hedge fund returns may be attributable to other unidentified risk factors or to strategy outperformance.

5.3.1 Impact of smoothing on OLS coefficient estimates

Worth noting, if one had ignored illiquidity, OLS coefficient estimates would have had different magnitudes and significance levels. The unsmoothing procedure forces alpha portions to be more attributed to available risk factors. As an illustration, market betas estimated with unsmoothed returns are substantially higher than their smoothed counterparts, as shown in Figure 4. Thus, if a hedge fund investor or a fund manager wishes to see how hedge fund strategy returns are correlated with and exposed to the equity market, he / she should be aware that illiquidity causes understatements of equity risk factor exposures. Hence, seemingly economically insignificant market betas become rather substantial if returns are unsmoothed. It is also worthwhile to mention that more illiquid strategies exhibit sharper increases in market betas than more liquid strategies. It means that if a hedge fund investor is to compare market exposures of various strategies, market betas measured on observed returns might be similar while market betas measured on underlying unsmoothed returns are completely different.

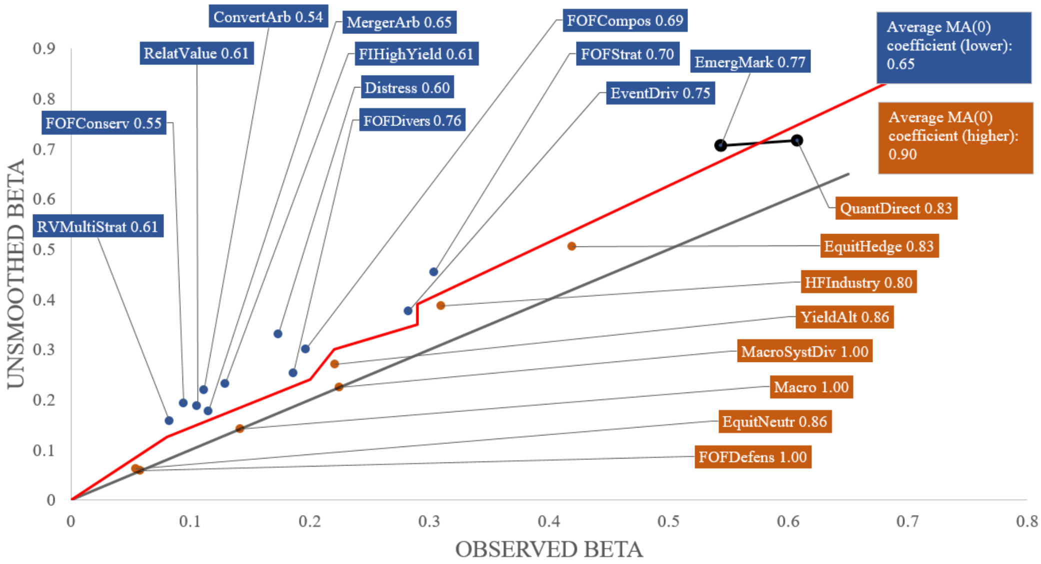


Figure 4: OLS regression market betas before and after the unsmoothing procedure. Data points represent an unsmoothed return OLS market beta (y-axis) and a smoothed (observed) return OLS market beta (x-axis), with corresponding labels of strategy name and MA(0) coefficients, i.e. the extent to which contemporaneous market return information is explaining the observed strategy returns. Dark gray line stands for a reference 45 degree line where smoothed and unsmoothed return OLS market betas are equivalent. Red line splits the strategies that have relatively lower MA(0) coefficients (blue) from ones with higher coefficients (orange). The average MA(0) coefficient is presented for both the strategies above (blue) and below (orange) the red line. The strategies connected by a black line are discussed more closely in the text. Short bias strategy (negative beta) and fixed income-asset backed strategy (no equity market factor in the regression) are omitted.

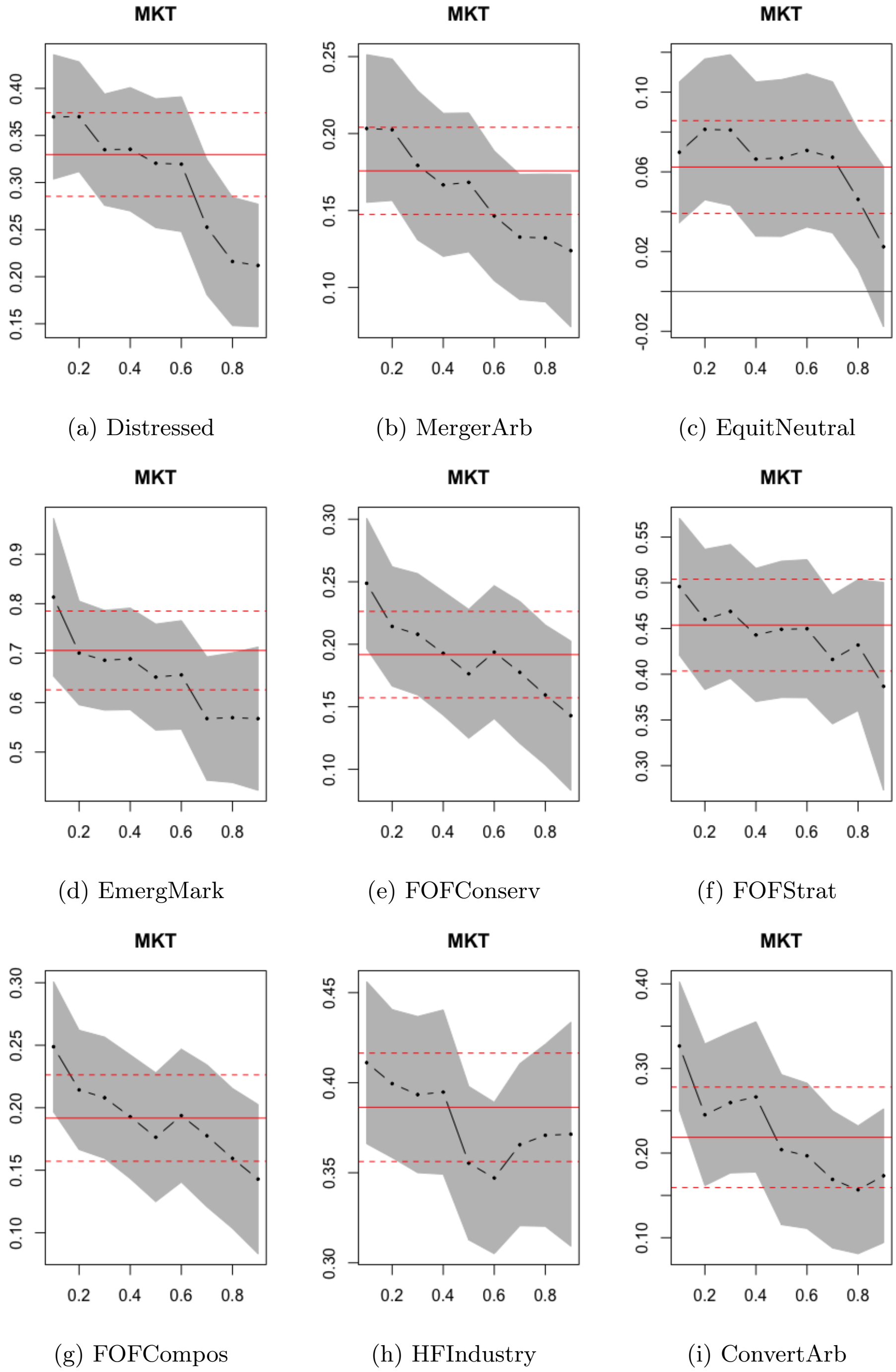
5.4 Quantile regressions

Nevertheless, as described in Section 4.4, risk factor exposures presented above are average exposures. To gauge exposures across strategy performance quantiles, unsmoothed returns are regressed on best subset risk factors with the quantile regression method. Decreasing equity market exposure along strategy performance quantiles is the common pattern across most hedge fund strategies. Figure 5 shows that this observation is valid across different categories. One could thus infer that average exposures as identified by OLS regressions are induced by lower tail exposures to a greater extent [1].

[1]When interpreting results from this thesis, one should be aware of the difference between quantiles of performance periods of strategies, captured by quantile regressions, and quantiles of performance periods of risk factors, e.g. the equity market factor, captured by market environment analysis. Market environment analysis (not presented) reveals that in the lowest 10% quantile of market returns most strategies (as expected except for short bias and market defensive funds of funds strategies) exhibit negative returns. Moreover, during three most pronounced market crashes most strategies (except for short bias, market defensive funds of funds, macro, macro systematic diversified strategies, in line with research, e.g. Fung and Hsieh (2002)) exhibit negative returns, often times being rather extreme. The focus of this thesis is, however, on worst performance periods of strategies, regardless of performance periods of risk factors.

This reveals insightful patterns for strategies. For example, the equity market neutral strategy has low exposure to the equity market, insignificantly different from 0, in best performance periods, meaning that managers pursuing this strategy are close to being truly equity market neutral only in best performance periods. Therefore, a hedge fund investor, who invests in equity market neutral funds because they perform regardless of how the equity market performs, should be aware of the tail market exposure that may be hidden by average market exposures. Moreover, as discovered by Mitchell and Pulvino (2001), worst performances of the merger arbitrage strategy coincided with sharpest declines in the equity market, while Fung and Hsieh (2004) argue that this relationship finds its roots in the systematic risk that merger transactions will fail at the same time across the market. Hence, when merger arbitrage funds perform poorly, their systematic risk exposure to a less corporate transaction prone market is stronger. Furthermore, the fixed income-convertible arbitrage strategy has reasonably higher tail exposures to the equity market factor as during equity market downturns a lot of convertible arbitrage trades failed miserably. Economic significance analysis reveals that 1% market return implies 0.33% return for the strategy in the lower 10% tail while it implies 0.17% return for the strategy when the strategy performed well (90% quantile). Statistical significance analysis reveals that in the lower 10% tail OLS coefficient estimates are located within lower halves of confidence intervals of quantile regression coefficient estimates for most hedge fund strategies, indicating that statistically speaking increases in exposures are not statistically significant for these strategies. However, confidence intervals are shifted upwards. In addition, for conservative funds of funds, composite funds of funds and convertible arbitrage strategies 5% tail coefficient estimates are statistically different from OLS coefficient estimates.

There are several exceptions (Figure 6) to the general declining market exposure trend. For example, the short bias strategy depicts increasing (in absolute terms) market exposure. Short bias funds generally perform poorly in bull markets. In bull markets they lack good short opportunities and thus potentially decrease their net negative exposure, hence lower (in absolute terms) market beta in the lower 10% tail (-0.63 beta). On the other hand, in bear markets, when short bias funds perform better (90% quantile), managers load their weapons being prepared to fire with shorting and thus increase their net negative market exposure (-1.01 beta). There is an additional aspect to consider. OLS coefficient estimates lie outside of confidence intervals of quantile regression coefficient estimates both in the 10% (lower) tail and in the 90% (upper) tail, implying that in these tails quantile regression coefficients differ statistically significantly from their OLS counterparts. As another example, macro hedge funds and market defensive funds of funds also have increasing market exposures. These strategies are not largely exposed to the equity market in periods of poor performance but are able to benefit to some extent from positive market movements. In fact, market defensive funds of funds are much more equity market neutral in the lower tail than so-called equity market neutral hedge funds.

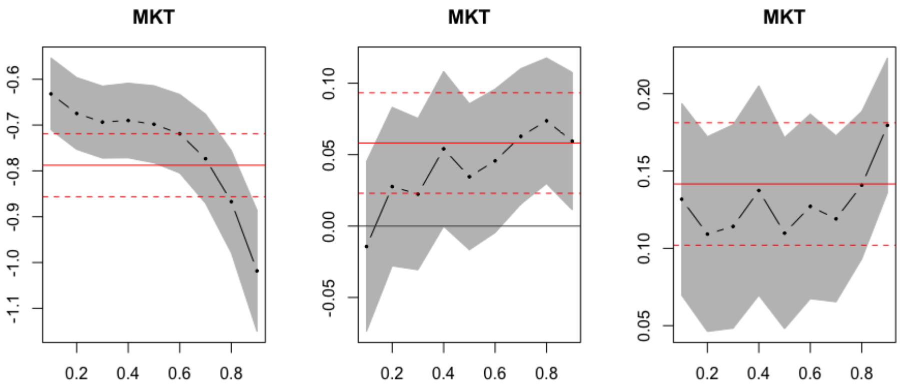


(a) Distressed (b) MergerArb (c) EquitNeutral

(d) EmergMark (e) FOFConserv (f) FOFStrat

(g) FOFCompos (h) HFIndustry (i) ConvertArb

Figure 5: Market betas across strategy performance quantiles. Each graph contrasts market betas along return quantiles with OLS market betas for various hedge fund strategies. Dashed black line stands for market betas from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS market betas. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0

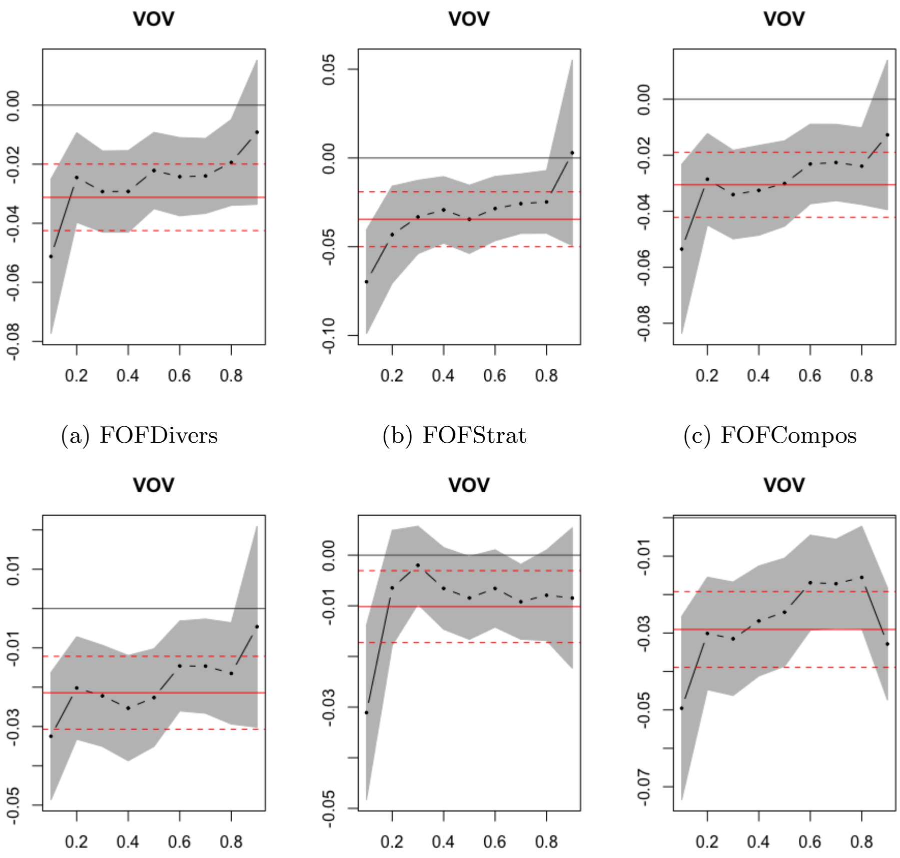


(a) ShortBias (b) FOFDefens (c) Macro

Figure 6: Market betas across strategy performance quantiles: exceptional patterns. Graph descriptions as per Figure 5

Exposures to volatility of volatilities have an increasing pattern for the hedge fund industry and funds of funds strategies, as shown in Figure 7. Thus, when the industry or funds of funds strategies, i.e. broad collections of hedge funds, underperform, they are heavily negatively exposed to swinging volatilities. This can be related to the broader understanding of hedge funds and the volatility of aggregate volatility factor as hedges typically assume stable volatilities and suffer from wildly changing volatility associated with elevated uncertainties, which is exactly what is captured by the factor. On the contrary, in best performance periods the exposure becomes statistically insignificant. Hence, the negative OLS coefficient is amplified by the more extreme lower tail exposure. In addition, similar patterns are applicable to other strategies. This reaffirms the more prominent volatility of volatilities factor exposures during crisis periods, i.e. when these strategies underperformed generally, found by Agarwal et al (2017).

Figure 8 presents trend following factor exposures across strategy performance quantiles for macro, macro systematic diversified and market defensive funds of funds strategies. They depict increasing coefficient estimates moving from the bottom quantile to the top quantile. In the periods of poor performance macro hedge fund returns are barely impacted by trend following style returns, exhibiting statistically insignificant coefficients. Poor macro strategy performance should thus be explained by the reasons other than poor trend following style performance. In other words, when macro strategies failed, the same was not necessarily true for the trend following style. However, when the macro strategy performance is exceptional, it is in part driven by the ability to capture benefits of the trend following style. The behaviour of market defensive funds of funds is inherited from underlying investments which include macro strategies. It is important to adduce the fact that in the lower 10% tail quantile regression coefficients differ from OLS coefficient estimates in a statistically significant way. Over and above that, for macro and defensive funds of funds strategies in this tail confidence bounds of quantile regression coefficients and OLS coefficients do not intersect altogether, implying the statistical strength of coefficient differences.

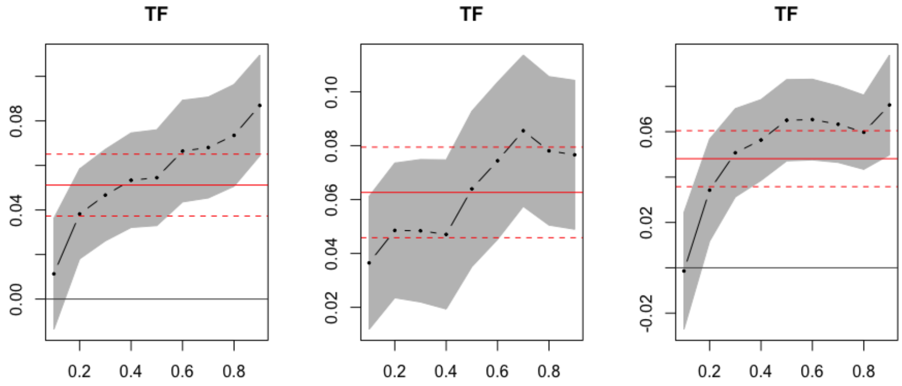


(a) FOFDivers (b) FOFStrat (c) FOFCompos

(d) HFIndustry (e) EquitNeutral (f) EventDriv

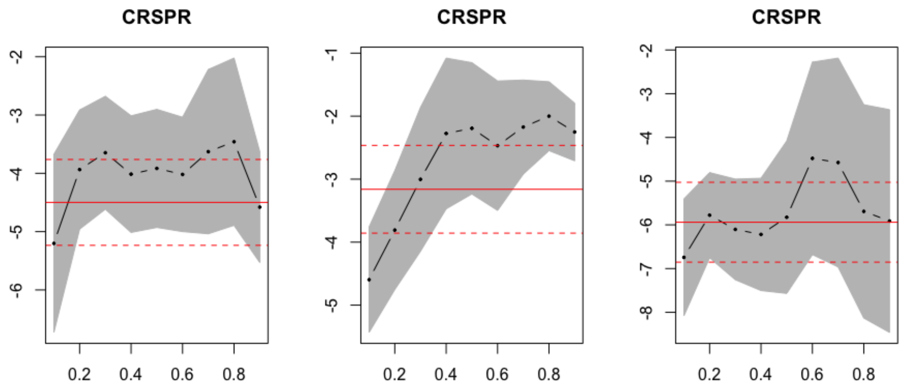
Figure 7: Volatility of volatilities betas across strategy performance quantiles. Each graph contrasts volatility of volatilities betas along return quantiles with OLS volatility of volatilities betas for various hedge fund strategies. Dashed black line stands for volatility of volatilities betas from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS volatility of volatilities betas. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0

As demonstrated in Figure 9, most relative value strategies depict decreasing (in absolute terms) credit spread exposure. The difference in exposures is most obvious in the lower tail of strategy returns. Hence, poor performance was largely affected by lowering credit qualities in the market, illustrated by widening credit spreads, rather than specific relative value opportunity failures. Economically, for fixed income corporate funds, for example, in the lower 10% tail quantile, widening credit spread by 1 percentage point, means negative 6.8% return while it leads to negative 6% on average as captured by the OLS coefficient estimate.



(a) Macro (b) MacroSystDiv (c) FOFDefens

Figure 8: Trend following betas across strategy performance quantiles. Each graph contrasts trend following betas along return quantiles with OLS trend following betas for various hedge fund strategies. Dashed black line stands for trend following betas from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS trend following betas. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0



(a) RVMultiStrat (b) FIAssetBack (c) FIHighYield

Figure 9: Credit spread betas across strategy performance quantiles. Each graph contrasts credit spread betas along return quantiles with OLS credit spread betas for various hedge fund strategies. Dashed black line stands for credit spread betas from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS credit spread betas. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0

From the patterns described above one could infer that OLS coefficient estimates misrepresent tail exposures of hedge fund strategies. For OLS estimates to provide a reliable picture of tail exposures, quantile regression coefficients should have been the same across performance quantiles. As one can see from Figure 5 - Figure 9, this is generally not the case. The distortion, however, differs depending on the strategy and the factor concerned, which is key because strategy differences in risk exposures cannot be taken for granted, both from the investor perspective and from the fund manager perspective. Furthermore, from the statistical point of view, distortions are insignificant in many cases where confidence intervals of quantile regression coefficient estimates largely overlap with OLS coefficient estimates. In these cases one has to show caution when making inferences.

Table 3 presents quantile regression coefficient estimates for each hedge fund strategy estimated at the 5% performance quantile. For instance, while OLS regression analysis would unveil that 1% market return implies 0.71% return for the emerging markets strategy, the 5% tail exposure analysis suggests 1% market return implies 1.13% return for this strategy. The jump of 0.42 in market beta is considered economically significant. As another example for the emerging markets strategy, OLS regressions conclude that 1% size spread results in 0.26% return for the strategy but quantile regressions amplify the perceived relationship, revealing that it results in 0.63% return. Yet another example, while OLS regression analysis would reveal that 1 percentage point jump in interest rates implies negative 2.90% return for the convertible arbitrage strategy, the 5% quantile analysis exposes that this jump implies a much milder negative 1.49% return.

Table 3: Quantile regression coefficient estimates of regressions of hedge fund strategy unsmoothed returns at the 5% quantile on the subset of risk factors chosen by the OLS best subset regression method. Column names as per Table 2

Strategy	Intercept	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	-0.0289	NA	NA	NA	-4.0703	NA	0.4225	0.0916
MergerArb	-0.0089	NA	NA	NA	NA	-0.0218	0.2627	0.0315
EquitNeutral	-0.0058	NA	NA	NA	NA	-0.0236	0.0992	NA
QuantDirect	-0.0289	NA	NA	NA	NA	NA	0.7671	0.2589
ShortBias	-0.0468	NA	NA	NA	NA	NA	-0.7497	-0.7973
EmergMark	-0.0634	-0.0213	NA	NA	NA	NA	1.1251	0.6294
EquitHedge	-0.0081	NA	NA	NA	NA	-0.0348	0.5634	0.3263
EventDriv	-0.0020	NA	NA	NA	NA	-0.0536	0.4244	0.2498
FOFConserv	-0.0024	NA	NA	NA	-1.6788	-0.0605	0.2503	NA
FOFDivers	-0.0004	NA	NA	NA	NA	-0.0768	0.2792	0.1819
FOFDefens	-0.0133	NA	-0.0008	NA	NA	-0.0200	0.0418	NA
FOFStrat	-0.0057	NA	NA	NA	NA	-0.0752	0.4985	0.3828
FOFCompos	-0.0034	NA	NA	NA	NA	-0.0705	0.3504	0.1614
HFIndustry	-0.0035	NA	NA	NA	NA	-0.0409	0.4487	0.2236
Macro	-0.0055	NA	0.0065	NA	NA	-0.0453	0.1097	NA
MacroSystDiv	-0.0261	NA	0.0389	NA	NA	NA	0.1291	NA
RelatValue	-0.0123	NA	NA	-1.1730	-3.6379	NA	0.2413	NA
FIAssetBack	-0.0123	NA	NA	NA	-3.3971	NA	NA	NA
ConvertArb	-0.0254	NA	NA	-1.4872	-5.2242	NA	0.3323	NA
FIHighYield	-0.0207	NA	NA	-1.3385	-6.1036	NA	0.2487	NA
RVMultiStrat	-0.0136	NA	NA	-0.9088	-4.8286	NA	0.1544	NA
YieldAlt	-0.0302	NA	NA	NA	-3.8033	NA	0.3604	NA

5.4.1 Impact of smoothing on quantile regression coefficient estimates

If in the quantile regression analysis one had ignored illiquidity, tail risk exposures would have been substantially skewed (Appendix 12). As in the case of OLS regressions, market betas in the 5% tail estimated with unsmoothed returns are higher than their observed counterparts, as shown in Figure 10. However, the economic significance of the exposure increase is typically greater in the case of quantile regressions. Hence, illiquidity causes even more extreme understatements of equity risk exposures for the tails of return distributions. For instance, for the emerging markets strategy whereas OLS analysis sees market beta increasing from 0.51 with smoothed returns to 0.71 with unsmoothed returns, 5% quantile regression analysis evidences market beta jumping from 0.62 to 1.13. To drive the point home, an investor in the strategy will typically see the reported market beta of 0.51 and receive a “gift” of 0.62 tail market beta and 1.13 tail underlying market beta. In addition, more illiquid strategies also exhibit sharper increases in tail market betas than more liquid strategies, as presented in Figure 10. Whereas an investor might be bamboozled with reported (based on OLS regressions with smoothed returns) market betas for the emerging markets strategy that are equal (even slightly lower) to the betas for the quantitative directional strategy, he / she should see that underlying tail market betas (based on quantile regressions with unsmoothed returns) are far away from each other, i.e. 1.13 for the emerging markets strategy and 0.77 for the quantitative directional strategy.

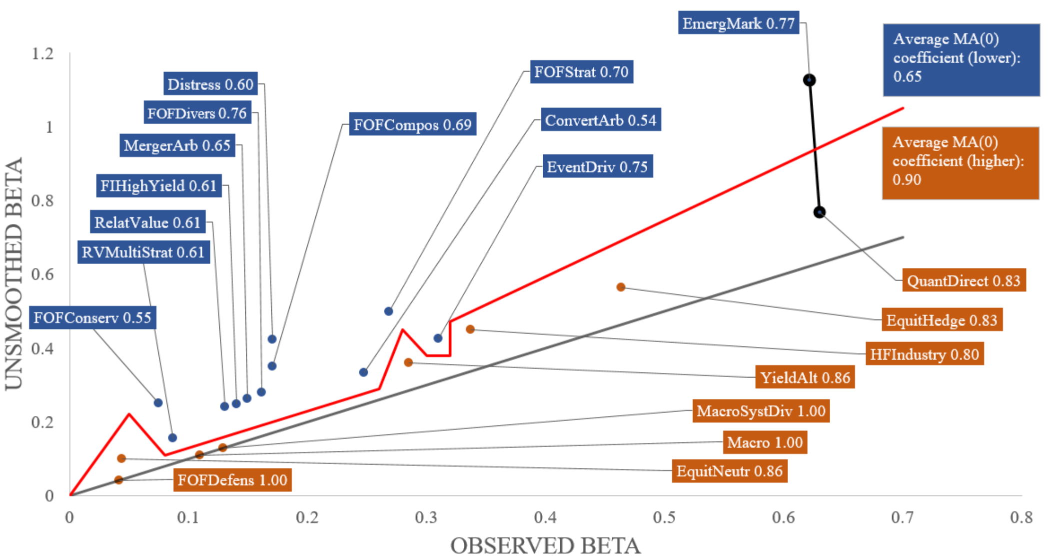


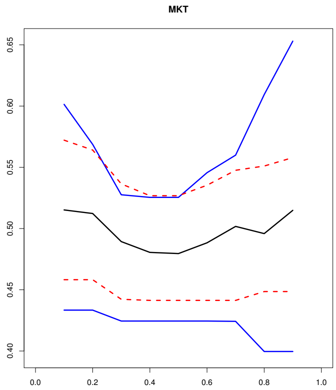
Figure 10: 5% quantile regression market betas before and after the unsmoothing procedure. Data points represent an unsmoothed return 5% quantile regression market beta (y-axis) and a smoothed (observed) return 5% quantile regression market beta (x-axis), with corresponding labels of strategy name and MA(0) coefficients, i.e. the extent to which contemporaneous market return information is explaining the observed strategy returns. Dark gray line stands for a reference 45 degree line where smoothed and unsmoothed return 5% quantile regression market betas are equivalent. Red line splits the strategies that have relatively lower MA(0) coefficients (blue) from ones with higher coefficients (orange). The average MA(0) coefficient is presented for both the strategies above (blue) and below (orange) the red line. Strategies connected by a black line are discussed more closely in the text. Short bias strategy (negative beta) and fixed income-asset backed strategy (no equity market factor in the regression) are omitted.

5.4.2 Extremal confidence intervals

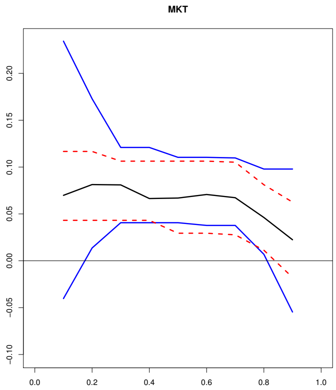
Nevertheless, as noted in Section 4.4.1, confidence bounds estimated and presented in Figure 5 - Figure 9 may be inaccurate given small sample size and normal approximations in the tails. Basing confidence intervals on extreme value theory supports this concern. Figure 11 shows that extremal confidence intervals differ from normal confidence intervals for market beta quantile regression coefficients. More specifically, extremal confidence intervals are wider than normal ones in lower and upper tails of strategy return distributions as Gaussian laws serve as a better approximation at the middle of the distribution than at the tails (Chernozhukov et al, 2017). Therefore, uncertainty regarding tail market risk exposures increases when one relaxes normality assumptions and instead models tail behaviors with Pareto-type tails. While the difference per se is universal across strategies, most apparent patterns occur for equity hedge and funds of funds strategies. As these strategy categories are found to be most highly exposed to the equity market economically (Table 2 - Table 3), assessing tail market exposure confidence intervals for these categories is paramount. Furthermore, extremal confidence intervals also influence inferences about statistical significance of quantile regression coefficients. Whereas with normal confidence intervals the equity market neutral strategy is found to have statistically significant market beta in the 10% tail, it loses statistical significance with extremal confidence intervals, which is more consistent with the definition of this strategy. The macro systematic diversified strategy also loses statistical significance of the market beta in the 10% tail. Hence, extremal quantile regressions can be helpful in, among others, identifying statistically significant factors in the lower tail for further analysis. However, as a big picture, while extremal confidence intervals decrease confidence in the accuracy of estimated tail exposures, they typically do not dramatically change inferences about statistical significance of most factors, making normal inference generally acceptable.

5.4.3 Extrapolated quantile regression coefficient estimates

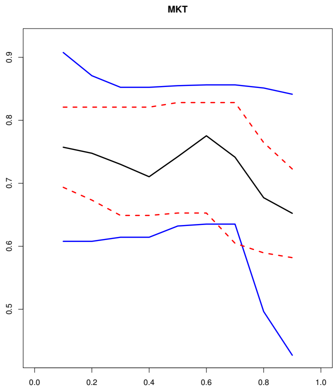
Following the discussion in Section 4.4.1, extrapolated quantile regression coefficients are estimated for the 1% tail of strategy return distributions and presented in Table 4. Comparing these coefficients with the 5% quantile regression coefficients in Table 3, one notices elevated market exposures for the extrapolated 1% tail. As an example, whereas 1% market return implies 0.1% return for the equity market neutral strategy according to the 5% tail exposure analysis, it implies 0.2% return in the extrapolated 1% tail case. Such an economically significant increase in market beta, i.e. doubling the exposure, for this strategy in the extrapolated case is warranted because, as can be seen from Figure 6, the equity market neutral strategy exhibits increasing market exposure if one moves from upper return distribution tails towards lower tails. Extrapolating the pattern further to the 1% tail generates a more extreme exposure. As another example of the same observation, while the emerging markets strategy has 5% tail market beta of 1.13, the coefficient jumps to 2.12 in the extrapolated 1% tail case, stemming from the increasing market beta towards lower tails of the strategy return distribution.



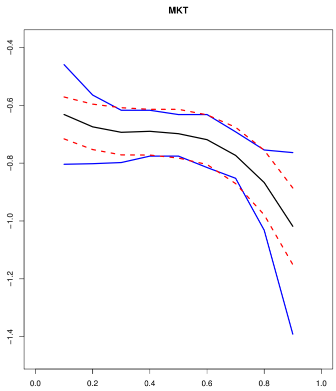
(a) EquitHedge



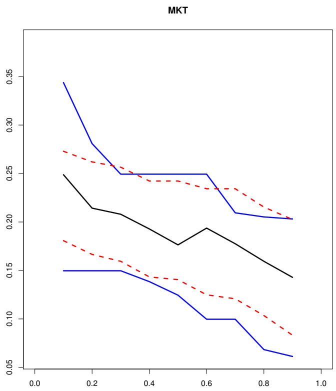
(b) EquitNeutral



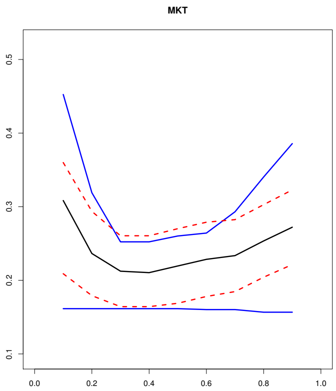
(c) QuantDirect



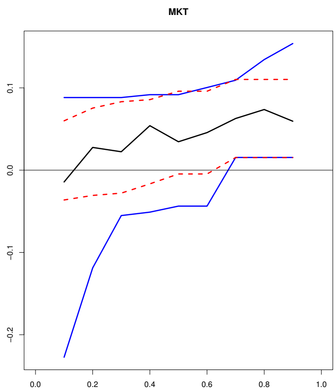
(d) ShortBias



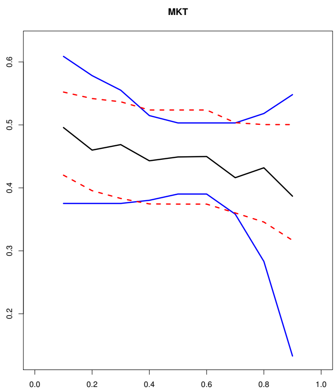
(e) FOFConserv



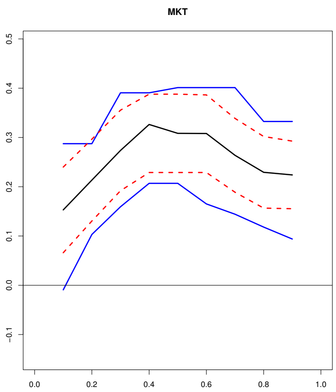
(f) FOFDivers



(g) FOFDefens



(h) FOFStrat



(i) MacroSystDiv

Figure 11: Extremal and normal quantile regression confidence intervals of quantile market betas. Each graph contrasts extremal confidence intervals with normal confidence intervals of market betas along return quantiles for various hedge fund strategies. Black line stands for market betas from 10% strategy return quantile to 90% strategy return quantile. Dashed red lines stand for normal confidence intervals of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight blue lines stand for extremal confidence intervals of quantile regression estimates as proposed by Chernozhukov et al (2017). Where applicable, straight black line is a line through 0

Table 4: Quantile regression coefficient estimates of regressions of hedge fund strategy unsmoothed returns at the 1% quantile on the subset of risk factors chosen by the OLS best subset regression method, extrapolated from the 5% quantile. Column names as per Table 2

Strategy	Intercept	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	-0.0813	NA	NA	NA	-3.7908	NA	0.6296	0.2370
MergerArb	-0.0264	NA	NA	NA	NA	-0.0411	0.4936	-0.2604
EquitNeutral	-0.0286	NA	NA	NA	NA	0.0017	0.1979	NA
QuantDirect	-0.0438	NA	NA	NA	NA	NA	0.7926	0.1123
ShortBias	-0.1035	NA	NA	NA	NA	NA	-1.0386	-1.4277
EmergMark	-0.1381	-0.4530	NA	NA	NA	NA	2.1161	1.2791
EquitHedge	-0.0296	NA	NA	NA	NA	-0.0474	0.7990	0.3555
EventDriv	-0.0197	NA	NA	NA	NA	-0.0664	0.5561	0.3005
FOFConserv	-0.0070	NA	NA	NA	-1.9588	-0.1223	0.2549	NA
FOFDivers	0.0048	NA	NA	NA	NA	-0.1427	0.2038	0.0979
FOFDefens	-0.0276	NA	0.0010	NA	NA	-0.0262	0.2146	NA
FOFStrat	-0.0189	NA	NA	NA	NA	-0.0920	0.5069	0.6315
FOFCompos	-0.0054	NA	NA	NA	NA	-0.1050	0.3429	0.0619
HFIndustry	-0.0142	NA	NA	NA	NA	-0.0713	0.5854	0.1878
Macro	-0.0141	NA	-0.0111	NA	NA	-0.0813	0.0300	NA
MacroSystDiv	-0.0442	NA	0.0460	NA	NA	NA	0.0602	NA
RelatValue	-0.0217	NA	NA	-1.1372	-3.6064	NA	0.3072	NA
FIAssetBack	-0.0534	NA	NA	NA	-3.9176	NA	NA	NA
ConvertArb	-0.0455	NA	NA	0.3999	-4.3638	NA	0.3512	NA
FIHighYield	-0.0389	NA	NA	0.4851	-4.3755	NA	0.2454	NA
RVMultiStrat	-0.0262	NA	NA	0.5857	-3.8014	NA	0.1019	NA
YieldAlt	-0.0579	NA	NA	NA	-3.9796	NA	0.5554	NA

5.5 Application 1: Conditional quantiles

The results above explain risk factor exposures of hedge fund strategies. These exposures may be used in further analysis for various purposes. However, this thesis focuses on the risk measurement purpose. Although risk factor exposures provide a valuable insight for risk measurement per se by highlighting tail beta coefficients, they do not answer the key risk measurement concern: "How bad might things turn?" Thus, these risk exposures are used, as discussed in Section 4.5, for risk measurement purposes within two frameworks, namely the conditional quantile estimation and the conditional stress testing. Figure 12 shows conditional quantiles for the hedge fund industry using full-sample 5% tail quantile regression estimates and 1% extrapolated tail estimates. Visually, 5% conditional quantile captures the worst returns well. As expected, 1% conditional quantiles are more extreme than 5% conditional quantiles and are able to capture practically all substantially negative returns. To summarize both observations, most extreme negative return realizations of the hedge fund industry are well captured by conditional quantiles. A few exceptions, which one would naturally expect to occur considering the 1% or 5% assumed tail, happen primarily when both conditional quantiles and actual returns are mild. Thus, conditional quantiles yield an important measure to investors who pay more attention to the most extreme negative returns.

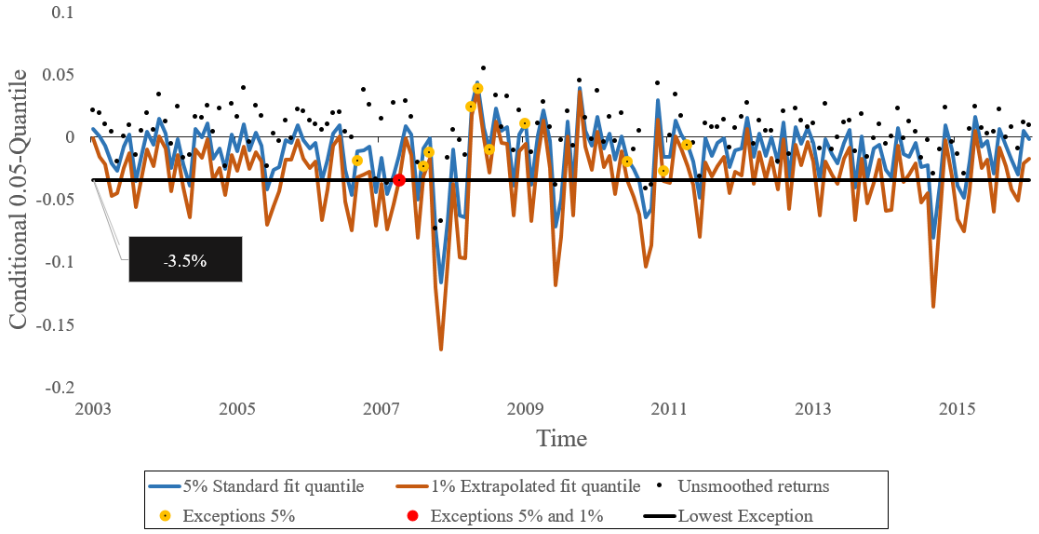


Figure 12: Conditional quantiles of hedge fund industry returns from December 2003 to December 2016. Blue line stands for conditional quantiles at each month estimated using full-sample normal quantile regression coefficient estimates in the 5% tail. Orange line stands for conditional quantiles at each month estimated using full-sample quantile regression coefficient estimates in the 1% tail, extrapolated from the 5% tail. Black dots represent unsmoothed hedge fund industry returns. Black dots with yellow rings are showing unsmoothed hedge fund industry return "exceptions", in relation to the conditional quantiles, at the 5% level. The black dot with a red ring shows an "exception" in relation to both the 5% and 1% conditional quantiles. The black horizontal line refers to the worst exception with a corresponding label.

5.5.1 Evaluation of conditional quantile models with Kupiec tests

Kupiec tests confirm the quality of the constructed conditional quantiles. As can be seen from Table 5, 5% conditional quantiles across hedge fund strategies yield probabilities of exceptions, i.e. actual returns lower than modeled by conditional quantiles, that fluctuate quite closely around the assumed 5% tail. The null hypothesis that the assumed tail probability is equal to the actual exception probability cannot be rejected for most hedge fund strategies. The only exception is the short bias strategy where the conditional quantile model turns out to be too conservative. This exception is justified mainly since the 5% tail alpha for the short bias strategy is one of the most poor (-4.68%), meaning that regardless of risk factor realizations at each particular month, the conditional quantile calculation starts from quite a negative base for this strategy. However, as the main purpose of these models is to evaluate extreme riskiness of hedge fund strategies, conservatism of the model is preferred over aggressiveness. Moreover, 1% conditional quantiles produce exception probabilities that are generally either too conservative, in fact producing no exceptions at all, or close to the assumed 1% tail. The null hypothesis is rejected for 9 strategies while it cannot be rejected for remaining 13 strategies. On the other hand, 8 of these 9 rejected models are models that imply no single exception. When one looks at the 1% tail, one should expect 2-3 exceptions given the number of observations used in this thesis. Since the main interest is kept on avoiding extreme losses, conservative models are again preferred. However, 1% conditional quantile model ends up being too aggressive for the emerging markets strategy. As noted above, exceptions mainly occur when actual returns are not substantially negative. In fact, the 2.12 market beta used for this strategy in the 1% case makes conditional quantiles too high when market produces great returns. Thus, when the market performs particularly well, returns of emerging markets funds sometimes fall short of conditional expectations.

Table 5: Kupiec test results for conditional quantile models. Pexception5% and Pexception1% - actual probabilities to observe an exception from a conditional quantile model for each strategy according to historical data for 5% conditional quantile model and 1% conditional quantile model respectively. Kpvalue5% and Kpvalue1% - p-values of Kupiec (1995) tests of risk model adequacy for 5% conditional quantile model and 1% conditional quantile model respectively. p-values below 10% stand for rejection of conditional quantile model on a 90% confidence level, p-values above 10% stand for non-rejection of conditional quantile model on a 90% confidence level

Strategy	Pexception5%	Kpvalue5%	Pexception1%	Kpvalue1%
Distressed	3.18%	0.26	0%	0.08
MergerArb	4.46%	0.75	0%	0.08
EquitNeutral	5.10%	0.96	0.64%	0.62
QuantDirect	3.18%	0.26	0%	0.08
ShortBias	1.27%	0.01	0.64%	0.62
EmergMark	3.18%	0.26	3.18%	0.03
EquitHedge	5.73%	0.68	0%	0.08
EventDriv	5.73%	0.68	0.64%	0.62
FOFConserv	5.73%	0.68	0%	0.08
FOFDivers	3.18%	0.26	0.64%	0.62
FOFDefens	4.46%	0.75	0%	0.08
FOFStrat	5.10%	0.96	1.91%	0.31
FOFCompos	3.82%	0.48	0.64%	0.62
HFIndustry	7.01%	0.28	0.64%	0.62
Macro	2.55%	0.12	0%	0.08
MacroSystDiv	7.01%	0.28	0.64%	0.62
RelatValue	3.82%	0.48	1.91%	0.31
FIAssetBack	3.82%	0.48	1.91%	0.31
ConvertArb	4.46%	0.75	2.55%	0.10
FIHighYield	3.18%	0.26	0%	0.08
RVMultiStrat	5.10%	0.96	1.91%	0.31
YieldAlt	5.10%	0.96	1.27%	0.74

It cannot escape one's notice that positive results from Kupiec tests could have been predicted to some extent since coefficient estimates used to estimate conditional quantiles were obtained with quantile regressions by focusing on the 5% tail. Having mentioned that, it is important to stress that quantile regressions show exposures in worst performance periods while Kupiec tests capture exceptions over the whole period each month, regardless of whether it experiences a good or bad performance. Thus, it is of value to employ Kupiec tests to validate the model. It is indeed found that Kupiec test exceptions primarily occur in performance periods other than the worst ones. Hence, these results lead to, first, confirmation of the quality of conditional quantile models and, second, low levels of concern that conditional quantiles are not able to capture extreme losses.

5.6 Application 2: Conditional stress testing

Conditional quantiles estimated above provide an answer to the question: "Given the risk factor realization, what was the conditional expectation for the strategy return at that particular month?” They show an investor in hindsight how poorly a strategy can perform given risk factor realizations at that month. Thus, these estimates are valuable for explanatory purposes. According to the results in this thesis, they show that even most extreme losses across hedge fund strategies may be well explained by risk factor realizations and tail exposures. Therefore, hedge fund investors and fund managers know how bad things can get if historical risk factor realizations repeat. However, as noted in Section 4.5.2, if investors or managers wish to assess future riskiness, more forward-looking measures that incorporate risk factor interdependencies such as conditional stress testing are employed. Table 6 - Table 8 show results of conditional stress tests which apply OLS coefficients, 5% standard tail coefficients and 1% extrapolated tail coefficients respectively. Using OLS estimates results in more conservative simulated losses compared to using tail-based coefficients from quantile regressions. Whereas the maximum negative simulated loss for the hedge fund industry is -2.66% with OLS estimates, it is -5.49% with 5% tail estimates and -8.71% with 1% tail estimates. These results can come in handy for investors and managers that would like to assess the tail risk the relevant hedge fund strategies are exposed to, answering the question: “How extreme can losses be in the future?”

Table 6: Conditional stress testing results based on OLS coefficient estimates. Values stand for simulated returns based on stressing the corresponding factor as a ”leading factor”, evaluating consequent responses of other factors and applying OLS coefficient estimates. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-1.00%	0	-2.50%	-0.52%
MergerArb	0	0	0	0	-0.18%	-0.95%	0.01%
EquitNeutral	0	0	0	0	0.06%	-0.13%	0
QuantDirect	0	0	0	0	0	-5.11%	-1.66%
ShortBias	0	0	0	0	0	-5.53%	-3.48%
EmergMark	-1.42%	0	0	0	0	-5.26%	-0.99%
EquitHedge	0	0	0	0	-1.02%	-3.53%	-1.16%
EventDriv	0	0	0	0	-0.91%	-2.53%	-0.57%
FOFConserv	0	0	0	-0.70%	-0.82%	-1.64%	0
FOFDivers	0	0	0	0	-1.03%	-1.91%	-0.58%
FOFDefens	0	-0.05%	0	0	-0.14%	0.11%	0
FOFStrat	0	0	0	0	-1.57%	-3.53%	-1.25%
FOFCompos	0	0	0	0	-1.09%	-2.26%	-0.60%
HFIndustry	0	0	0	0	-0.85%	-2.66%	-0.68%
Macro	0	0.14%	0	0	-0.31%	-0.48%	0
MacroSystDiv	0	0.07%	0	0	0	-0.70%	0
RelatValue	0	0	0.93%	-0.48%	0	-1.33%	0
FIAssetBack	0	0	0	-0.09%	0	0	0
ConvertArb	0	0	0.92%	-1.21%	0	-2.05%	0
FIHighYield	0	0	1.05%	-1.22%	0	-2.14%	0
RVMultiStrat	0	0	0.85%	-0.72%	0	-1.33%	0
YieldAlt	0	0	0	-0.68%	0	-1.95%	0

Table 7: Conditional stress testing results based on quantile regression coefficient estimates at the 5% quantile. Values stand for simulated returns based on stressing the corresponding factor as a ”leading factor”, evaluating consequent responses of other factors and applying quantile regression coefficient estimates at the 5% quantile. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-5.61%	0	-6.39%	-5.43%
MergerArb	0	0	0	0	-2.96%	-3.42%	-2.79%
EquitNeutral	0	0	0	0	-1.75%	-1.93%	0
QuantDirect	0	0	0	0	0	-8.74%	-7.32%
ShortBias	0	0	0	0	0	-10.50%	-10.90%
EmergMark	-9.42%	0	0	0	0	-13.70%	-12.50%
EquitHedge	0	0	0	0	-5.76%	-6.64%	-5.96%
EventDriv	0	0	0	0	-5.08%	-5.72%	-4.76%
FOFConserv	0	0	0	-4.12%	-4.62%	-4.74%	0
FOFDivers	0	0	0	0	-5.05%	-5.16%	-4.54%
FOFDefens	0	-2.11%	0	0	-2.21%	-2.20%	0
FOFStrat	0	0	0	0	-6.64%	-6.97%	-6.48%
FOFCompos	0	0	0	0	-5.24%	-5.58%	-4.65%
HFIndustry	0	0	0	0	-4.71%	-5.49%	-4.88%
Macro	0	-2.04%	0	0	-2.72%	-2.64%	0
MacroSystDiv	0	-3.11%	0	0	0	-3.11%	0
RelatValue	0	0	-2.07%	-2.71%	0	-2.88%	0
FIAssetBack	0	0	0	-2.02%	0	0	0
ConvertArb	0	0	-3.43%	-4.07%	0	-4.86%	0
FIHighYield	0	0	-3.30%	-4.29%	0	-4.79%	0
RVMultiStrat	0	0	-2.16%	-3.00%	0	-3.20%	0
YieldAlt	0	0	0	-5.23%	0	-6.05%	0

Severity of losses may come from two sources. The first one is the difference in alphas used as means in conditional stress testing framework and the second one is the difference in risk factor exposures and their relationships with each other. Considering both sources together helps in determining a final stress test risk measure. Alphas cannot be neglected since they show contributions from other risk factors not included in regressions for each strategy as well as from idiosyncratic performance. They are especially important for the strategies with low explanatory power of regressions since in these cases they comprise the major part of the final contribution. However, differences in alphas may make valuable insights about risk factor exposures and risk factor interdependencies blurred. To disentangle the effect of the second source only, conditional stress tests are run without taking alphas into consideration (Appendix 13 - Appendix 15). Several important results emerge. First, the market factor is the dominating factor for most hedge fund strategies as stressing the market factor yields the most extreme losses in a vast majority of cases. It confirms the findings on economic significance of the factor, suggesting that the performance of the equity market is the most important factor for hedge funds. Second, shocks to the market return factor as the “leading factor” in the OLS case dominate in terms of return severity compared to shocking other factors whereas this pattern is less pronounced when tail coefficients are applied. This indicates that correlations between risk factors are stronger in the tails, which is a valuable insight from a risk management perspective. Hence, regardless of a subjective choice of any particular risk factor from a best subset as a “leading factor”, conditional stress testing results are similar when an investor or manager applies tail coefficients compared to OLS coefficients.

Table 8: Conditional stress testing results based on coefficient estimates at the 1% quantile, extrapolated from the 5% quantile. Values stand for simulated returns based on stressing the corresponding factor as a "leading factor", evaluating consequent responses of other factors and applying coefficient estimates at the 1% quantile, extrapolated from the 5% quantile. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-11.83%	0	-12.96%	-11.86%
MergerArb	0	0	0	0	-6.10%	-6.94%	-5.68%
EquitNeutral	0	0	0	0	-2.83%	-3.67%	0
QuantDirect	0	0	0	0	0	-10.18%	-8.35%
ShortBias	0	0	0	0	0	-18.79%	-20.27%
EmergMark	-20.30%	0	0	0	0	-27.01%	-25.11%
EquitHedge	0	0	0	0	-9.70%	-10.98%	-9.76%
EventDriv	0	0	0	0	-8.14%	-9.00%	-7.70%
FOFConserv	0	0	0	-7.26%	-8.28%	-7.96%	0
FOFDivers	0	0	0	0	-7.18%	-6.89%	-6.04%
FOFDefens	0	-3.14%	0	0	-3.89%	-4.20%	0
FOFStrat	0	0	0	0	-9.10%	-9.26%	-9.37%
FOFCompos	0	0	0	0	-6.89%	-7.11%	-5.80%
HFIndustry	0	0	0	0	-7.76%	-8.71%	-7.64%
Macro	0	-4.78%	0	0	-5.09%	-4.69%	0
MacroSystDiv	0	-4.96%	0	0	0	-4.68%	0
RelatValue	0	0	-3.14%	-3.87%	0	-4.11%	0
FIAssetBack	0	0	0	-5.37%	0	0	0
ConvertArb	0	0	-6.68%	-6.13%	0	-6.94%	0
FIHighYield	0	0	-5.92%	-5.84%	0	-6.36%	0
RVMultiStrat	0	0	-4.03%	-3.95%	0	-4.05%	0
YieldAlt	0	0	0	-8.76%	0	-10.00%	0

Third, stress testing results for the strategies heavily exposed to both volatility of volatilities and equities, i.e. equity hedge and funds of funds strategies, reveal that there is a stronger negative factor correlation in the tail. Applying quantile coefficients gives rise to far more similar severity of resulting strategy losses compared to OLS results, which implies lower (in absolute terms) correlation in the non-tail setting than in tail setting. For instance, in the OLS case stress tests for diversified funds of funds suggest simulated losses of -2.15% and -3.03% when having the volatility of aggregate volatility and the market factor as the "leading factor" respectively. At the same time, in the 5% tail case the corresponding losses are -5.00% and -5.12%. Thus, one has to be aware of these two factors going in opposite direction in extreme strategy performance periods compared to normal times. Fourth, conditional stress testing results for relative value strategies exhibit different correlation patterns for bond and equity market factors on average and in the tails of strategy returns. When stressing bond factor and applying OLS coefficients, negative correlations with the market factor mainly lead to positive simulated returns. On the other hand, when stressing this factor and applying tail coefficients, positive tail correlations with the market factor lead to negative returns. Thus, one has to acknowledge the possibility of these two factors moving in various directions depending on circumstances. Fifth, as expected, applying 1% tail coefficients leads to larger simulated losses compared to applying 5% tail estimates.

Worth noting, conditional stress testing results suggest similar risk exposures for the hedge fund industry and funds of funds. For example, using 5% quantile regression coefficients for stress testing and the market risk factor as the leading factor, composite funds of funds yield negative 5.58% return while the hedge fund industry, which excludes funds of funds, produce negative 5.49%. Bessler and Kurmann (2013) assert that risk management is one of the most valuable services that investors, especially retail, have difficulty performing themselves, thus investing in hedge funds through a fund of funds mediator. However, as evidenced by their risk exposures, funds of funds maintain similar risk profiles to the hedge fund industry since the difference in stress testing results is rather small economically. Thus, when selecting a fund of funds, one should keep in mind that generally funds of funds do not have substantially lower tail risk exposures than the hedge fund industry so that superior risk management approach shall be justified by an individual fund of funds.

5.6.1 Comparison of strategy rankings from stress tests and standard risk metrics

To compare and contrast conditional stress testing with more standard risk metrics used in the hedge fund industry, strategy rankings are constructed. The purpose is to assign the "safest" (1) ranking to the least risky hedge fund strategy and the "most dangerous" (22) ranking to the most risky strategy, in order then to compare the internal relative rankings across risk metrics to assist in making inferences about the differences in the risk measurement methodologies. The rankings are presented in Table 9. The rankings indicate that while standard risk metrics typically rank hedge fund strategies in a similar way, conditional stress testing results lead to several differences which need to be highlighted. First, the merger arbitrage strategy is found to be riskier according to conditional stress tests. Its factor exposures, especially in the tails, make it more prone to movements in relevant risk factors, in line with the previous results described in this thesis. On the contrary, the macro systematic diversified strategy is found to be less risky according to conditional stress testing results as well as according to 1% expected tail loss, which signifies about its less extreme riskiness. As a high level big picture view, conditional stress testing methodology not only aids in evaluating the tail risk more accurately, resulting in more extreme loss estimates, but also, based on heavy risk factor exposures, signals about strategies that are more risky than could have been initially thought without scrutinizing risk factor exposures.

5.7 Robustness checks

5.7.1 Kitchen sink quantile regressions

As noted in Section 4.4, the same subset of risk factors is used in this study in both OLS and quantile regression analysis. Thus, one of the limitations of this study is that a risk factor may not contribute to explaining variation in hedge fund returns on average, as captured by the OLS best subset regression method used in this thesis, but may nevertheless be statistically significant across several performance quantiles. Patterns in these risk factors across performance quantiles are hence omitted from the analysis in this thesis. The emerging markets strategy serves as an illustration of this observation (Appendix 16). Apart from defined relationships, it is notable that the strategy depicts declining (in absolute terms) government bond exposure. Whereas interest rate exposure is statistically insignificant on average and in good performance periods, merger arbitrageurs are statistically significantly negatively exposed to interest rate movements in the lower tail of performance distribution. 1 percentage point increase in interest rates implies negative 1.5% return for merger arbitrage funds in the 10% tail. Although initially these results may come at a surprise since merger arbitrage funds claim they would be eager to experience higher interest rates as theoretically they would widen the spread in merger deals investors demand as a compensation (The Wall Street Journal, 2014), these results support expert thoughts that as interest rates rise significantly, it becomes expensive to finance M&A deals, existing deals fail and PE firms are no longer able to afford new deals (Barron's, 2014), leading to merger arbitrage strategy struggles in the tail. Moreover, while market liquidity exposure is also statistically insignificant on average and in good performance periods, the strategy is statistically significantly positively exposed to market liquidity in the lower tail as market liquidity troughs are adverse when merger arbitrageurs struggle.

Table 9: Risk metrics internal strategy rankings. Each column presents rankings of strategies according to corresponding risk metrics. SDuns - sample standard deviation of monthly unsmoothed returns. KP2 - Kappa order two (Sortino risk metric). KP3 - Kappa order three. KP4 - Kappa order four. V5 - historical Value at Risk estimated for 5% threshold. E5 - historical Conditional Value at Risk (expected tail loss) estimated for 5% threshold by averaging observations worse than 5% Value at Risk. V1 - historical Value at Risk estimated for 1% threshold. E1 - historical Conditional Value at Risk (expected tail loss) estimated for 1% threshold by averaging observations worse than 1% Value at Risk. C - minimum simulated return of conditional stress tests based on OLS coefficient estimates. C5n - minimum simulated return of conditional stress tests based on quantile regression coefficient estimates at the 5% quantile. C1e - minimum simulated return of conditional stress tests based on coefficient estimates at the 1% quantile, extrapolated from the 5% quantile

Strategy	SDuns	KP2	KP3	KP4	V5	E5	V1	E1	C	C5n	C1e
Distressed	15	13	13	13	11	14	16	13	15	17	20
MergerArb	2	2	2	2	4	2	2	2	6	8	9
EquitNeutral	1	1	1	1	1	1	1	1	2	1	1
QuantDirect	20	20	20	19	20	20	20	19	20	20	18
ShortBias	22	22	22	22	22	22	22	22	22	21	21
EmergMark	21	21	21	21	21	21	21	21	21	22	22
EquitHedge	18	18	16	16	19	18	18	17	19	18	19
EventDriv	14	15	14	14	14	15	15	15	16	15	15
FOFConserv	7	3	4	6	6	6	7	6	9	9	13
FOFDivers	9	10	11	10	12	11	12	10	10	12	12
FOFDefens	3	7	3	3	9	4	3	3	3	3	4
FOFStrat	19	19	18	18	18	17	17	18	18	19	16
FOFCompos	11	9	10	9	13	10	13	11	14	14	11
HFIndustry	13	14	12	12	15	12	14	12	17	13	14
Macro	8	8	5	5	10	8	8	5	4	4	6
MacroSystDiv	10	12	6	4	16	9	6	4	5	6	5
RelatValue	5	5	7	7	2	5	11	9	8	5	3
FIAssetBack	4	4	9	11	3	3	5	7	1	2	7
ConvertArb	17	16	19	20	7	16	9	20	12	11	10
FIHighYield	12	11	15	15	8	13	10	14	13	10	8
RVMultiStrat	6	6	8	8	5	7	4	8	7	7	2
YieldAlt	16	17	17	17	17	19	19	16	11	16	17

However, despite the importance of these patterns, using "kitchen sink" regressions may obfuscate key factor patterns and divert attention to analyzing non-core relationships. This point is well illustrated for the equity market neutral strategy (Appendix 17). Although a few additional patterns emerge, most crucial relationships, i.e. with the market factor and the volatility of volatilities factor, are less prominent, compared to patterns shown in Figure 5 and Figure 7. In addition, using the same subset of risk factors in both OLS and quantile regression analysis helps to directly compare OLS and quantile regression coefficients for the same factor. For example, the OLS market beta for the equity market neutral strategy estimated in a "kitchen sink" framework is 0.07 whereas the same coefficient in a best subset OLS framework is 0.06. Although economically the difference seems to be negligible, it is not for the equity market neutral strategy, making the comparison less straightforward. Furthermore, using the same risk factors for OLS and quantile regression analysis facilitates focus on the importance of using quantile regressions in the risk measurement framework where differences come from crucial characteristics of the methods used rather than from factors.

5.7.2 Standard error type choice in quantile regressions

As discussed in Section 4.4, there are various options of standard errors of quantile regression coefficients one can choose. In order to ensure consistency with previous literature (Chernozhukov et al, 2017), Powell "sandwich" standard errors are used in this thesis. Alternative standard error types produce different standard error bounds, as illustrated on the example of the market beta for the hedge fund industry (Appendix 18). Several inferences are notable. First, whereas standard errors obtained by inverting a rank test are asymmetric, meaning that lower and upper confidence bound are not on same distances from the coefficient estimate, standard errors obtained by estimating a variance-covariance matrix are symmetric. Second, among standard errors obtained by estimating a variance-covariance matrix the one that assumes i.i.d. errors produces tighter confidence bounds for tail coefficient estimates, compared to two other ones that assume non-i.i.d. settings. Third, Powell "sandwich" standard errors used in this thesis produce the widest confidence intervals across most quantiles, implying that statistical significance conclusions made based on these standard errors would be ones of the most conservative, i.e. several coefficient estimates, which would have been regarded statistically significant with other standard error types, can be deemed statistically insignificant based on Powell "sandwich" standard errors. However, alternative standard error types do not lead to dramatically different results, making the results of this thesis robust to standard error type choice.

6 Discussion

This thesis applies quantile regressions to measure risk factor exposures of hedge fund strategies and presents two applications in the risk measurement field. It is important to critically assess the results from this thesis, especially in light of several controversial decisions needed to be made with regards to methodology.

First, the unsmoothing procedure applied in this thesis follows the standard approach, suggested by Getmansky et al (2004), employed most commonly in the literature. As noted in Section 5.1, this approach may suffer from drawbacks from the econometric point of view as it is found that MA(q) models may be inferior to other process specifications, such as, for example, AR(p) models or ARMA(p,q) models. As a note of caution, however, one has to be equipped with theoretical motivations while employing different time series processes to account for autocorrelation. MA(q) models used in this thesis possess a good property from a theoretical standpoint because they assume dependence of current period observed returns only on a series of “true” returns. Moreover, the unsmoothing model employed in this thesis is unconditional, i.e. the fraction of the “true” hedge fund return is reflected contemporaneously whereas the remainder is reflected in future periods, regardless of the actual value of this return. Literature notes that hedge fund manager behaviour may be more complicated, e.g. smoothing may be an elevated issue in worst performance periods in order to mitigate capital flight (Bollen and Pool, 2008). Hence, conditional models may be employed. Furthermore, smoothing analysis is performed prior to regression analysis, meaning that for smoothing analysis purposes returns are not assumed to depend on any independent variables (risk factors). There are methods available in the literature to account for dependence on risk factors in smoothing analysis (Getmansky et al, 2004).

Second, best subsets of risk factors identified within the OLS framework are assumed to be best subsets of risk factors for all return distribution quantiles. This assumption is made for the sake of a direct comparison in risk factor exposures between OLS and quantile regression approaches. It is relaxed to some extent in robust checks where “kitchen sink” regressions are examined for select strategies. However, there are ways to identify best subsets of risk factors across different return quantiles (Meligkotsidou et al, 2009). These methods should be preferred if the purpose is to capture all relevant exposures in the tails. For example, if a hedge fund investor is concerned about tail exposures of prospective investments, he / she might remove OLS factors that lose significance in the tail as well as add factors that gain significance in the tail. If a hedge fund manager is to identify what factors may be key to the fund’s bad performance, most relevant factors to the tail specifically should be scrutinized.

Third, while making inferences from quantile regression analysis, one has to keep in mind several statistical issues. First, a small number of historical monthly observations limits statistical significance of results in general. For example, to estimate 10% quantile exposures, only 28 observations are used, which leads to small sample problems. To obtain more statistically robust results it is thus advisable to use as many available observations as possible. Second, wide confidence intervals of quantile regression coefficient estimates in many cases lead to statistical insignificance of differences between quantile regression and OLS coefficient estimates. However, it is still important to note a trend in coefficient developments across quantiles.

Finally, the study is conducted on hedge fund indices and risk factors that are most widely used in the hedge fund industry as well as academic research and which are available for the period analyzed. Hedge Fund Research provides a much wider range of HFRI strategy indices. However, the indices not used in this thesis are available for shorter time periods.

As sample size is crucial for the methods used in this thesis, e.g. quantile regressions, these other strategies are omitted. Thus, hedge fund investors interested in investments in other strategies may consider performing such analyses on other strategies as well but have to be aware of arising statistical issues. Additionally, one might be interested in conducting such analyses on hedge fund indices offered by other database vendors, e.g. Lipper TASS, BarclayHedge, EurekaHedge. One has to be aware though of differences in how these vendors account for data biases discussed in Section 3.1, as well as differences in how they construct hedge fund strategy indices. Furthermore, other risk factors may be added if one has theoretical motivations as well as sufficient data at hand.

The risk measurement applications provided in this thesis are important for empirical applications. Despite being backward-looking, conditional quantile methodology helps capture explanatory links between risk factors and hedge fund returns for risk measurement purposes. It is also useful in evaluating whether it is appropriate to use risk factor exposures to estimate riskiness by validating risk metric quality over time. Based on same principles but adding a forward-looking aspect, conditional stress testing methodology may be used by hedge fund investors and managers responsible for risk management in operational risk management activities. This methodology should be used if one is interested in the impact of a tail event while capturing empirically estimated links between hedge fund returns and risk factors in the data. Basing these methodologies on quantile regression coefficients, rather than their OLS counterparts, improves the empirical fit of tail risk exposures that may be used in risk management.

Yet these applications may be elaborated further. For instance, one can use extended window coefficient estimates that are based on the information that is available up to each month to model realistic situations. However, one has to be aware that small sample problems in this case would be intensified. One can also use rolling window coefficient estimates that are based on the most recent information that is available up to each month to disregard observation which may be outdated. Nevertheless, in this case small sample problems would be intensified even more. In addition, for conditional stress tests based on quantiles one can choose the quantile cutoff more elaborately. Having mentioned that, one has to keep in mind the importance of balancing the proximity to the tail with the number of data points left beyond the cutoff threshold. Furthermore, for empirical appilcations in real situations, one can validate various approaches to conditional stress testing by employing the framework similar to the one applied in this thesis for conditional quantiles, adding the forward-looking aspect on top.

7 Conclusion

Given the wide range of assets and derivatives that hedge funds invest into as well as the often complex dynamic trading strategies employed, comprehending different strategies' risk exposures is therefore not a straightforward task. The nature of hedge fund returns is often most characterized by non-normality. Being leptokurtic and asymmetric, i.e. having high excess kurtosis and negative skewness, is a common trait contributing to this feature. Common methods of conditional mean regressions, e.g. an OLS regression, only take into consideration how risk factors impact hedge fund returns on average.

The abovementioned aspects motivate the use of more intricate methods to examine hedge funds. The concept of quantile regressions offers more efficient and robust estimates given the common non-normality of hedge fund data. These reveal how hedge fund return dependencies on factors vary across quantiles of fund performances. Tail factor exposures are in that way revealed and can differ significantly from mean dependencies found by a simple OLS regression. This provides a valuable insight that risk originating from a specific factor can in some cases be underestimated by a mean coefficient regression. As this thesis presents, a strategy can, in the bottom performance quantile, show evidence of high factor exposure whereas, in the top quantile, factor exposure be insignificant or vice versa. As the slope estimates from OLS and quantile regressions differ significantly in several cases, one can conclude that hedge fund strategy returns do not have a constant variance property. Taking this implication into account, a more comprehensive risk assessment is made possible by using both conditional quantile and conditional stress testing approaches. The conditional quantiles prove to capture extreme losses well, which suggests that this is an adequate method to use by investors to gauge risk of extreme losses. The conditional stress tests provide a more forward looking perspective, and, more importantly, highlight the effect of strong factor tail dependencies, and the importance thereof from a risk management point of view.

In addition, the important implication from this thesis is the difference in risk exposures across hedge fund strategies. Hedge funds may not be regarded as a homogenous group and thus riskiness benchmarks and factors used should be appropriate when evaluating hedge fund risk levels.

Being able to assess hedge fund risk in a more efficient and robust way is in the interest of both investors as well as internally at hedge funds. Going forward, it can be interesting to implement other forward looking metrics based on quantile regression estimates, such as Monte Carlo simulations. However, this requires careful analysis when making distributional and stochastic assumptions. Moreover, the conducted study may also be extended to the individual hedge fund level. As pointed in the literature (Fung and Hsieh, 2002), the results will be fundamentally different in three ways. First, hedge fund managers decide to choose various degrees of leverage. Hence, managers can escalate or alleviate risk exposures, reflected in risk factor betas, by changing leverage. Second, hedge fund managers within the strategy do not represent a homogenous group and thus greatly differ in trade execution efficiency. Third, managers can also vary in strategies and specific securities. This divergence will show up in betas since it may partly describe factor exposures. Furthermore, an additional contribution might be to differentiate between the subsets of factors used for linear and quantile regression purposes, as in Meligkotsidou et al (2009). These extensions may provide important implications for hedge fund managers and investors who pursue rigorous risk management policies.

8 References

1. Ackermann, C., et al. (1999). The Performance of Hedge Funds: Risk, Return and Incentives. The Journal of Finance, 54(3), 833-874.
2. Agarwal, R., & Jorion, P. (2010). Hidden Survivorship in Hedge Fund Returns. Financial Analyst Journal, 66, 69-74.
3. Agarwal, V., & Naik, N. (2000). On Taking the 'Alternative' Route: The Risks, Rewards, and Performance of Persistence of Hedge Funds. Journal of Alternative Investments, 2(4), 6-23.
4. Agarwal, V., & Naik, N. (2004). Risk and Portfolio Decisions Involving Hedge Funds. Review of Financial Studies, 17(1), 63-98.
5. Agarwal, V., et al. (2017). Tail Risk in Hedge Funds: A Unique View from Portfolio Holdings. Journal of Financial Economics, 1-27.
6. Agarwal, V., et al. (2017). Volatility of aggregate volatility and hedge fund returns. Journal of Financial Economics, 1-20.
7. Allen, D., et al. (2013). A Panel-Based Quantile Regression Analysis of Funds of Hedge Funds, in Reconsidering Funds of Hedge Funds (Elsevier), 261-272.
8. Asness, C., et al. (2001). Do hedge funds hedge? The Journal of Portfolio Management 28, 6-19.
9. Avramov, D., et al. (2013). Hedge Fund Return Predictability Under the Magnifying Glass. Journal of Financial and Quantitative Analysis, 48(4), 1057-1083.
10. Bali, T., et al. (2014). Macroeconomic risk and hedge fund returns. Journal of Financial Economics, 114, 1-19.
11. Barron's (2014). Rising Interest Rates Will Hurt These Hedge Funds, April 26. URL: https://www.barrons.com/articles/rising-interest-rates-will-hurt-these-hedge-funds-1398490696.
12. Bessler, W., & Kurmann P. (2013). Funds of Hedge Funds, Efficient Portfolios, and Investor Clienteles, in Reconsidering Funds of Hedge Funds (Elsevier), 451-477.
13. Bollen, N. (2013). Zero-R2 Hedge Funds and Market Neutrality. Journal of Financial and Quantitative Analysis, 48(2), 519-547.
14. Bollen, N., & Pool, V. (2008). Conditional Return Smoothing in the Hedge Fund Industry. Journal of Financial and Quantitative Analysis, 43(2), 267-298.
15. Brooks, C. (2014). Introductory econometrics for finance: Chris Brooks. Third edition, Cambridge University Press.
16. Brooks, C., & Kat, H. (2002). The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors. Journal of Alternative Investments, 5(3), 26-44.
17. Brown, S., et al. (1999). Offshore Hedge Funds: Survival and Performance, 1989-95. Journal of Business, 72, 91-117.
18. Buraschi, A., et al. (2014). When there is no place to hide: correlation risk and the cross section of hedge fund returns. Review of Financial Studies, 27, 581-616.
19. Carretta, A., & Mattarocci, G. (2013). Choice of Risk Measure in Evaluating UCITS Funds of Hedge Funds, in Reconsidering Funds of Hedge Funds (Elsevier), 71-87.
20. Cavenaile, L., et al. (2011). The Impact of Illiquidity and Higher Moments of Hedge Fund Returns on Their Risk-Adjusted Performance and Diversification Potential. Journal of Alternative Investments, 13(4), 9-29.

21. Chernozhukov, V., et al. (2017). Extremal Quantile Regression: An Overview, prepared for the Handbook of Quantile Regression, 1-32.
22. Cogneau, P., et al. (2013). Predicting Funds of Hedge Funds Attrition Through Performance Diagnostics, in Reconsidering Funds of Hedge Funds (Elsevier), 163-181.
23. Edwards, F., & Caglayan, M. (2001). Hedge Fund Performance and Manager Skill. Journal of Futures Markets, 21(11), 1003-1028.
24. Eurekahedge (2007). November 2007 Hedge Fund Performance Commentary, December. URL:
http://www.eurekahedge.com/Research/News/769/07˙dec˙Eurekahedge˙Report˙online.
25. Financial Times (2011). Hedge fund indices' accuracy in question, March 6. URL: https://www.ft.com/content/16e4fb60-46ad-11e0-967a-00144feab49a.
26. Foerster, S. (2006). What drives equity market neutral hedge fund returns? Working Paper. Business School, University of Ontario.
27. Fung, W., & Hsieh, D. (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. The Review of Financial Studies, 10(2), 275-302.
28. Fung, W., & Hsieh, D. (2001). The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. Review of Financial Studies, 14(2), 313-341.
29. Fung, W., & Hsieh, D. (2002). Asset-Based Style Factors for Hedge Funds. Financial Analyst Journal, 58(5), 16-27.
30. Fung, W., & Hsieh, D. (2004). Hedge Fund Benchmarks: A Risk Based Approach. Financial Analyst Journal, 60, 65-80.
31. Getmansky, M., et al. (2004). An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. Journal of Financial Economics, 74(3), 529-609.
32. Gnedenko B. (1943). On the Limiting Distribution of the Maximum Term in a Random Series. Richard L. Smith, University of Surrey and University of North Carolina at Chapel Hill.
33. Gregoriou, G. (2013). Reconsidering funds of hedge funds: the financial crisis and best practices in UCITS, tail risk, performance, and due diligence. Elsevier.
34. Guizot, A. (2007). The Hedge Fund Compliance and Risk Management Guide. Chichester: Wiley.
35. Kaplan, P., & Knowles, J. (2004). Kappa: A Generalized Down-side Risk-adjusted Performance Measure. Journal of Performance Measurement, 8(1), 42-54.
36. Koenker, R., & Bassett, G. (1978). Regression Quantiles. Econometrica, 46(1), 33-50.
37. Kupiec, P. (1995). Techniques for verifying the accuracy of risk measurement models, Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System (U.S.), 95-24.
38. Lamm, R. (2013). After the Crisis, in Reconsidering Funds of Hedge Funds (Elsevier), 1-13.
39. Land, A., & Doig, A. (1960). An Automatic Method of Solving Discrete Programming Problems, Econometrica, 28(3), 497-520.
40. Lhabitant, F. (2008). Hedge Fund Indices for European Retail Investors: An Oxymoron. The Journal of Financial Transformation, 23(10), 145-153.
41. Liang, B. (1999). On the Performance of Hedge Funds. Financial Analysts Journal, 55(4), 72-85.

42. Liang, B. (2000). Hedge Funds: the Living and the Dead. Journal of Financial and Quantitative Analysis, 35, 309-327.
43. Liang, B., & Park, H. (2010). Predicting Hedge Fund Failure: A Comparison of Risk Measures. Journal of Financial and Quantitative Analysis, 45(1), 199-222.
44. Malkiel, B., & Saha. A. (2005). Hedge Funds: Risk and Return. Financial Analysts Journal, 61(6), 80-88.
45. Meligkotsidou, L., et al. (2009). Quantile Regression Analysis of Hedge Fund Strategies. Journal of Empirical Finance, 16(2), 264-279.
46. Mitchell, M., & Pulvino, T. (2001). Characteristics of Risk in Risk Arbitrage. Journal of Finance, 56(6), 2135-2175.
47. Okunev, J., & White, D. (2003). Hedge Fund Risk Factors and Value at Risk of Credit Trading Strategies, working paper, University of New South Wales.
48. Pastor, L., & Stambaugh, R. (2003). Liquidity Risk and Expected Stock Returns. The Journal of Political Economy, June, 642-685.
49. Powell, J. (1991). Estimation of monotonic regression models under quantile restrictions. Nonparametric and semiparametric methods in Econometrics, Cambridge University Press, New York, NY, 357-384.
50. Sadka, R. (2010). Liquidity Risk and the Cross-Section of Hedge-Fund Returns. Journal of Financial Economics, 98(1), 54-71.
51. Semmler, W., et al. (2013). Seeking Alpha: The Performance of Funds of Hedge Funds, in Reconsidering Funds of Hedge Funds (Elsevier), 303-330.
52. Siragusa, S. (2013). Funds of Hedge Funds Strategies and Implications for Asset Management, in Reconsidering Funds of Hedge Funds (Elsevier), 367-378.
53. Sokolowska, E. (2015). The Principles of Alternative Investments Management. Springer.
54. Svenska Dagbladet - SvD (2017). Investerare i USA flyr aktiv förvaltning - till indexfonder, Investors in the US escape active investments - to index funds, July 17. URL: https://www.svd.se/investerare-i-usa-flyr-aktiv-forvaltning–till-indexfonder.
55. The Wall Street Journal (2014). Merger Funds: More Tame Than Reputation, November 3. URL:
https://www.wsj.com/articles/merger-arbitrage-funds-draw-investors-1415048446.
56. Titman, S., & Tiu, C. (2011). Do the Best Hedge Funds Hedge? Review of Financial Studies, 24(1), 123-168.
57. Vrontos, S. (2015). Hedge Funds Managerial Skill Revisited: A Quantile Regression Approach. University of Essex, 1-28.
58. Wu, Y., & Liu Y. (2009). Variable selection in quantile regression. Statistica Sinica 19, 801-817.
59. Xu, E., et al. (2011). An Examination of Hedge Fund Survivor Bias and Attrition Before and During the Global Financial Crisis. Journal of Alternative Investments, 13(4), 40-52.

9 Appendices

Appendix 1. HFRI strategy index descriptions

HFIndustry. HFRI Fund Weighted Composite Index. The HFRI Fund Weighted Composite Index is a global, equal-weighted index of over 2,000 single-manager funds that report to HFR Database. Constituent funds report monthly net of all fees performance in US Dollar and have a minimum of $50 Million under management or a twelve (12) month track record of active performance. The HFRI Fund Weighted Composite Index does not include Funds of Hedge Funds.

EquitNeutral. HFRI EH: Equity Market Neutral Index. Equity Market Neutral strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and leverage is frequently employed to enhance the return profile of the positions identified. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Equity Market Neutral Strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

QuantDirect. HFRI EH: Quantitative Directional Index. Quantitative Directional strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Quantitative Directional Strategies typically maintain varying levels of net long or short equity market exposure over various market cycles.

ShortBias. HFRI EH: Short Bias Index. Short-Biased strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. Short Biased strategies may vary the investment level or the level of short exposure over market cycles, but the primary distinguishing characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets. Investment theses may be fundamental or technical and nature and manager has a particular focus, above that of a market generalist, on identification of overvalued companies and would expect to maintain a net short equity position over various market cycles.

EquitHedge. HFRI Equity Hedge (Total) Index. Equity Hedge: Investment Managers who maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. EH managers would typically maintain at least 50% exposure to, and may in some cases be entirely invested in, equities, both long and short.

Distressed. HFRI ED: Distressed/Restructuring Index. Distressed/Restructuring strategies which employ an investment process focused on corporate fixed income instruments, primarily on corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity as a result of either formal bankruptcy proceeding or financial market perception of near term proceedings. Managers are typically actively involved with the management of these companies, frequently involved on creditors' committees in negotiating the exchange of securities for alternative obligations, either swaps of debt, equity or hybrid securities. Managers employ fundamental credit processes focused on valuation and asset coverage of securities of distressed firms; in most cases portfolio exposures are concentrated in instruments which are publicly traded, in some cases actively and in others under reduced liquidity but in general for which a reasonable public market exists. In contrast to Special Situations, Distressed Strategies employ primarily debt (greater than 60%) but also may maintain related equity exposure.

MergerArb. HFRI ED: Merger Arbitrage Index. Merger Arbitrage strategies which employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction. Merger Arbitrage involves primarily announced transactions, typically with limited or no exposure to situations which pre-, post-date or situations in which no formal announcement is expected to occur. Opportunities are frequently presented in cross border, collared and international transactions which incorporate multiple geographic regulatory institutions, which typically involve minimal exposure to corporate credits. Merger arbitrage strategies typically have over 75% of positions in announced transactions over a given market cycle.

EventDriv. HFRI Event-Driven (Total) Index. Event-Driven: Investment Managers who maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including but not limited to mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. Event Driven exposure includes a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure.

Macro. HFRI Macro (Total) Index. Macro: Investment Managers which trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ RV techniques, Macro strategies are distinct from RV strategies in that the primary investment thesis is predicated on predicted or future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposes to EH, in which the fundamental characteristics on the company are the most significant are integral to investment thesis.

MacroSystDiv. HFRI Macro: Systematic Diversified Index. Systematic: Diversified strategies have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning. Strategies which employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across individual instruments or asset classes. Strategies typically employ quantitative process which focus on statistically robust or technical patterns in the return series of the asset, and typically focus on highly liquid instruments and maintain shorter holding periods than either discretionary or mean reverting strategies. Although some strategies seek to employ counter trend models, strategies benefit most from an environment characterized by persistent, discernable trending behavior. Systematic: Diversified strategies typically would expect to have no greater than 35% of portfolio in either dedicated currency or commodity exposures over a given market cycle.

RelatValue. HFRI Relative Value (Total) Index. Investment Managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Managers employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. Fixed income strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. RV position may be involved in corporate transactions also, but as opposed to ED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

FIAssetBack. HFRI RV: Fixed Income-Asset Backed Index. Fixed Income: Asset Backed includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a fixed income instrument backed physical collateral or other financial obligations (loans, credit cards) other than those of a specific corporation. Strategies employ an investment process designed to isolate attractive opportunities between a variety of fixed income instruments specifically securitized by collateral commitments which frequently include loans, pools and portfolios of loans, receivables, real estate, machinery or other tangible financial commitments. Investment thesis may be predicated on an attractive spread given the nature and quality of the collateral, the liquidity characteristics of the underlying instruments and on issuance and trends in collateralized fixed income instruments, broadly speaking. In many cases, investment managers hedge, limit or offset interest rate exposure in the interest of isolating the risk of the position to strictly the yield disparity of the instrument relative to the lower risk instruments.

ConvertArb. HFRI RV: Fixed Income-Convertible Arbitrage Index. Fixed Income: Convertible Arbitrage includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a convertible fixed income instrument. Strategies employ an investment process designed to isolate attractive opportunities between the price of a convertible security and the price of a nonconvertible security, typically of the same issuer. Convertible arbitrage positions maintain characteristic sensitivities to credit quality the issuer, implied and realized volatility of the underlying instruments, levels of interest rates and the valuation of the issuer's equity, among other more general market and idiosyncratic sensitivities.

FIHighYield. HFRI RV: Fixed Income-Corporate Index. Fixed Income: Corporate includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a corporate fixed income instrument. Strategies employ an investment process designed to isolate attractive opportunities between a variety of fixed income instruments, typically realizing an attractive spread between multiple corporate bonds or between a corporate and risk free government bond. Fixed Income: Corporate strategies differ from Event Driven: Credit Arbitrage in that the former more typically involve more general market hedges which may vary in the degree to which they limit fixed income market exposure, while the later typically involve arbitrage positions with little or no net credit market exposure, but are predicated on specific, anticipated idiosyncratic developments.

RVMultiStrat. HFRI RV: Multi-Strategy Index. Multi-Strategies employ an investment thesis is predicated on realization of a spread between related yield instruments in which one or multiple components of the spread contains a fixed income, derivative, equity, real estate, MLP or combination of these or other instruments. Strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. In many cases these strategies may exist as distinct strategies across which a vehicle which allocates directly, or may exist as related strategies over which a single individual or decision making process manages. Multi-strategy is not intended to provide broadest-based mass market investors appeal, but are most frequently distinguished from others arbitrage strategies in that they expect to maintain ¿30% of portfolio exposure in 2 or more strategies meaningfully distinct from each other that are expected to respond to diverse market influences.

YieldAlt. HFRI RV: Yield Alternatives Index. Yield Alternative strategies employ an investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread contains a derivative, equity, real estate, MLP or combination of these or other instruments. Strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. Strategies employ an investment process designed to isolate opportunities in yield oriented securities, which can include equity, preferred, listed partnerships (MLPs), REITs and some other corporate obligations. In contrast to fixed income arbitrage, yield alternative contain primarily non-fixed income securities, and in contrast to equity hedge strategies, the investment thesis is more predicated on the yield realized from the securities than on price appreciation of the underlying securities.

FOFConserv. HFRI FOF: Conservative Index. FOFs classified as 'Conservative' exhibit one or more of the following characteristics: seeks consistent returns by primarily investing in funds that generally engage in more 'conservative' strategies such as Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage; exhibits a lower historical annual standard deviation than the HFRI Fund of Funds Composite Index. A fund in the HFRI FOF Conservative Index shows generally consistent performance regardless of market conditions.

FOFDivers. HFRI FOF: Diversified Index. FOFs classified as 'Diversified' exhibit one or more of the following characteristics: invests in a variety of strategies among multiple managers; historical annual return and/or a standard deviation generally similar to the HFRI Fund of Fund Composite index; demonstrates generally close performance and returns distribution correlation to the HFRI Fund of Fund Composite Index. A fund in the HFRI FOF Diversified Index tends to show minimal loss in down markets while achieving superior returns in up markets.

FOFDefens. HFRI FOF: Market Defensive Index. FOFs classified as 'Market Defensive' exhibit one or more of the following characteristics: invests in funds that generally engage in short-biased strategies such as short selling and managed futures; shows a negative correlation to the general market benchmarks (S&P). A fund in the FOF Market

Defensive Index exhibits higher returns during down markets than during up markets.

FOFStrat. HFRI FOF: Strategic Index. FOFs classified as 'Strategic' exhibit one or more of the following characteristics: seeks superior returns by primarily investing in funds that generally engage in more opportunistic strategies such as Emerging Markets, Sector specific, and Equity Hedge; exhibits a greater dispersion of returns and higher volatility compared to the HFRI Fund of Funds Composite Index. A fund in the HFRI FOF Strategic Index tends to outperform the HFRI Fund of Fund Composite Index in up markets and underperform the index in down markets.

FOFCompos. HFRI Fund of Funds Composite Index. Fund of Funds invest with multiple managers through funds or managed accounts. The strategy designs a diversified portfolio of managers with the objective of significantly lowering the risk (volatility) of investing with an individual manager. The Fund of Funds manager has discretion in choosing which strategies to invest in for the portfolio. A manager may allocate funds to numerous managers within a single strategy, or with numerous managers in multiple strategies. The minimum investment in a Fund of Funds may be lower than an investment in an individual hedge fund or managed account. The investor has the advantage of diversification among managers and styles with significantly less capital than investing with separate managers. PLEASE NOTE: The HFRI Fund of Funds Index is not included in the HFRI Fund Weighted Composite Index.

EmergMark. HFRI Emerging Markets (Total) Index. Emerging Markets funds invest, primarily long, in securities of companies or the sovereign debt of developing or 'emerging' countries. Emerging Markets regions include Africa, Asia ex-Japan, Latin America, the Middle East and Russia/Eastern Europe. Emerging Markets - Global funds will shift their weightings among these regions according to market conditions and manager perspectives.

Appendix 2

Table 10: Hedge fund strategy returns summary statistics. Mean - arithmetic average of returns, annualized by multiplying monthly means by 12. Std - sample standard deviation of returns, annualized by multiplying monthly sample standard deviations by $\sqrt{12}$. MaxDD - maximum drawdown of returns. Skew - return distribution sample skewness. Exck - return distribution sample kurtosis in excess of normal kurtosis (3). BJ test - Bera-Jarque test for normality: 1 stands for rejection of the normal distribution hypothesis for the return distribution, 0 stands for non-rejection of the normal distribution hypothesis for the return distribution. ADF test - Augmented Dickey-Fuller test for data stationarity: 1 stands for stationary return data (rejection of the unit root null hypothesis), 0 stands for non-stationary return data (non-rejection of the unit root null hypothesis)

Strategy	Mean	Std	MaxDD	Skew	Exck	BJ test	ADF test
Distressed	8.48%	6.16%	27.4%	-1.38	4.8	1	1
MergerArb	7.00%	3.45%	8.1%	-1.39	5.7	1	1
EquitNeutral	5.23%	3.02%	9.2%	-0.23	2.2	1	1
QuantDirect	9.29%	11.70%	31.1%	-0.41	1.3	1	1
ShortBias	-0.80%	17.20%	64.2%	0.43	3.5	1	1
EmergMark	7.95%	13.20%	43.4%	-0.87	4.4	1	1
EquitHedge	9.21%	8.86%	30.6%	-0.19	2.2	1	1
EventDriv	9.14%	6.54%	24.8%	-1.18	4.0	1	1
FOFConserv	4.72%	3.86%	20.4%	-1.70	7.6	1	1
FOFDivers	4.67%	5.74%	21.8%	-0.45	4.5	1	1
FOFDefens	5.69%	5.34%	10.9%	0.06	0.5	0	1
FOFStrat	5.44%	8.06%	26.8%	-0.55	4.3	1	1
FOFCompos	4.91%	5.63%	22.2%	-0.65	4.1	1	1
HFIndustry	7.92%	6.70%	21.4%	-0.57	2.8	1	1
Macro	6.80%	6.24%	10.7%	0.30	1.3	1	1
MacroSystDiv	8.17%	7.58%	11.8%	0.22	-0.3	0	1
RelatValue	7.61%	4.10%	18.0%	-2.69	15.5	1	1
FIAssetBack	8.69%	3.91%	13.5%	-3.42	24.1	1	1
ConvertArb	7.27%	6.65%	35.3%	-2.88	27.2	1	1
FIHighYield	5.95%	5.42%	28.2%	-2.15	11.2	1	1
RVMultiStrat	6.25%	4.12%	21.5%	-2.51	15.2	1	1
YieldAlt	7.74%	7.82%	28.1%	-0.87	2.6	1	1

Appendix 3

Table 11: Worst historical observed returns of hedge fund strategies. Return - minimum (most negative) observed return. Date - month corresponding to minimum (most negative) observed return

Strategy	Return	Date
Distressed	-8.5%	08/1998
MergerArb	-5.7%	08/1998
EquitNeutral	-2.9%	09/2008
QuantDirect	-13.3%	08/1998
ShortBias	-21.2%	02/2000
EmergMark	-21.0%	08/1998
EquitHedge	-9.5%	10/2008
EventDriv	-8.9%	08/1998
FOFConserv	-5.9%	09/2008
FOFDivers	-7.8%	08/1998
FOFDefens	-5.4%	08/1998
FOFStrat	-12.1%	08/1998
FOFCompos	-7.5%	08/1998
HFIndustry	-8.7%	08/1998
Macro	-6.4%	02/1994
MacroSystDiv	-4.4%	11/2007
RelatValue	-8.0%	10/2008
FIAssetBack	-9.2%	10/1998
ConvertArb	-16.0%	10/2008
FIHighYield	-10.7%	10/2008
RVMultiStrat	-8.4%	10/2008
YieldAlt	-8.8%	11/2008

Appendix 4

Table 12: Standard risk metrics descriptions

Risk Metric	Formula	Description
Standard deviation	$\frac{1}{t_2}(R_t - \frac{1}{t_2}\sum_{t=t_1}^{t_2}(R_t))^2$	Risk unit in terms of standard deviation of returns.
Probability of Shortfall	$\frac{1}{t_2-t_1} \cdot \sum_{t=t_1}^{t_2} max\vert -R_t, 0\vert^0$	The historical probability of losses. Constructed with negative values of the performance distributions.
Absolute Shortfall	$\frac{1}{t_2-t_1} \cdot \sum_{t=t_1}^{t_2} max(-R_t, 0)^1$	Lower partial moment mean, i.e. mean loss.
Kappa order two	$\sqrt[2]{\frac{1}{t_2 - t_1} \cdot \sum_{t=t_1}^{t_2} max(-R_t, 0)^2}$	Uses second order lower partial moment. Considers the distribution's variance.
Kappa order three	$\sqrt[3]{\frac{1}{t_2 - t_1} \cdot \sum_{t=t_1}^{t_2} max(-R_t, 0)^3}$	Uses third order lower partial moment. Considers the distribution's skewness.
Kappa order four	$\sqrt[4]{\frac{1}{t_2 - t_1} \cdot \sum_{t=t_1}^{t_2} max(-R_t, 0)^4}$	Uses fourth order lower partial moment. Considers the distribution's kurtosis.

Appendix 5

Table 13: Industry risk metrics across hedge fund strategies. Std - sample standard deviation of monthly returns. PS - Probability of Shortfall. AS - Absolute Shortfall. Kappan2 - Kappa order two (Sortino). Kappan3 - Kappa order three. Kappan4 - Kappa order four. MaxDD - maximum drawdown of returns. Definitions of risk metrics are as per Appendix 4

Strategy	Std	PS	AS	Kappan2	Kappan3	Kappan4	MaxDD
Distressed	1.78%	0.269	0.0039	0.0114	0.0190	0.0260	27.4%
MergerArb	1.00%	0.233	0.0018	0.0057	0.0101	0.0147	8.1%
EquitNeutral	0.87%	0.251	0.0015	0.0045	0.0072	0.0097	9.2%
QuantDirect	3.39%	0.382	0.0095	0.0214	0.0316	0.0405	31.1%
ShortBias	4.95%	0.556	0.0179	0.0334	0.0479	0.0619	64.2%
EmergMark	3.82%	0.378	0.0113	0.0261	0.0412	0.0568	43.4%
EquitHedge	2.56%	0.345	0.0064	0.0150	0.0228	0.0297	30.6%
EventDriv	1.89%	0.287	0.0042	0.0117	0.0194	0.0266	24.8%
FOFConserv	1.11%	0.262	0.0025	0.0076	0.0130	0.0181	20.4%
FOFDivers	1.66%	0.335	0.0043	0.0106	0.0169	0.0229	21.8%
FOFDefens	1.54%	0.382	0.0040	0.0083	0.0119	0.0154	10.9%
FOFStrat	2.33%	0.382	0.0065	0.0154	0.0242	0.0330	26.8%
FOFCompos	1.63%	0.349	0.0043	0.0105	0.0167	0.0227	22.2%
HFIndustry	1.93%	0.331	0.0046	0.0115	0.0183	0.0249	21.4%
Macro	1.80%	0.411	0.0042	0.0092	0.0137	0.0180	10.7%
MacroSystDiv	2.19%	0.415	0.0059	0.0112	0.0148	0.0176	11.8%
RelatValue	1.18%	0.193	0.0019	0.0079	0.0153	0.0222	18.0%
FIAssetBack	1.13%	0.142	0.0017	0.0077	0.0155	0.0234	13.5%
ConvertArb	1.92%	0.229	0.0035	0.0139	0.0281	0.0421	35.3%
FIHighYield	1.56%	0.265	0.0036	0.0111	0.0197	0.0282	28.2%
RVMultiStrat	1.19%	0.215	0.0022	0.0081	0.0154	0.0225	21.5%
YieldAlt	2.26%	0.353	0.0058	0.0145	0.0228	0.0299	28.1%

Appendix 6

Table 14: Historical VaR and ETL risk metrics across hedge fund strategies. VaR5% - historical Value at Risk estimated for 5% threshold. ETL5% - historical Conditional Value at Risk (expected tail loss) estimated for 5% threshold by averaging observations worse than 5% Value at Risk. VaR1% - historical Value at Risk estimated for 1% threshold. ETL1% - historical Conditional Value at Risk (expected tail loss) estimated for 1% threshold by averaging observations worse than 1% Value at Risk

Strategy	VaR5%	ETL5%	VaR1%	ETL1%
Distressed	2.18%	4.16%	5.71%	7.43%
MergerArb	1.16%	2.02%	2.66%	3.77%
EquitNeutral	0.94%	1.67%	2.53%	2.73%
QuantDirect	5.05%	7.32%	8.59%	10.40%
ShortBias	7.38%	10.90%	12.30%	16.10%
EmergMark	5.48%	8.38%	10.10%	15.30%
EquitHedge	3.59%	5.28%	7.23%	8.42%
EventDriv	2.35%	4.22%	5.58%	7.70%
FOFConserv	1.50%	2.73%	3.67%	5.22%
FOFDivers	2.27%	3.69%	5.33%	6.67%
FOFDefens	1.92%	2.62%	2.82%	3.83%
FOFStrat	3.32%	5.12%	6.95%	9.08%
FOFCompos	2.30%	3.58%	5.48%	6.74%
HFIndustry	2.54%	3.88%	5.55%	7.22%
Macro	2.06%	3.06%	3.69%	4.62%
MacroSystDiv	2.78%	3.31%	3.64%	3.92%
RelatValue	1.01%	2.69%	5.02%	6.58%
FIAssBack	1.14%	2.54%	3.28%	5.90%
ConvertArb	1.88%	4.35%	3.96%	10.70%
FIHighYield	1.90%	3.97%	4.87%	7.61%
RVMultiStrat	1.18%	2.78%	3.23%	6.04%
YieldAlt	2.80%	5.40%	7.56%	8.13%

Appendix 7

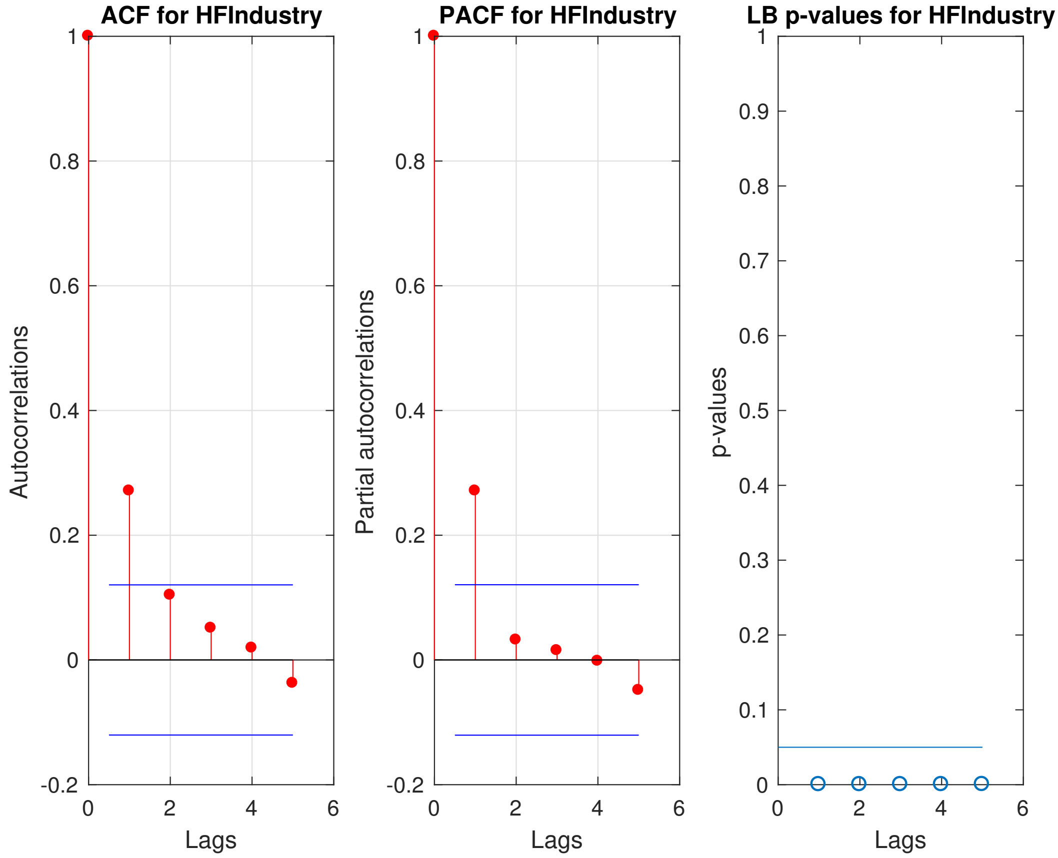


Figure 13: Autocorrelation analysis of hedge fund industry returns. Graph on the left presents autocorrelation function of returns up to lag 5. Spikes stand for autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph in the middle presents partial autocorrelation function of returns up to lag 5. Spikes stand for partial autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph on the right presents p-values for Ljung-Box tests for residual autocorrelation against 5% significance level threshold: if the p-value at lag n is lower than 5% significance level threshold, the first n autocorrelation coefficients up to lag n are jointly statistically significant from zero

Appendix 8

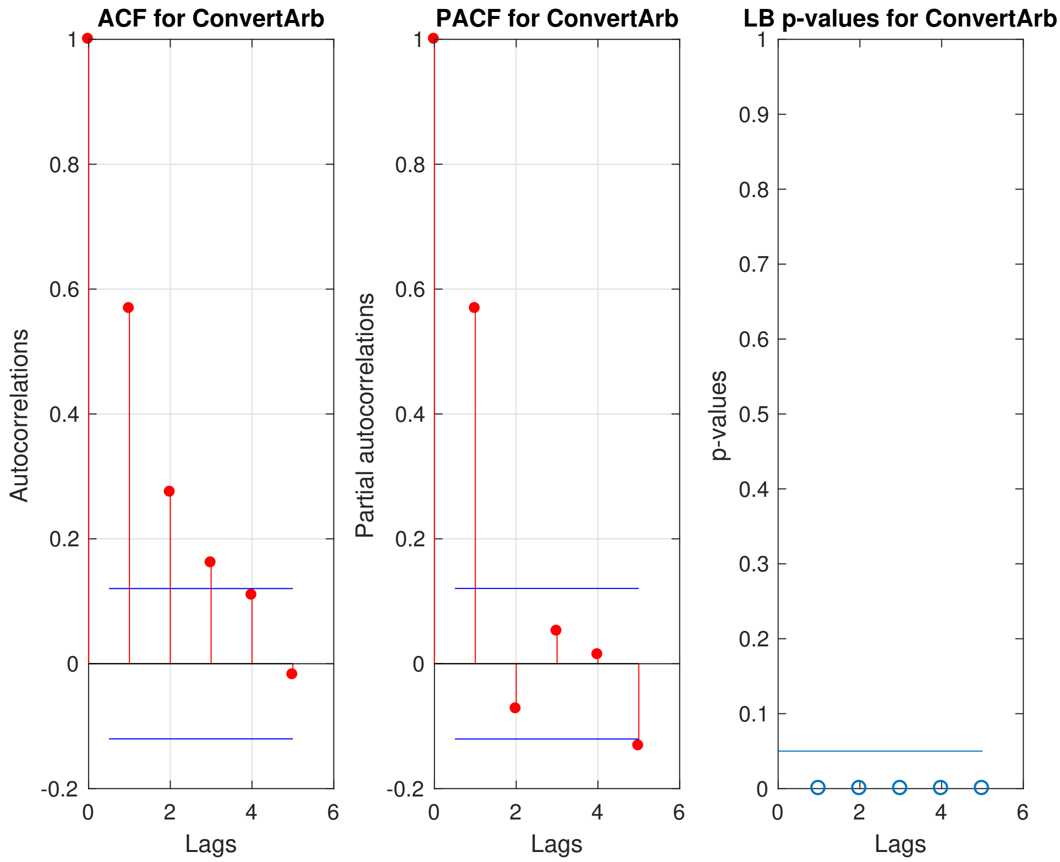


Figure 14: Autocorrelation analysis of fixed income-convertible arbitrage strategy returns. Graph on the left presents autocorrelation function of returns up to lag 5. Spikes stand for autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph in the middle presents partial autocorrelation function of returns up to lag 5. Spikes stand for partial autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph on the right presents p-values for Ljung-Box tests for residual autocorrelation against 5% significance level threshold: if the p-value at lag n is lower than 5% significance level threshold, the first n autocorrelation coefficients up to lag n are jointly statistically significant from zero

Appendix 9

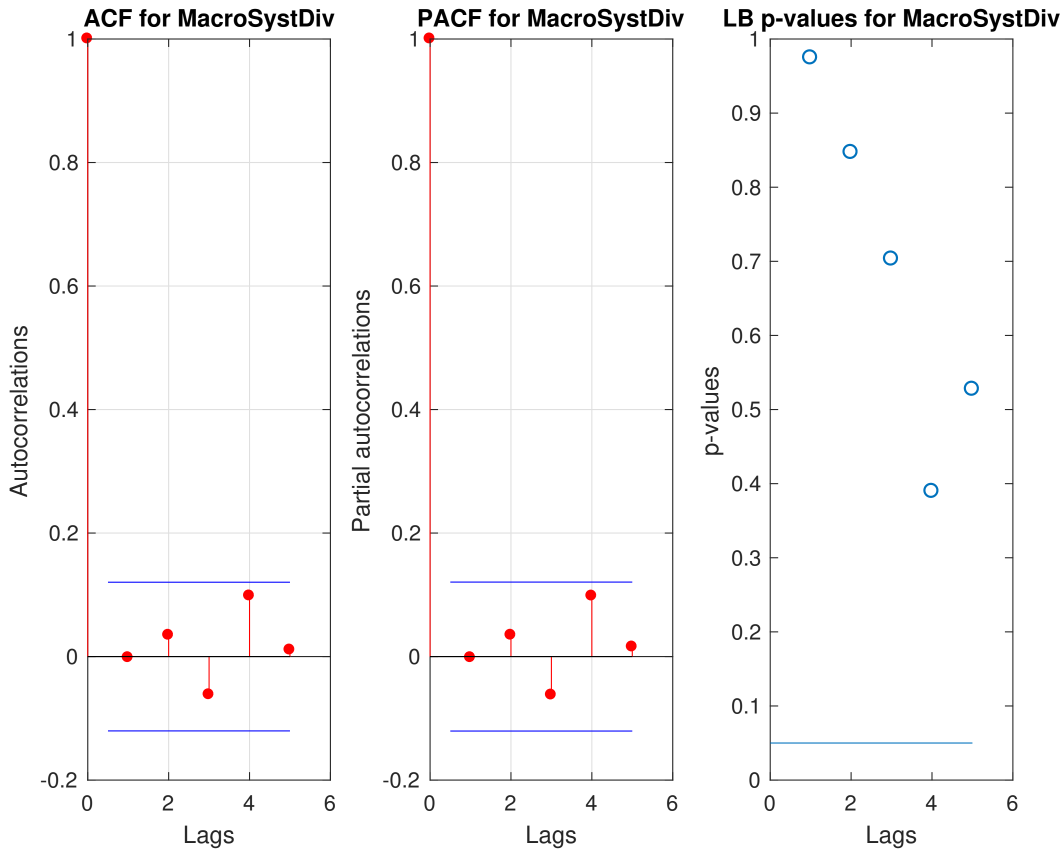


Figure 15: Autocorrelation analysis of macro systematic diversified strategy returns. Graph on the left presents autocorrelation function of returns up to lag 5. Spikes stand for autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph in the middle presents partial autocorrelation function of returns up to lag 5. Spikes stand for partial autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph on the right presents p-values for Ljung-Box tests for residual autocorrelation against 5% significance level threshold: if the p-value at lag n is lower than 5% significance level threshold, the first n autocorrelation coefficients up to lag n are jointly statistically significant from zero

Appendix 10

Table 15: MA(q) model choice with information criteria and autocorrelation analysis. Table presents MA(q) model orders q. AIC - Akaike information criterion. SBIC - Schwarz's Bayesian information criterion. HQC - Hannan-Quinn information criterion. ACF and PACF analysis - order suggested by graphical analysis of autocorrelation and partial autocorrelation plots

Strategy	AIC	SBIC	HQC	ACF and PACF analysis
Distressed	4	2	4	2
MergerArb	3	3	3	1-3
EquitNeutral	4	1	3	1
QuantDirect	1	1	1	1
ShortBias	2	0	1	0
EmergMark	1	1	1	1
EquitHedge	3	1	1	1
EventDriv	3	1	1	1
FOFConserv	3	3	3	3
FOFDivers	3	1	3	1
FOFDefens	0	0	0	0
FOFStrat	2	2	2	1-2
FOFCompos	3	2	2	1
HFIndustry	2	1	1	1
Macro	1	0	0	0
MacroSystDiv	0	0	0	0
RelatValue	4	2	2	2
FIAssetBack	4	2	4	2
ConvertArb	4	2	4	2
FIHighYield	3	2	2	2
RVMultiStrat	4	2	2	2
YieldAlt	3	1	1	1

Appendix 11

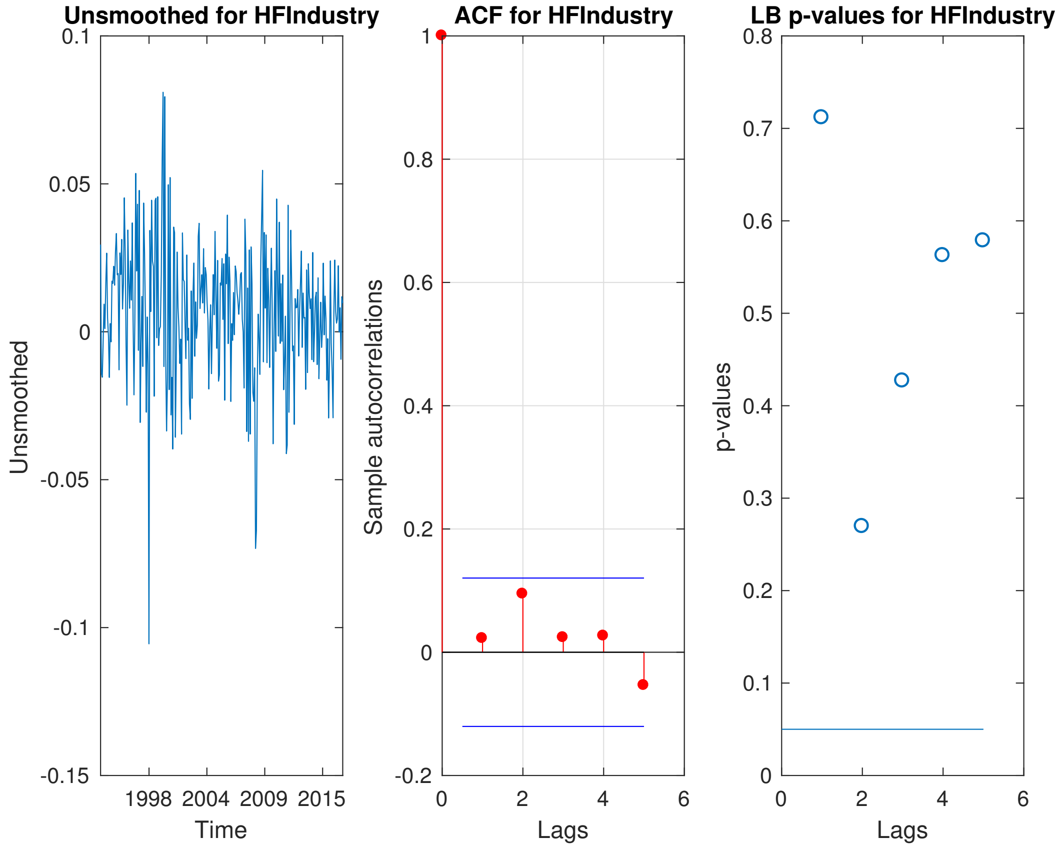


Figure 16: Autocorrelation analysis of unsmoothed hedge fund industry returns. Graph on the left presents time series of unsmoothed returns, i.e. MA(1) model residuals. Graph in the middle presents autocorrelation function of unsmoothed returns up to lag 5. Spikes stand for autocorrelation function coefficients at respective lags. Blue lines stand for upper and lower confidence bounds at 95% confidence. Graph on the right presents p-values for Ljung-Box tests for residual autocorrelation against 5% significance level threshold: if the p-value at lag n is lower than 5% significance level threshold, the first n autocorrelation coefficients up to lag n are jointly statistically significant from zero

Appendix 12

Table 16: Quantile regression coefficient estimates of regressions of hedge fund strategy smoothed (observed) returns at the 5% quantile on the subset of risk factors chosen by the OLS best subset regression method. Column names as per Table 2

Strategy	Intercept	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	-0.0148	NA	NA	NA	-4.1075	NA	0.1703	0.0480
MergerArb	0.0005	NA	NA	NA	NA	-0.0264	0.1494	0.0335
EquitNeutral	-0.0012	NA	NA	NA	NA	-0.0302	0.0437	NA
QuantDirect	-0.0248	NA	NA	NA	NA	NA	0.6298	0.3193
ShortBias	-0.0468	NA	NA	NA	NA	NA	-0.7497	-0.7973
EmergMark	-0.0471	0.0514	NA	NA	NA	NA	0.6218	0.5045
EquitHedge	0.0023	NA	NA	NA	NA	-0.0560	0.4638	0.2833
EventDriv	0.0059	NA	NA	NA	NA	-0.0562	0.3098	0.1223
FOFConserv	0.0052	NA	NA	NA	-1.8309	-0.0516	0.0749	NA
FOFDivers	0.0052	NA	NA	NA	NA	-0.0729	0.1615	0.0741
FOFDefens	-0.0133	NA	-0.0008	NA	NA	-0.0200	0.0418	NA
FOFStrat	0.0037	NA	NA	NA	NA	-0.0894	0.2686	0.2000
FOFCompos	0.0050	NA	NA	NA	NA	-0.0718	0.1709	0.0836
HFIndustry	0.0023	NA	NA	NA	NA	-0.0456	0.3370	0.2120
Macro	-0.0055	NA	0.0065	NA	NA	-0.0453	0.1097	NA
MacroSystDiv	-0.0261	NA	0.0389	NA	NA	NA	0.1291	NA
RelatValue	-0.0066	NA	NA	-0.6956	-3.4261	NA	0.1306	NA
FIAssetBack	-0.0081	NA	NA	NA	-3.1667	NA	NA	NA
ConvertArb	-0.0160	NA	NA	-2.3491	-6.4626	NA	0.2471	NA
FIHighYield	-0.0130	NA	NA	-0.6234	-4.9608	NA	0.1403	NA
RVMultiStrat	-0.0075	NA	NA	-0.6041	-3.9819	NA	0.0868	NA
YieldAlt	-0.0258	NA	NA	NA	-3.5803	NA	0.2853	NA

Appendix 13

Table 17: Conditional stress testing results based on OLS coefficient estimates without intercepts. Values stand for simulated returns based on stressing the corresponding factor as a "leading factor", evaluating consequent responses of other factors and applying OLS coefficient estimates without intercepts. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-1.43%	0	-2.94%	-0.95%
MergerArb	0	0	0	0	-1.01%	-1.78%	-0.82%
EquitNeutral	0	0	0	0	-0.63%	-0.82%	0
QuantDirect	0	0	0	0	0	-5.27%	-1.83%
ShortBias	0	0	0	0	0	-6.14%	-4.09%
EmergMark	-1.40%	0	0	0	0	-5.23%	-0.96%
EquitHedge	0	0	0	0	-1.91%	-4.42%	-2.05%
EventDriv	0	0	0	0	-2.23%	-3.85%	-1.90%
FOFConserv	0	0	0	-1.67%	-1.79%	-2.61%	0
FOFDivers	0	0	0	0	-2.15%	-3.03%	-1.70%
FOFDefens	0	-1.42%	0	0	-1.51%	-1.26%	0
FOFStrat	0	0	0	0	-2.68%	-4.64%	-2.36%
FOFCompos	0	0	0	0	-2.17%	-3.35%	-1.69%
HFIndustry	0	0	0	0	-1.83%	-3.64%	-1.66%
Macro	0	-1.39%	0	0	-1.84%	-2.00%	0
MacroSystDiv	0	-0.47%	0	0	0	-1.25%	0
RelatValue	0	0	0.47%	-0.95%	0	-1.80%	0
FIAssetBack	0	0	0	-0.82%	0	0	0
ConvertArb	0	0	0.52%	-1.61%	0	-2.45%	0
FIHighYield	0	0	0.75%	-1.51%	0	-2.44%	0
RVMultiStrat	0	0	0.47%	-1.09%	0	-1.71%	0
YieldAlt	0	0	0	-1.11%	0	-2.38%	0

Appendix 14

Table 18: Conditional stress testing results based on quantile regression coefficient estimates at the 5% quantile without intercepts. Values stand for simulated returns based on stressing the corresponding factor as a "leading factor", evaluating consequent responses of other factors and applying quantile regression coefficient estimates at the 5% quantile without intercepts. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-2.72%	0	-3.51%	-2.55%
MergerArb	0	0	0	0	-2.07%	-2.53%	-1.90%
EquitNeutral	0	0	0	0	-1.17%	-1.36%	0
QuantDirect	0	0	0	0	0	-5.84%	-4.42%
ShortBias	0	0	0	0	0	-5.84%	-6.24%
EmergMark	-3.08%	0	0	0	0	-7.38%	-6.20%
EquitHedge	0	0	0	0	-4.95%	-5.84%	-5.15%
EventDriv	0	0	0	0	-4.88%	-5.52%	-4.57%
FOFConserv	0	0	0	-3.88%	-4.38%	-4.50%	0
FOFDivers	0	0	0	0	-5.00%	-5.12%	-4.50%
FOFDefens	0	-0.79%	0	0	-0.88%	-0.88%	0
FOFStrat	0	0	0	0	-6.07%	-6.40%	-5.91%
FOFCompos	0	0	0	0	-4.90%	-5.24%	-4.30%
HFIndustry	0	0	0	0	-4.36%	-5.13%	-4.53%
Macro	0	-1.49%	0	0	-2.17%	-2.09%	0
MacroSystDiv	0	-0.50%	0	0	0	-0.50%	0
RelatValue	0	0	-0.84%	-1.48%	0	-1.66%	0
FIAssetBack	0	0	0	-0.79%	0	0	0
ConvertArb	0	0	-0.89%	-1.53%	0	-2.32%	0
FIHighYield	0	0	-1.23%	-2.21%	0	-2.72%	0
RVMultiStrat	0	0	-0.79%	-1.63%	0	-1.84%	0
YieldAlt	0	0	0	-2.21%	0	-3.02%	0

Appendix 15

Table 19: Conditional stress testing results based on coefficient estimates at the 1% quantile, extrapolated from the 5% quantile, without intercepts. Values stand for simulated returns based on stressing the corresponding factor as a "leading factor", evaluating consequent responses of other factors and applying coefficient estimates at the 1% quantile, extrapolated from the 5% quantile, without intercepts. Column names as per Table 2

Strategy	LIQ	TF	BND	CRSPR	VOV	MKT	SZSPR
Distressed	0	0	0	-3.70%	0	-4.83%	-3.74%
MergerArb	0	0	0	0	-3.46%	-4.30%	-3.04%
EquitNeutral	0	0	0	0	0.03%	-0.81%	0
QuantDirect	0	0	0	0	0	-5.80%	-3.97%
ShortBias	0	0	0	0	0	-8.44%	-9.91%
EmergMark	-6.49%	0	0	0	0	-13.20%	-11.30%
EquitHedge	0	0	0	0	-6.74%	-8.02%	-6.80%
EventDriv	0	0	0	0	-6.17%	-7.03%	-5.73%
FOFConserv	0	0	0	-6.56%	-7.58%	-7.26%	0
FOFDivers	0	0	0	0	-7.66%	-7.36%	-6.52%
FOFDefens	0	-0.38%	0	0	-1.13%	-1.44%	0
FOFStrat	0	0	0	0	-7.21%	-7.36%	-7.48%
FOFCompos	0	0	0	0	-6.34%	-6.56%	-5.25%
HFIndustry	0	0	0	0	-6.34%	-7.30%	-6.22%
Macro	0	-3.36%	0	0	-3.68%	-3.28%	0
MacroSystDiv	0	-0.54%	0	0	0	-0.26%	0
RelatValue	0	0	-0.97%	-1.70%	0	-1.94%	0
FIAssetBack	0	0	0	-0.03%	0	0	0
ConvertArb	0	0	-2.13%	-1.58%	0	-2.40%	0
FIHighYield	0	0	-2.03%	-1.95%	0	-2.46%	0
RVMultiStrat	0	0	-1.41%	-1.34%	0	-1.43%	0
YieldAlt	0	0	0	-2.98%	0	-4.21%	0

Appendix 16

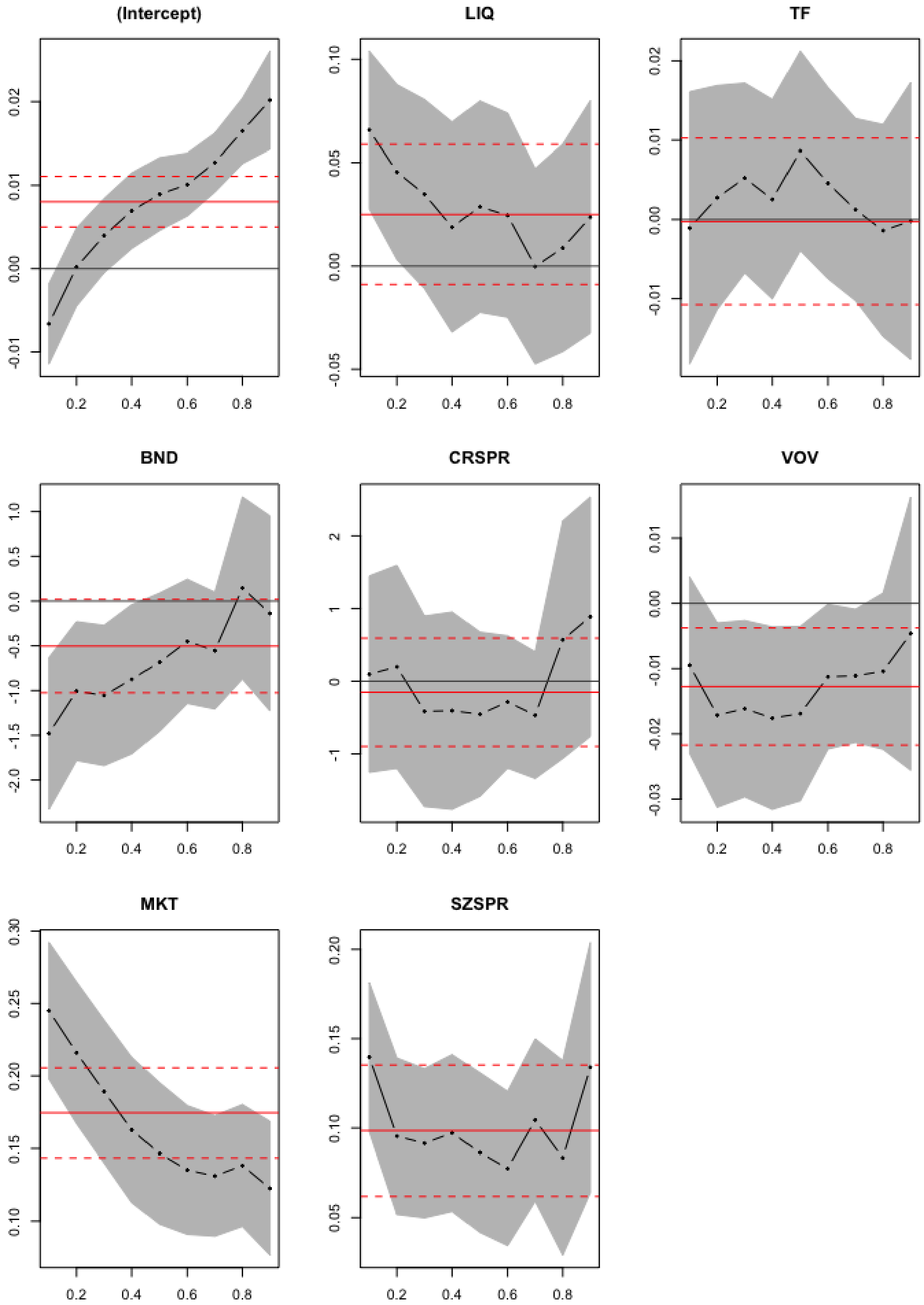


Figure 17: "Kitchen sink" quantile regression coefficients across merger arbitrage strategy performance quantiles. Each graph contrasts corresponding coefficients along return quantiles with OLS coefficients for the merger arbitrage strategy. Dashed black line stands for coefficients from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS coefficients. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0

Appendix 17

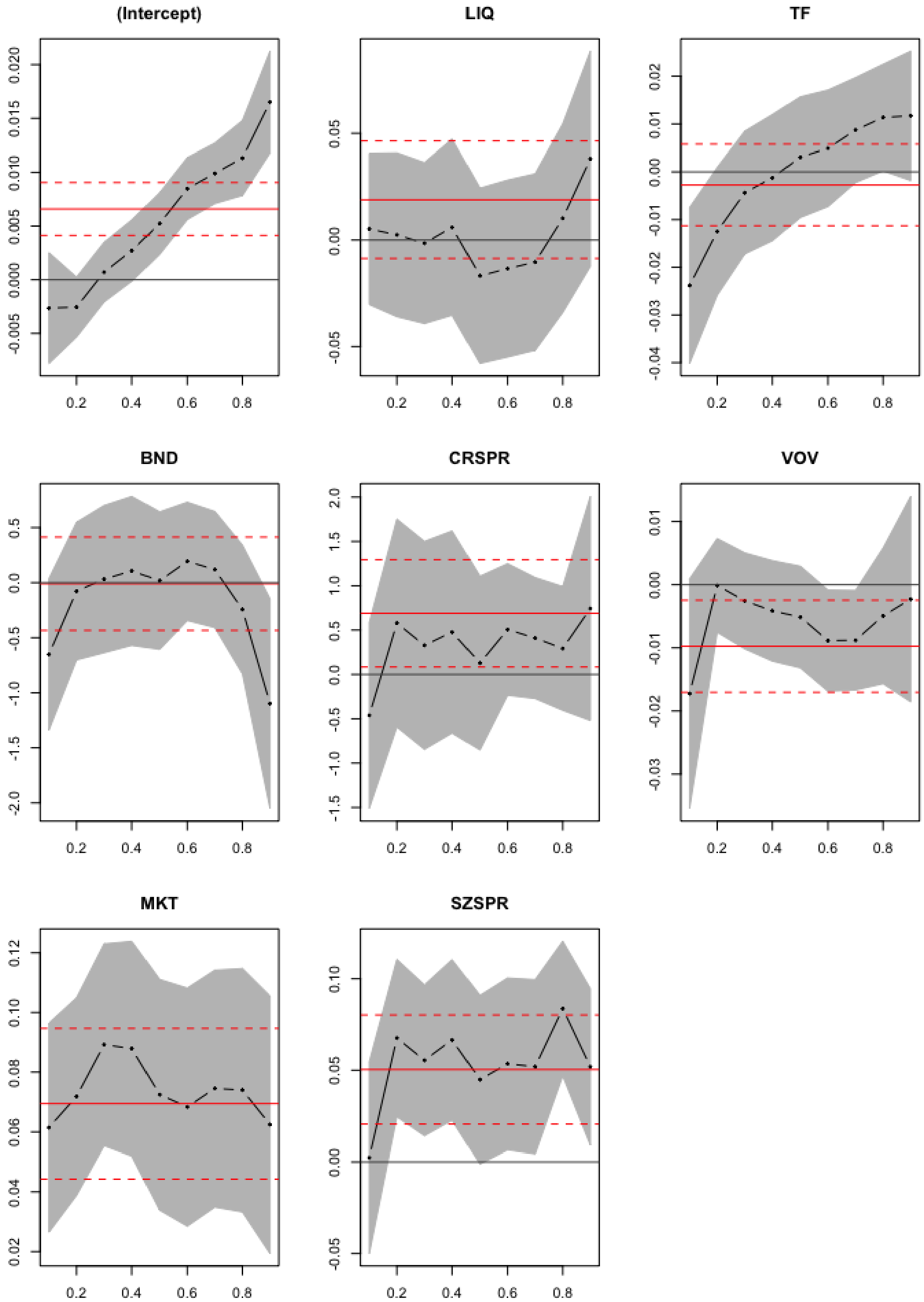
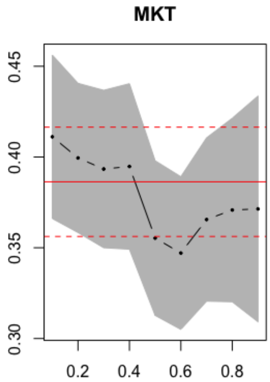
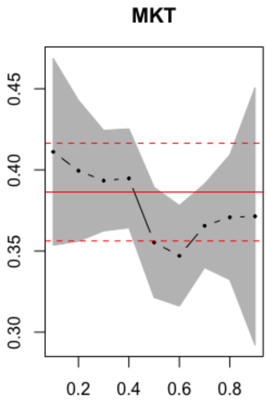


Figure 18: "Kitchen sink" quantile regression coefficients across equity market neutral strategy performance quantiles. Each graph contrasts corresponding coefficients along return quantiles with OLS coefficients for the equity market neutral strategy. Dashed black line stands for coefficients from 10% strategy return quantile to 90% strategy return quantile. Grey shaded areas represent standard errors of quantile regression estimates which use a kernel estimate of the sandwich as proposed by Powell (1990). Straight red line stands for OLS coefficients. Dashed red lines represent standard errors of OLS regression estimates. Where applicable, straight black line is a line through 0

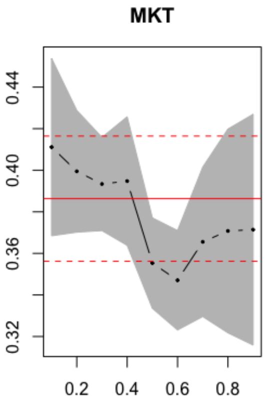
Appendix 18



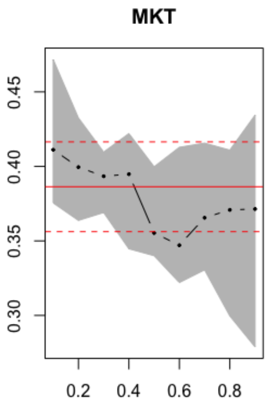
(a) Powell



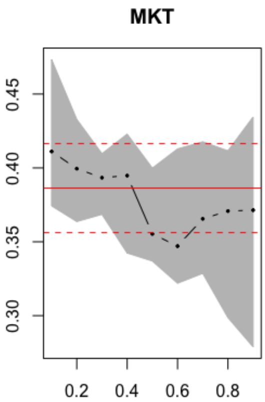
(b) Hendricks-Koenker



(c) I.i.d.



(d) I.i.d. rank



(e) Non-i.i.d. rank

Figure 19: Standard error alternative choices for market betas across performance quantiles for the hedge fund industry. Each graph presents market betas along return quantiles as per Figure 5(h). Grey shaded areas represent various standard error types for quantile regression estimates