Charles University in Prague
Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS:

Risk factor modeling of Hedge Funds' strategies

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.
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Prague, January, 2017

Signature

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Abstract:

This thesis aims to identify main driving market risk factors of different strategies implemented by hedge funds by looking at correlation coefficients, implementing Principal Component Analysis and analyzing "loadings" for first three principal components, which explain the largest portion of the variation of hedge funds' returns. In the next step, a stepwise regression through iteration process includes and excludes market risk factors for each strategy, searching for the combination of risk factors which will offer a model with the best "fit", based on The Akaike Information Criterion – AIC and Bayesian Information Criterion – BIC. Lastly, to avoid counterfeit results and overcome model uncertainty issues a Bayesian Model Average – BMA approach was taken.

Key words: Hedge Funds, hedge funds' strategies, market risk, principal component analysis, stepwise regression, Akaike Information Criterion, Bayesian Information Criterion, Bayesian Model Averaging

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Acronyms

HF	Hedge Fund
FoF	Hedge Fund of Fund
AuM	Asset under management
NAV	Net Asset Value
CCMR	Counterparty Credit Risk Management
CTA	Commodity Trading Advisor
CISDM	Center for International Securities and Derivatives Markets

GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
LTCM	Long Term Capital Management
SEC	Security Exchange Commission
ETF	Exchange-Traded-Futures
CME	Chicago Mercantile Exchange
BH	BarclayHedge
BofAML	Bank of America Merrill Lynch
MSCI	Morgan Stanley Capital International
VaR	Value at Risk
ES	Expected Shortfall
PCA	Principal Component Analysis
PC	Principal Component
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMA	Bayesian Model Averaging
PIP	Posterior Inclusion Probability

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Master's Thesis Proposal

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Proposed Topic:

Risk factor modeling of Hedge Funds' strategies.

Motivation:

Since the first hedge funds were originated in 1950s, represented by A.W. Jones who was first to introduce new investment practices like short selling, leverage, incentive fee of 20% of the profits and investing his personal money in alignment with investors', these investment funds have evolved significantly, according to Stulz (2007). Nowadays hedge funds are trying to specialize in using particular strategies or investing in limited range of asset classes, while Fund and Hsieh (1999) find that the number of hedge funds was more than halved in period from 1968 to 1984 due to extensive usage of leverage by long/short hedge funds and at the same time neglecting importance of hedging the risk, which was to great extent manifested during and after stock market crash in 1973 -74.

Founded in 1994, Long – Term Capital Management hedge (LTCM) fund was involved in bonds arbitrage trading by using mathematical models to predict prices and massive leverage – it had capital of $4.8 billion but $120 billion assets under management. In 1998, Russian financial crisis caused LTCM to suffer severe losses in amount almost equal to its total capital, so it had to be bailed by FED, preventing financial meltdown. Alexander (2009) argues that hedge funds may create systemic risk if a hidden web of interconnected contracts can lead, in a systemic event, to a drain on liquidity of the markets, particularly through "herding", i.e. a behavior, where a large number of hedge funds take the same positions.

According to Ineichen (2012), hedge funds' asset under management (AuM) has grown from $491 billion to $2.19 trillion from 2000 to 2012, while 3.7% of hedge funds control over 60% of AuM. These trends impose importance of examining the impact of different market conditions on hedge fund industry primarily reflected in low interest rates which are encouraging some of these funds to extensively use leverage and consequently increase their overall exposure to broader financial market. From theoretical point of view hedge funds, as active market participants should contribute to market efficiency and liquidity through their frequent trading and exploiting arbitrage opportunities. Kambhu et al. (2007) stressed out that hedge funds' link to the real economy might occur through banks' direct exposures to hedge funds, disruptions to capital markets that hinder credit provisions or allocations, or indirect effects as bank problems tend to feed back into the broader financial markets.

Hypotheses:

Hypothesis 1: Interest rates environment has significant impact on hedge funds' performance.

Hypothesis 2: Hedge funds implementing different strategies are exposed to different risk factors.

Hypothesis 3: Hedge funds tend use to financial derivatives, primarily options as main financial instrument to execute trading strategies.

Hypothesis 4: Hedge funds are to large extent exposed to risky asset types like high yielding and emerging market bonds and options.

Methodology:

This thesis aims to identify main driving market risk factors of different strategies implemented by hedge funds by looking at correlation coefficients; implementing Principal Component Analysis and analyzing "loadings" for first three principal components, which explain the largest portion of the variation of hedge funds' returns. In the next step, a stepwise regression through iteration process, includes and excludes market risk factors for each strategy, searching for the combination of factors which will offer a model with the best "fit", based on The Akaike Information Criterion – AIC and Bayesian Information Criterion – BIC. Lastly, to avoid counterfeit results and overcome model uncertainty issues a Bayesian Model Average - BMA approach was taken.

Data regarding hedge funds' strategies monthly performances were obtained from BarclayHedge Alternative Investment database. Indices for ten most commonly known strategies were subject of analysis: Convertible Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro and Multi Strategy. Robustness check was performed on monthly returns of Center for International Securities and Derivatives Markets (CISDM) strategy indices. CISDM demonstrates median return of hedge funds utilizing following strategies: Convertible Arbitrage, Distressed Securities, Equity Long/Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage and Global Macro. As a representative of market exposure, factors were divided in five main groups: 1) interest rate oriented risk factors; 2) bonds and option adjusted spreads risk factors; 3) equity and volatility risk factors, 4) Fama – French portfolio risk factors and 5) Fung and Hseih trend following factors straddles on options. As short term interest rates risk factor a 3 – Month Treasury Constant Maturity rate was used while as representative of long term interest rates a 10 – Years Treasury Constant Maturity rate was taken. As additional representative of interest rate risk, spreads between 3 – Month Treasury Constant Maturity rate and 1 – Year Treasury Constant Maturity rate against Federal Funds rate were taken into consideration. In order to investigate effect of bonds' yields on hedge funds performance, Bank of America Merrill Lynch indices have been used to replicate performances of high grade, risky high yielding and emerging market bonds and options. Both interest rates and bonds indices were obtained from FRED database. As a representative of equity oriented risk factors, Morgan Stanley Capital International (MSCI) Indices for developed and emerging markets were obtained from MSCI database. As a volatility measure Chicago Board Options Exchange Volatility Index – VIX obtained from FRED was used. Furthermore, 5 Fama – French portfolio risk factors were obtained from Kenneth R. French database. Lastly, Fung and Hseih trend following factors expressed as look back straddles on options on interest rates, bonds, commodities, currencies, stocks were taken from Timely Portfolio database. Time frame of analysis is 15 years, starting from August 2001 until August 2016.

Expected Contribution:

I will tend to identify the main external market risk factors driving hedge funds' performance. Moreover, I will endeavor to develop models for risk assessment of specific strategies implemented by hedge funds based on exposures to particular market risk factors. Practical application could be found among Funds of hedge Funds, which exclusively invest in hedge funds, and other types of institutional investing, considering the fact that there is an upward trend in number of pension funds, endowments and other institutional investors which have recently started to invest in hedge funds.

Outline:

1. Introduction

2. Literature review

3. Theoretical Framework: Features and Strategies

4. Data

5. Methodology and Empirical findings

6. Conclusion

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Chapter 1
Introduction

Financial innovation throughout the history played an important role for capital and money markets; sometimes positive but in some instances extremely negative with devastating and global consequences. Development of stock exchange, modern banks and insurance companies, mutual and other types of investment funds and financial derivatives set up foundations for high level of complexity of overall financial world we are able to observe today. Nowadays in particular, financial innovation is taking momentum on many fronts (Delimatsis 2012). First, technological advancement and substitution of human labor as an active participant on financial markets by technological solutions have had a significant impact on economies of scale mainly expressed in larger volumes but especially in higher frequency of transactions executed on the financial markets (Fischer and Mayerlen 2008). Second, development of complex financial derivatives played a crucial role in changing the financial industry, like for instance development of Black-Sholes model and example of Long Term Capital Management (LTCM) in 1997/8 (Edwards 1999). Third, the function of financial regulation in setting up "the rules of the game" and ensuring efficiency, transparency and stability has demonstrated rather ex-post approach towards financial innovation than proactiveness. Bearing in mind previously stated arguments, relatively new type of investment funds which are often referred as Alternative Investments, are interconnected with all those aspects to certain extent and have a growing significance in the world of finance – hedge funds (HFs). Since the first hedge fund was established in 1949 by A.W. Jones, they have notably evolved with the respect to investment practices and implemented strategies, ownership and fees structure and in regulatory treatment (Stulz 2007). Furthermore, as modern days hedge funds rely on extensive usage of financial derivatives and complex trading algorithms which are considered to be proprietary and not disclosed to the investors (Boasson and Boasson 2011), backed up with top cutting-edge technological solutions to exercise their trading strategies and operations, it is reasonably to argue that these facts make them an important constituent of financial complexity on the contemporary financial markets.

Therefore, this thesis aims to examine which factors have contributed to fast growth of hedge fund industry, in particular in period 2006-2015 when total hedge fund universe expressed in terms of Asset under Management (AuM) has grown to nearly 3 trillion (Ineichen 2012). There are three main sources of hedge funds' financing: funds invested by investors, funds invested by managers in alignment with investors' funds and leverage (Fung and Hsieh 1999). Bearing in mind that leverage enables enhanced returns on deployed capital, it could be argued that low interest rate environment, particularly in period from 2008 until now, have had favorable impact on hedge funds' returns, since it enabled HFs to use more of borrowed funds and significantly increase their leverage levels and overall market exposure. For that reason, hedge funds have been able to place those borrowed funds on open market for obtaining securities and other instruments. Therefore, one of the goals and first hypothesis of this thesis aims to examine the impact of interest rates on hedge fund industry's performance. Furthermore, since hedge funds implement heterogeneous strategies, invest in wide range of asset types, financial derivatives (like bonds, stocks, indices, futures, swaps and options) and have exposure to various markets – second, third and fourth hypothesis tend to dig deeper and analyze the relationship between the performance of hedge funds' underlying investments and their corresponding monthly returns.

The structure of the thesis goes as follows: Chapter 2 goes through relevant academic papers written on this subject and discusses authors' methodology and main findings. Chapter 3 gives an insight in main HFs' features and structure from legal point of view and explains main types of the strategies which hedge funds implement. Chapter 4 is focused on the data sources and indicators which will be used in analysis, while Chapter 5 explains methodology applied for evaluation of the impact that broader market environment exercise on hedge funds' performance and points out main empirical findings. Lastly, Chapter 6 gives the finals comments and concluding remarks of the thesis.

Chapter 2
Literature review

According to Fung and Hsieh (2006), after Internet bubble crash that took place in early 2000s, institutional investors started to allocate their investments to hedge funds in response to underperformance of global equity markets. In their paper “Hedge Funds: An Industry in Its Adolescence” they stated that increasing institutional demand for hedge funds significantly contributed to exponential growth in AuM figures, while the number of hedge funds doubled over the next five years. They found out that in period 2000-2005 university endowments have increased their investments towards hedge funds from 5.1 % in to 16.6 % on a dollar weighted basis or in absolute figures from $11.3 billion to $49.6 billion for mentioned period, while pension endowments increased their exposure from $3.2 billion to $29.9 billion. They argue that these developments had a positive impact on “institutionalization” of the hedge fund industry with the respect to increased transparency, better compliance, and higher operational standards (Fung and Hsieh 2006). Similarly, Stulz (2007) argues that since hedge funds acquire more institutional investors, the discretion of the managers is expected to decline to satisfy fiduciary responsibility of institutional investors. Consequently, as mangers become more constrained, it will be harder for them to achieve above average performance. Moreover, in a long run, Stulz expects for some strategies to become unprofitable as AuM figures keep growing, and that eventually hedge funds will converge to mutual funds with regards to regulation and profitability.

Following on Ang, Gorovyy and Inwegen (2011) study on hedge funds’ leverage, returns, volatilities on a total of 208 unique hedge funds in the sample with 8,136 monthly observations from 2004 to 2009 they found out that the average fund size expressed in AuM over the sample was $962 million while the median fund size was $430 million. The discrepancy between mean and median was explained by the presence of some large funds, having AuMs well over $10 billion. Moreover, they analyzed hedge funds level flows over the past three months using the return and AuM information by applying the following formula:

$$\mathrm{Flow_t} = \frac{\mathrm{AuM_t}}{\mathrm{AuM_{t-3}}} - (1 + \mathrm{R_{t-2}})(1 + \mathrm{R_{t-1}})(1 + \mathrm{R_t}) \tag{2.1}$$

where $\mathrm{Flow_t}$ represents past three-month flow in the hedge fund, $\mathrm{AuM_t}$ is assets under management at time t and R_t is the hedge fund return from t-1 to t. Their findings suggest that flows into hedge funds are on average positive, at 2.2% per month and exhibit a large average autocorrelation of 0.62. Furthermore, Ang et al. noticed counter-cyclical behavior of financial leverage implemented by hedge funds in comparison with the average leverage of investment banks, as hedge fund leverage declines in 2007 and continues to fall over the financial crisis in 2008 and 2009, while the leverage of financial institutions continues to rise relentlessly for the same period.

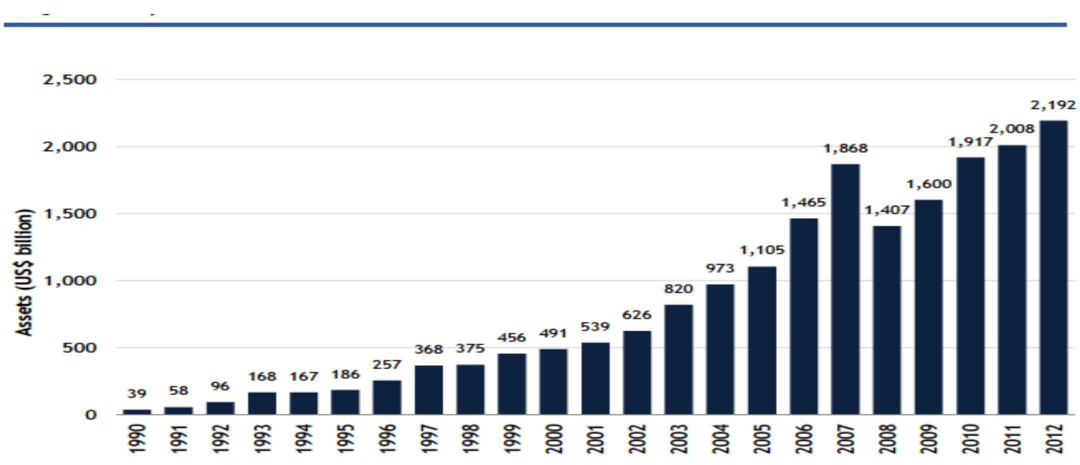

Figure 2.1: AuM in global hedge fund industry (1990 – Q3 2012)

Source: Ineichen, 2012

Founded in 1994, Long Term Capital Management (LTCM) was involved in bond arbitrage by applying Black – Scholes formula, after initial success it collapsed badly in 1998 following on Russian crisis and Asian currency crisis. In addition, Edwards (1999) stressed out that one of the main causes of such a development was LTCM's long exposures to high-yielding, less liquid, "junk" corporate bonds and emerging markets bonds, while it entered in derivative contracts which basically replicated short-selling of low-yielding and highly liquid bonds. LTCM managers believed that spread between these 2 asset classes was extensively wide and that it had to be narrowed down, partly as a consequence of the collapse of Asian currencies in 1997. Therefore, they borrowed $125 billion while having initial equity in amount of only $5 billion which yielded to leverage over 20 to 1 in 1997. Moreover, according to Edwards (1999) at the start of 1998, LTCM had notional value of derivatives contract in excess of $1 trillion: $697 billion exposure to interest rates swaps and $471 billion exposure to Exchange-Traded-Futures (ETF) contracts; therefore, due to the size of these exposures, it was straightforward that even small widening in spreads could easily wipe out LTCM equity. Due to the fact that leverage has both upward and downward effect, it could significantly amplify both profits and losses. "Coup the grace" for LTCM as explained by Edwards (1999) was Russian devaluation of the ruble and the declaration of moratorium on $13.5 billion of its Treasury debt. These developments had significant herding affect among investors who started to switch to less risky, low yielding bonds and high liquid, contrary to LTCM's expectations, forcing Federal Bank of New York to organize consortium of creditors meeting which included among others: Goldman Sachs, Merrill Lynch, J.P. Morgan, Morgan Stanley, Deutsche Bank, Barclays, Chase Manhattan, Credit Suisse, Lehman Brothers, Paribas and Societe Generale Bank. To conclude, author imposes three crucial questions: Did Fed acted prudently in organizing LTCM's rescue? Why were banks apparently so vulnerable to LTCM default, and was there a breakdown in financial regulation and supervisory oversight by banks? Does LTCM situation argue for hedge fund additional regulation of some sort? Similarly, Alexander (2009) argues that hedge funds may create systematic risk if hidden web interconnected contracts can lead, in a systematic event, to a drain on liquidity of the markets, particularly through "herding", i.e. a behavior, where large number of hedge funds take the same positions. Countrary, Boyson, Stahel and Stulz (2010) pointed out that liquidity spirals affect all assets for which hedge funds are the marginal investors, therefore hedge funds appear to share a common exposure to large liquidity shocks. Stulz (2007) argues that due to the fact LTCM refused to give any examples of its trades, potential investors had little idea of what they were doing, additionally he points out that on one side secrecy does help hedge fund managers protect their strategies from potential imitators; but on the other hand, secrecy makes it harder to assess the risk of a fund. He also argues that hedge funds often provide liquidity to the market, by buying securities that are temporarily depressed because of market disruptions. When talking about repercussions of LTCM case on broader financial market, Kambhu, Schuermann and Stiroh (2007) stressed out that financial regulators in United States considered that Counterparty Credit Risk Management (CCRM) - practices used by banks to evaluate credit risks and limits for counterparty exposures like implementation of risk reporting infrastructures, defining haircuts, margining, and collateral policies which should prevent market disruptions with potential systemic consequences – is the optimal way to control hedge fund leverage and limit systemic vulnerabilities, adding that since LTCM case, CCRM has been greatly improved.

Bollen and Whaley (2009) argued that when assessing hedge funds' performance, managers' freedom regarding their shifting in asset classes exposures, strategies and leverage levels in response to changing market conditions must be accounted for. In their analysis they allowed exposure levels to vary by employing an optimal changepoint regression that allows risk exposures to shift. These changes could be triggered by macro - economic conditions, credit arbitrage opportunities as well as M&A arbitrage activity and the corresponding level of leverage used by hedge funds. This dynamic nature of hedge funds further complicates due diligence activities including risk management and performance appraisal. They conducted analysis based on a sample containing 6,158 funds pooled out Center for International Securities and Derivatives Markets (CISDM) database in time frame 1994 until 2005, while robustness was checked by performing the same analyses using hedge funds sample from the Lipper TASS database during the same period. In their research they used two set of factors. The first set includes Fama–French factors which incorporate excess return of the market, the returns of the size and value portfolios and the squared returns of the size and value portfolios and Fung–Hsieh asset-based style factors which incorporate the change in yield of a 10-year Treasury note, dubbed the "credit spread", the yield on 10-year BAA corporate bonds less the yield of a 10-year Treasury note, returns of portfolios of options on bonds, foreign currencies, commodities, short-term interest rates and stock indexes. The second set, includes monthly relative price changes of highly active futures contracts on different underlying asset classes for example The Chicago Mercantile Exchange (CME)'s S&P 500 futures. Authors conducted analysis by using two models - the changepoint regression and stochastic beta model, whereas changepoint regression has shown superior results. The analysis had three main steps: first, they calibrated the simulations by turning to the actual monthly return data and finding the "optimal" constant parameter factor model by choosing the subset of factors that minimizes the Bayesian Information Criterion (BIC) using a maximum of three factors. Second, given the magnitudes of the factor loadings, they choose parameter values for a changepoint regression and a stochastic beta model and generate random returns in order to compare the ability of the changepoint regression and stochastic beta model to reject the null hypothesis that risk exposures are constant. Third, they perform a robustness check to determine whether fund fees could generate false rejections of the null in the changepoint regression by applying the following formula:

$$\mathrm{NAV_t} = \mathrm{NAV_{t-1}}\left(1 + \mathrm{R_t^{pre}}\right)\left(1 - \frac{0.01}{12}\right) \tag{2.2}$$

Then, if $\mathrm{NAV_t} > H$, the performance fee accrues as follows:

$$\mathrm{NAV_t} = \mathrm{NAV_{t-1}} - 0.20(\mathrm{NAV_t} - \mathrm{H}) \tag{2.3}$$

given that performance fees accrue monthly if the NAV is above H (high water mark); “1 and 20%” fee structure: monthly management fees are 1% per year and performance fees are 20% of profits. Within each quarter after-fee returns are computed first by updating the NAV each month to reflect pre-fee returns $\mathrm{R_t^{pre}}$ and the management fee. In their findings authors elaborated that over 40% of the live hedge funds experience a statistically significant shift in risk exposures in the sample. They showed that funds that switched had average Sharpe ratio of 0.4261 and they tend to switch early in the fund’s life, while the average Sharpe ratio for non - switchers was 0.3219 and added that switching funds are associated with superior performance and quickly attract mimickers. Following up on previous paper, Gilles and Olivier (2011) by applying time-varying coefficient model found that for positive alpha funds, the minimum percentage is 2.5% for event driven multi strategy and the maximum: 18.5% for CTA and Equity Long/Short strategies. As for negative alpha funds, the minimum percentage is 0% for Event Driven Multi Strategy, and maximum, 46% for the Emerging Market strategy. They argued that some strategies perform better when the markets are stable whereas other strategies obtain higher percentage of positive alphas during markets stresses. Furthermore, they pointed out that some non-directional strategies are not really market neutral and still keeping exposure to risk factors particularly during market stress.

Fuss, Kaiser and Adams (2007) stressed out that conventional Value at Risk (VaR) is not suitable measure of market risk, particularly in the case of skewed and fat-tailed returns which are typical for hedge funds industry, due to its assumption of normal distribution. In addition, they argue that monthly returns distributions of most hedge funds indices experience high negative skewness, positive excess kurtosis and, significantly positive first order serial correlation; which consequently leads in underestimating true volatility when applying broadly used mean–variance approach. In their paper "Value at risk, GARCH modeling and the forecasting of hedge fund return volatility" they used a GARCH-type Value at Risk (VaR) by modeling and forecasting conditional volatility, using GARCH and EGARCH, and then implementing the time-varying volatility in the VaR. Fuss et al. elaborated that, although skewness and kurtosis are not completely eliminated by the GARCH modeling, GARCH-type VaR offers an enhanced protection against downside risk in a portfolio including hedge funds.

Harri and Brorsen (2006) examined hedge funds' performance persistency arguing that styles that experienced the highest level of persistency in the performance are market neutral, event driven, short sales, and Funds of Funds (FoF), while Capocci and Hubner (2004) when analyzing hedge funds prior and after Asian crisis in 1996/7 found out that there was no significant difference between good and bad performing funds implementing Global Macro strategy, whereas some experienced persistent returns despite Asian crisis 1996/7, which could be explained by hypothesis that some successful funds benefited from the crisis. Moreover, Capocci and Hubner (2004) argue that best performing funds follow momentum strategies and usually avoid investing in emerging market bonds, whereas lower performing funds do. In addition, average return funds prefer high book-to-market stocks, whereas both best and worst performing funds may prefer low book-to-market ones.

Bussière, Hoerova and Klaus (2014) analyzed main driving factors of commonality in hedge funds returns by applying Principal Component Analysis (PCA). They pointed out that obtained Principal Components, as linear combinations of original variables, provide information regarding the fraction of variance in the dataset explained by each component and that "loadings" for each of components indicate the strenght of relationship between each risk factor and corresponding component. However, since PCA doesn't provide any interpretation and economic reasoning, to identify common risk factors in next step they applied stepwise regression procedure which recursively included and excluded risk factors based on Akaike Information Criterion (AIC). Main findings of Bussière et al. (2014) suggest that hedge funds with high level of commonality are mostly exposed to equity – oriented risk factors, while hedge funds with low commonality have only a small or no exposure to equity-oriented risk factors. Moreover, they found that exposure to emerging markets monotonically increases commonality.

Zhou (2013) performs risk modeling of hedge funds' strategies risk/returns profile by using 30 relevant risk factors. Contrary to Bussière et al., Zhou points out that stepwise regression approach becomes infeasible as number of factors used in regression increases. Therefore, he applied Bayesian Model Averaging (BMA) technique instead, and pointed out that it performs much better than AIC information criteria in selecting variables, as it selects multiple models based on each model's posterior probability while further combining the forecasts from each of the models weighted by their posterior probability. Zhou spefified following factor model, attributing the risk of a fund to a set of common factors:

$$Y = \alpha + \sum_{k=1}^{K} \beta_k X_k + \varepsilon \tag{2.4}$$

where Y is vector of the time series of the fund return during sample period, α return after stripping off the contribution from risk factors, β_k Exposure of the fund to risk factor k, X_k vector of the time series of the return (or level/change) of risk factors during sample period and ε vector of the time series of the fund idiosyncratic return during sample period, considering linear regression models in BMA process.

Havránek and Žigraiová (2015) also implemented Bayesian Model Averaging on investigating the impact of bank competition on financial stability, whereas term "financial stability" is referred to both bank-level stability and banking sector stability. They performed meta – data analysis where they examined different variants of stability model found in 31 different studies, depending on different variables used in literature to proxy financial stability and bank competition. Havránek and Žigraiová (2015) divided collected variables into 8 groups, however they stressed out that including all the variables at the same time is infeasible as it would lead to obtaining too many redundant regressors in the model specification. Therefore, they applied BMA to resolve the model uncertainty problem, with different subsets of all the 2^{35} possible combinations of explanatory variables as they had 35 regressors at disposal. To make the estimation feasible, Havránek and Žigraiová (2015) used the Monte Carlo Markov Chain algorithm to go through the most promising of the potential models by using bms package for R developed by Feldkircher and Zeugner, 2009.

Vrontos S.D., Vrontos I.D. and Giamouridis (2008) stressed out that the fact that existing equilibrium pricing theories are not explicit about which factors should enter the pricing regression along with the lack of transparency and the large number of possible market and trading strategy combinations hedge funds can follow renders the true set of pricing factors virtually unknown, thus introducing model uncertainty. They used Bayesian Model Averaging with incorporated heteroscedasticity to address uncertainty in hedge fund pricing and compared obtained results with, among others, stepwise regression procedure based on Akaike and Bayesian Information Criterion. Similarly to Zhou (2013), they favor Bayesian Model Averaging compared to other variable selection techniques and find that, overall BMA predicts hedge fund returns by about 33%-44% more efficiently than simple stepwise regression, 26%-56% than AIC and 16%-19% than BIC.

Chapter 3

Theoretical Framework: Features and Strategies

3.1 Hedge Funds' Features

Based on previous discussions, following features of hedge funds could be highlighted in comparison with other types of investment funds:

1. Active portfolio management: Hedge funds implement various management techniques and advanced strategies, like hedging their positions, investing in more complex financial derivatives and short-selling.

A *hedge* is an investment to reduce the risk of adverse price movements in an asset. Normally, a hedge consists of taking an offsetting position in a related financial derivative. A perfect hedge is one that eliminates all risk in a position or portfolio. In other words, the hedge is 100% inversely correlated to the vulnerable asset. The effectiveness of a derivative hedge is expressed in terms of delta, sometimes called the "hedge ratio." Delta is the amount the price of a derivative moves per $1.00 movement in the price of the underlying asset.

Derivatives are securities that move in terms of one or more underlying assets. Main derivatives include options, futures, swaps and forwards. The underlying assets can be stocks, bonds, commodities, currencies, indices and interest rates.[1]

An *option* is a financial derivative that represents a contract sold by one party (the option writer) to another party (the option holder). The contract offers the buyer the right, but not the obligation, to buy (call) or sell (put) a security or other financial asset at an agreed-upon price (the strike price) during a certain period or on a specific date (exercise date)[2].

[1] http://www.investopedia.com/terms/h/hedge.asp

[2] http://www.investopedia.com/terms/o/option.asp

Short selling is the sale of a security that is not owned by the seller, or that the seller has borrowed. Short selling is motivated by the belief that a security's price will decline, enabling it to be bought back at a lower price to make a profit. Short selling may be prompted by speculation, or by the desire to hedge the downside risk of a long position in the same security or a related one[3].

2. Leverage: Besides investors' money and their own money, hedge funds managers can use debt and borrowed funds to exercise their strategies and enhance returns.

3. Fees structure: Hedge funds usually have "2-20" fee structure, whereas charged managing fee varies from 1.5 - 2% of managed assets and 20% of achieved performance to investors (Ibbotson, Chen and Zhu 2001).

4. Legal structure: Hedge funds are private investment vehicles with managers acting as general partners and investing portion of their money in alignment with investor's money who acts as limited partners.

5. Accredited Investors: Typical investors into hedge funds are institutional investors, endowments such as pension funds and insurance companies, and wealthy individuals who satisfy certain level of wealth requirements (Alexander 2009).

6. Financial regulation: Since hedge funds are organized as partnerships, they are subject to lighter regulation treatment compared to for mutual funds. Moreover, most of hedge funds are organized as offshore funds under the regulation of "tax heavens" (Edwards 1999).

7. Liquidity: Hedge funds and investors usually agree on a lock-up period in which investors are not able to redeem their invested funds. Compared to mutual funds, which are highly liquid, hedge funds usually have monthly, quarterly or yearly liquidity, but in some cases, semi-monthly or weekly (Agarwal, Daniel and Naik 2004).

[3] http://www.investopedia.com/terms/s/shortselling.asp

8. High water mark: A requirement that the fund must recoup any prior losses before the investment manager may take a performance (incentive) fee. In addition to performance losses, prior losses may include any combination of fees that the investment manager charges, such as management and administrative fees[4].

9. Hurdle rate: The appreciation in fund performance that must be achieved before the investment manager may take a performance (incentive) fee[5].

3.2 Hedge Funds' Strategies

According to BarclayHedge Alternative Investment Database, one of the most common categorization of hedge fund strategies is: Convertible Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro and Multi Strategy:

1) Convertible Arbitrage Strategy involves purchasing a portfolio of convertible securities of the company, generally convertible bonds, and hedging a portion of the equity risk by selling short the underlying common stock. Certain managers may also seek to hedge interest rate exposure under some circumstances. Most managers employ some degree of leverage ranging from zero to 6:1. The equity hedge ratio may range from 30 to 100 percent. The average grade of bond in a typical portfolio is BB-, with individual ratings ranging from AA to CCC. However, as the default risk of the company is hedged by shorting the underlying common stock, the risk is considerably better than the unhedged bond's rating indicates[6].

2) Distressed Securities Strategy invests in, and may sell short, the securities of companies where the security's price has been, or is expected

[4] http://www.barclayhedge.com/research/definitions/High-Water-Mark-definition.html
[5] http://www.barclayhedge.com/research/definitions/Hurdle-Rate-definition.html
[6] http://www.barclayhedge.com/research/definitions/Convertible-Arbitrage-definition.html

to be, affected by a distressed situation. This may involve reorganizations, bankruptcies, distressed sales and other corporate restructurings. Depending on the manager's style, investments may be made in bank debt, corporate debt, trade claims, common stock, preferred stock and warrants. Strategies may be sub-categorized as "high-yield" or "orphan equities." Some managers may use leverage. Fund managers may run a market hedge using S&P put options or put option spreads[7].

3) Emerging Markets Strategy invests in securities of companies, or the sovereign debt of developing or "emerging" countries. Investments are primarily long. "Emerging Markets" include countries in Latin America, Eastern Europe, the former Soviet Union, Africa and parts of Asia. Emerging Markets - Global funds will shift their weightings among these regions according to market conditions and manager perspectives. In addition, some managers invest solely in individual regions[8].

Equity Hedge investing consists of a core holding of long equities hedged at all times with short sales of stocks and/or stock index options. Some managers maintain a substantial portion of assets within a hedged structure and commonly employ leverage. Where short sales are used, hedged assets may be comprised of an equal dollar value of long and short stock positions. Other variations use short sales unrelated to long holdings and/or puts on the S&P index and put spreads. Conservative funds mitigate market risk by maintaining market exposure from zero to 100 percent. Aggressive funds may magnify market risk by exceeding 100 percent exposure and, in some instances, maintain a short exposure. In addition to equities, some funds may have limited assets invested in other types of securities[9].

As main equity hedge based strategies, BarclayHedge Alternative Database identifies following substrategies: Long Bias, Long/Short and Market Neutral.

[7] http://www.barclayhedge.com/research/definitions/Distressed-Securities-definition.html
[8] http://www.barclayhedge.com/research/definitions/Emerging-Markets-definition.html
[9] http://www.barclayhedge.com/research/definitions/Equity-Hedge-definition.html

4) Equity Long Bias Strategy: Equity Long/Short managers are typically considered long-biased when the average net long exposure of their portfolio is greater than 35%[10].

5) Equity Long/Short Strategy is directional strategy which involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional or sector specific[11].

6) Equity Market Neutral Strategy seeks to profit by exploiting pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions. Typically, the strategy is based on quantitative models for selecting specific stocks with equal dollar amounts comprising the long and short sides of the portfolio. One example of this strategy is to build portfolios made up of long positions in the strongest companies in several industries and taking corresponding short positions in those showing signs of weakness. Another variation is investing long stocks and selling short index futures[12].

7) Event Driven Strategy is also known as "corporate life cycle" investing. This involves investing in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. The portfolio of some Event-Driven managers may shift in majority weighting between Risk Arbitrage and Distressed Securities, while others may take a broader scope. Instruments include long and short common and preferred stocks, as well as debt securities and options. Leverage may be used by some managers. Fund

[10] http://www.barclayhedge.com/research/indices/ghs/Equity_Long_Bias_Index.html
[11] http://www.barclayhedge.com/research/indices/ghs/Equity_Long_Short_Index.html
[12] http://www.barclayhedge.com/research/definitions/Equity-Market-Neutral-definition.html

managers may hedge against market risk by purchasing S&P put options or put option spreads[13].

8) Fixed Income Arbitrage Strategy: The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, US and non-US government bond arbitrage and forward yield curve arbitrage[14].

9) Global Macro Strategy involves investing by making leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange and physical commodities. Macro managers employ a "top down" global approach, and may invest in any markets using any instruments to participate in expected market movements. These movements may result from forecasted shifts in world economies, political fortunes or global supply and demand for resources, both physical and financial. Exchange traded and over-the-counter derivatives are often used to magnify these price movements[15].

10) Multi Strategy: Multi-Strategy funds are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines. The use of many strategies, and the ability to reallocate capital between them in response to market opportunities, means that such funds are not easily assigned to any traditional category[16].

[13] http://www.barclayhedge.com/research/definitions/Event-Driven-definition.html
[14] http://www.barclayhedge.com/research/indices/ghs/Fixed_Income_Arbitrage_Index.html
[15] http://www.barclayhedge.com/research/definitions/Macro-definition.html#
[16] http://www.barclayhedge.com/research/indices/ghs/Multi_Strategy_Index.html

Chapter 4

Data

4.1 Hedge Fund data

Analyzed sample contains 181 observation covering period of 15 years starting from August 2001 until August 2016 incorporating recovery period after Russian crisis and Asian currency crisis in late 1990s, Internet bubble crash in early 2000s and financial crisis of 2008/9. Dataset is structured in the following manner: information regarding hedge funds' strategies performances were obtained from BarclayHedge Alternative Investment database. BarclayHedge (BH) strategy indices are calculated as equally weighted averages of monthly returns net of managing and performance fees for ten most commonly known strategies: Convertible Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro and Multi Strategy.

Table 4.1: Number of funds incorporated in BH Strategy Indices

Index:	# of Funds
Convertible Arbitrage	27
Distressed Securities	43
Emerging Markets	417
Equity Long Bias	379
Equity Long Short	445
Equity Market Neutral	102
Event Driven	139
Fixed Income Arbitrage	34
Global Macro	156
Multi Strategy	105

Source: BarclayHedge Database

Table 4.1 Indicates that most of the hedge funds reporting to BarlayHedge database are involved in equity oriented and emerging market strategies, while relative value based strategies like Convertible Arbitrage, Distressed Securities and Fixed Income Arbitrage represent a niche. However, Ineichen (2012) points out that number of funds as well as AuM figures managed by hedge funds following relative value based strategies is growing on the account of more traditional equity hedge and macro oriented strategies:

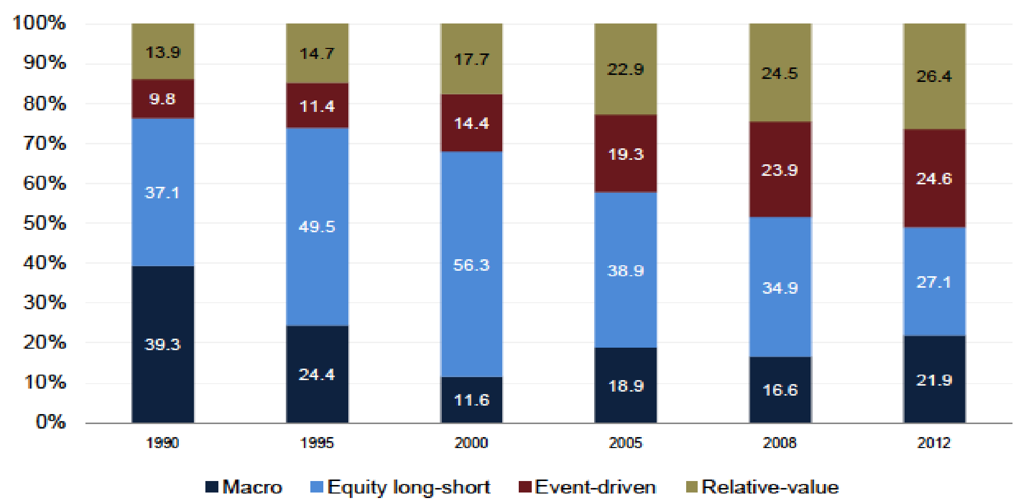

Figure 4.1: Hedge fund industry breakdown by strategy type (1990 – Q3 2012)

Source: Ineichen, 2012

Robustness check was performed on monthly returns of CISDM (Center for International Securities and Derivatives Markets) strategy indices which are constructed as equally weighted averages of the funds incorporated in specific index. CISDM demonstrates median return of hedge funds utilizing following strategies: Convertible Arbitrage, Distressed Securities, Equity Long/Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage and Global Macro.

4.2 Market Risk Factors

Market exposure risk factors are divided in five main groups: 1) interest rate oriented risk factors; 2) bonds and option adjusted spreads risk factors; 3) equity and volatility risk factors, 4) 5 Fama – French portfolio risk factors and 5) Fung and Hseih trend following factors straddles on options.

Table 4.2: Market risk factors proxies and abbreviations

Interest rate risk factors proxies	Bonds and Options proxies	Equity risk factors proxies	Fama - French portfolio risk factors	Fung - Hseih trend following factors
3–Month Treasury Constant Maturity - **X3MTB**	BofAML "a" grade bonds and option risk factors spreads – **ABOND and AOPSP**	MSCI Developed Markets Index - **MSCIDM**	Small Minus Big - **SMB**	Lookback straddles on bonds - **PTFSBD**
10–Years Treasury Constant Maturity - **X10YTCM**	BofAML "BB" grade bonds and option adjusted spreads – **BBOND and BOPSP**	MSCI Emerging Markets Index - **MSCIEM**	High Minus Low - **HML**	Lookback straddles on stocks - **PTFSSTK**
3–Month Treasury Constant Maturity minus Federal Funds Rate - **X3MTBMFR**	BofAML "CCC" grade bonds and option adjusted spreads – **CBOND and COPSP**	Chicago Board Options Exchange Volatility Index - **VIX**	Robust Minus Weak - **RMW**	Lookback straddles on commodities - **PTFSCOM**
1–Year Treasury Constant Maturity minus Federal Funds Rate - **X1YTBMFR**	BofAML high investment grade emerging markets bonds and option adjusted spreads – **EMHGBOND and EMHGOPSP**		Conservative Minus Aggressive - **CMA**	Lookback straddles on currencies - **PTFSFX**
	BofAML below investment grade emerging markets bonds and option adjusted spreads – **EMBGBOND and EMBGOPSP**		excess return on the market – **Rm.Rf**	Lookback straddles on interest rates - **PTFSIR**

As short term interest rates proxy a 3–Month Treasury Constant Maturity rate was used while as representative of long term interest rates a 10–Years Treasury Constant Maturity rate was taken. Furthermore, spreads of 3–

Month Treasury Constant Maturity rate and 1-Year Treasury Constant Maturity rate against Federal Funds rate were taken into consideration. To proxy effects of bonds' returns and option adjusted spreads on hedge funds performance, Bank of America Merrill Lynch (BofAML) indices were used to replicate yields on high grade, below grade and emerging market bonds. As a proxy of equities' performance, Morgan Stanley Capital International (MSCI) equity indices for developed and emerging markets were used. As a volatility measure Chicago Board Options Exchange Volatility Index – VIX obtained from FRED was considered.

4.2.1 Interest rates risk factors proxies:

As previously discussed, many hedge funds strategies depend on interest rates' movements. Furthermore, hedge funds trading techniques like short selling, arbitrage and derivatives investing might also be influenced by development on interest rates markets. Therefore, to capture the impact of short term interest rates, a 3–Month Treasury Constant Maturity rate together with spread between this rate against Federal Funds rate were taken as proxies. Moreover, the spread of 1–Year Treasury Constant Maturity rate against Federal Funds rate was also considered, whereas Federal Funds rate is described as central interest rate in the U.S. financial market at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight[17]. Short term interest rates play an important role when deciding to borrow a security and short it, because it expected that price decline in underlying asset will be higher than interest which needs to be paid at the end of transaction. Spreads' dynamic plays crucial role for strategies which employ arbitrage techniques like Fixed Income Arbitrage and Convertible Arbitrage. As proxy of long term interest rates, a 10–Year Treasury Constant Maturity rate was taken, as some hedge

[17] https://fred.stlouisfed.org/series/DFF

funds styles like Long Bias, Multi Strategy might have long term investment horizons.

4.2.2 Bond oriented risk factors proxies:

Hedge fund strategies like Convertible Arbitrage, Distressed Securities, Global Macro and Multi Strategy exhibit high exposure to bond markets. To examine the impact of return on bonds with different investment grade rating and their corresponding option adjusted spreads, Bank of America Merrill Lynch monthly average effective yields have been used. Ratings off these bonds are based on average of Moody’s, S&P and Fitch ratings.

Option adjusted spreads of bonds represent difference between yield on bonds and risk-free investment, which takes into consideration embedded option. In case of callable bonds, bond issuer has right to purchase bond back prior to bond maturity. This scenario could happen in case of decreasing interest rates, when company wants to refinance its debt under lower interest. In case of puttable bonds, bond holder has right to be reimbursed for the principal, prior to bond’s maturity. This scenario could happen in case of increasing interest rates, when bond holder is aware that he could earn higher interest if he would place his investment somewhere else to earn higher interest.

As representative of high investment grade bonds with low risk, US dollar denominated “a” investment grade rated corporate bonds publically issued in the US domestic market[18] were used. US corporate bonds with “B”[19] grade rating were taken as moderately risky investment, while US corporate bonds with grading “CCC or below”[20] were taken as representative of below grade – high yielding bonds, often referred as “junk bonds”. Moreover, since hedge funds extensively use bonds with embedded options,

[18] https://fred.stlouisfed.org/series/BAMLC0A3CA
[19] https://fred.stlouisfed.org/series/BAMLH0A2HYBEY
[20] https://fred.stlouisfed.org/series/BAMLH0A3HYCEY

option adjusted spreads between above described bond yields and spot T – bill were considered as well. Criteria for inclusion in Bank of America Merrill Lynch “a” grade effective yields on bonds and option – adjusted spreads indices are following: securities must have an investment grade rating (based on an average of Moody's, S&P, and Fitch) and an investment grade rated country of risk (based on an average of Moody's, S&P, and Fitch foreign currency long term sovereign debt ratings). Each security must have greater than 1 year of remaining maturity, a fixed coupon schedule, and a minimum amount outstanding of $250 million. While criteria for inclusion in “B” and “CCC or bellow” differ in terms of minimum amount outstanding which is set up to $100 million, while securities must have below investment grade rating based on an average of Moody's, S&P, and Fitch.

Since some hedge funds’ styles like Emerging Markets strategy invests solely in securities originated in emerging markets, while other strategies like Global Macro and Multi Strategy also invest in those markets in search for higher returns and diversification benefits, effective yields and option – adjusted spreads on high grade and below investment grade emerging markets bonds were considered as well. Criteria for inclusion in Bank of America Merrill Lynch emerging index are following: securities must be rated AAA through BBB3[21] for high grade and lower than BB1 for below investment grade[22] bonds; be US dollar (USD) or Euro denominated non-sovereign debt publicly issued within the major domestic and Eurobond markets; the issuer of debt must have risk exposure to countries other than members of the FX G10 (US, Japan, New Zealand, Australia, Canada, Sweden, UK, Switzerland, Norway, and Euro Currency Members), all Western European countries, and territories of the US. Each security must also be denominated in USD or Euro with a time to maturity greater than 1 year and have a fixed coupon. For inclusion in the index, investment grade rated bonds of qualifying issuers

[21] https://fred.stlouisfed.org/series/BAMLEMIBHGCRPIEY
[22] https://fred.stlouisfed.org/series/BAMLEMHBHYCRPIEY

must have at least 250 million (Euro or USD) in outstanding face value for high grade or 100 million (Euro or USD) for below investment grade bonds.

4.2.3 Equity and volatility oriented risk factors:

To proxy the impact of performance on equity markets on hedge funds strategies like Equity Long/Short, Equity Long Bias and Equity Market Neutral Main, Morgan Stanley Capital International (MSCI) - indices were used. To distinguish between performance of stocks of the companies operating in developed and emerging markets, MSCI (IMI) World Index[23] which Covers more than 4,500 securities across large, mid and small-cap size segments in 23 developed markets and MSCI (IMI) Emerging Markets Index [24] - which covers more than 2,600 securities across large, mid and small-cap size segments 23 emerging markets were used.

As a stock market volatility index, Chicago Board Options Exchange Volatility Index – VIX was used. VIX measures market expectation of near term volatility conveyed by stock index option prices[25] as it is constructed by using implied volatilities of a wide range of S&P 500 options. It is also known as and "investors' fear gauge."

4.2.4 Fama – French Portfolio risk factors:

The Fama/French 5 factors are constructed using the 6 value-weight portfolios formed on size and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment.

SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios:

[23] https://www.msci.com/world
[24] https://www.msci.com/emerging-markets
[25] http://www.cboe.com/data/mktstat.aspx

$$\text{SMB}_{(B/M)} = 1/3\ (\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) \\ - 1/3\ (\text{Big Value} + \text{Big Neutral} + \text{Big Growth}) \quad (4.1)$$

$$\text{SMB}_{(OP)} = 1/3\ (\text{Small Robust} + \text{Small Neutral} + \text{Small Weak}) \\ - 1/3\ (\text{Big Robust} + \text{Big Neutral} + \text{Big Weak}) \quad (4.2)$$

$$\text{SMB}_{(INV)} = 1/3\ (\text{Small Conservative} + \text{Small Neutral} + \text{Small Aggressive}) \\ - 1/3\ (\text{Big Conservative} + \text{Big Neutral} + \text{Big Aggressive}) \quad (4.3)$$

$$\text{SMB} = 1/3\ \text{SMB} = 1/3(\text{SMB}_{(B/M)} + \text{SMB}_{(OP)} + \text{SMB}_{(INV)}). \quad (4.4)$$

HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios:

$$\text{HML} = 1/2\ (\text{Small Value} + \text{Big Value}) \\ - 1/2\ (\text{Small Growth} + \text{Big Growth}). \quad (4.5)$$

RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios:

$$\text{RMW} = 1/2\ (\text{Small Robust} + \text{Big Robust}) \\ - 1/2\ (\text{Small Weak} + \text{Big Weak}). \quad (4.6)$$

CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios:

$$\text{CMA} = 1/2\ (\text{Small Conservative} + \text{Big Conservative}) \\ - 1/2\ (\text{Small Aggressive} + \text{Big Aggressive}). \quad (4.7)$$

Rm-Rf, the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate[26].

Fama – French "Small Minus Big" portfolio risk factor, also known as momentum factor, is relevant for those funds which tend to go long and invest in small cap stocks or other securities, while hedging their positions by going short on large cap. Furthermore, by introducing "High Minus Low" portfolio risk factor, they distinguish between growth investing and value investing, whereas growth investing is applied when investor expect large upward movement in price of security, i.e. small caps stock; while value investing is applied when current market price of the security is considered as undervalued (investor would take long position) or overvalued (investor would take short position). Additionally, Fama and French took into consideration operating profitability of the stocks in portfolio, whereas it would be logical in long term to go long and purchase stocks with robust operating profitability and short the stocks with weak operating profitability. Lastly, they also include "Conservative Minus Aggressive" risk factor, which could be interpreted as investing in stocks which come from saturated industries (i.e. oil or chemicals) and pay steady dividends having low price volatility, compared to investing in stocks or convertible bonds of the companies coming from turbulent industries, like technology or software development, where stock prices are much more volatile with higher upward, but also downward potential. All these factors to some extent reflect investment practices of Equity Hedge strategies, but could be also applied to Convertible Arbitrage, Event Driven, Global Macro and Multi Strategy.

4.2.5 Fung and Hseih trend following factors

The Fung and Hsieh (2001, 2004) approach creates a basic trend-following strategy called the primitive trend-following strategy (PTFS) using

[26] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

structured options called lookback straddles. A lookback straddle has a payoff equal to the difference between the maximum price and the minimum price of the underlying asset during the life of the option. Fung and Hsieh used exchange-traded options to replicate lookback straddles. Lookback straddle, as a combination of call option (allows the holder to purchase underlying asset at the lowest price) and put option (allows the holder to sell underlying asset at the highest price), delivers the ex-post maximum payout for any given trend – following strategy. Authors used historical returns on various indices from most active financial markets: bonds – PTFSBD, interest rates – PTFSIR, stocks – PTFSSTK, commodities – PTFSCOM and foreign exchange – PTFSFX.

Chapter 5

Methodology and Empirical findings

Empirical design is divided in 4 main parts: performance and risk analysis, correlation and Principal Component Analysis, Stepwise regression based on Akaike and Bayesian Information Criterions and Bayesian Model Averaging. Performance and risk analysis is performed to extract more information regarding each strategy's descriptive statistics and risk/return tradeoffs, but also to evaluate interconnectedness and commonalities among strategies. PCA, Stepwise regression and Bayesian Model Averaging approaches are taken to identify main factors driving hedge funds performance for each strategy and evaluate thesis hypothesizes:

Hypothesis 1: Interest rates environment has significant impact on hedge funds' performance.

Hypothesis 2: Hedge funds implementing different strategies are exposed to different risk factors.

Hypothesis 3: Hedge funds tend use to financial derivatives, primarily options, as main financial instrument to execute trading strategies.

Hypothesis 4: Hedge funds are to large extent exposed to risky asset types like high yielding and emerging market bonds and options.

5.1 Performance and Risk Analysis

When analyzing hedge funds' historical performance there are several indicators used by investors, whereas cumulative performance (also referred as wealth index) and drawdown represent a starting point when assessing a hedge fund. Cumulative performance expresses an aggregate amount which potential investment has gained or lost throughout specified investment period, while drawdowns show negative side of standard deviation of hedge fund performance:

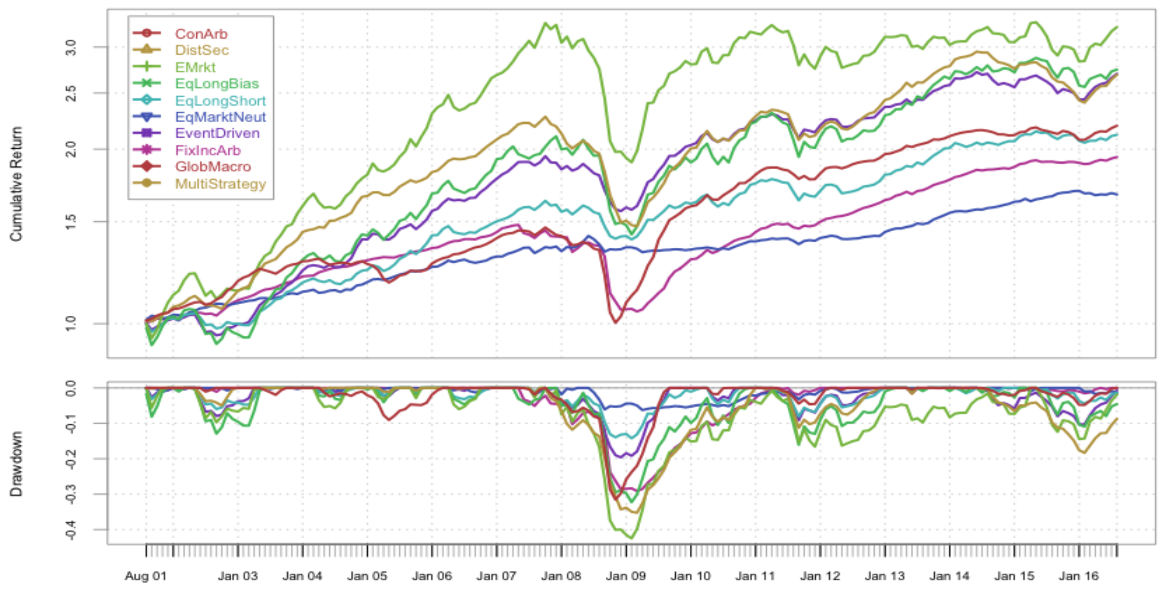

Figure 5.1.1: Cumulative Returns and Drawdowns of BH Strategy Indices (August 2001 – August 2016)

At the first glance on Figure 5.1 it is observable that financial crisis 2008/09 is period of drawdown (also referred as valley period) for all strategies. Prior to financial crisis, Emerging Market strategy has demonstrated the most aggressive growth of over 300%, but also the deepest drawdown during the crisis in 2008/9, while starting from 2010 until 2016, it has been almost flat in terms of performance and fluctuating around pre – crisis level. Multi Strategy and Global Macro also suffered severe drawdowns, whereas Global Macro recovered faster and got back on the same trend after the crisis, while the slope of cumulative performance of Multi Strategy isn't as steep as it was prior the crisis. Hedge funds following Equity Market Neutral strategy suffered the shallowest drawdown, on the other hand cumulative performance is the lowest compared to other strategies (167%) and has a rather gentle slope. Equity Long/Short strategy has also demonstrated shallow drawdown together with Event Driven strategy during financial crisis, while in terms of cumulative performance, trend has the almost the same slope as in pre-crisis period. It is worth mentioning that Equity Long/Short and Equity Long Bias strategies suffered drawdowns in early 2000s due to the Internet bubble, while Long Bias seems to be overperforming after financial crisis (although it took the longest time to recover), particularly in period starting from mid 2011 until now.

When comparing multiple financial assets, in this case hedge funds, it is convenient to use annualized returns, standard deviations and Sharpe ratios of strategies, since it offers a reference point for easy comparison, although it requires a bit of estimating. Sharpe ratio represents excess return to risk free investment per unit of risk, usually represented by variance or standard deviation, whereas higher Sharpe ratio offers better performance of “risk” and return. Obtaining annualized figures implies scaling the observations to annual scale by adjusting each hedge fund strategy’s return, standard deviation and Sharpe ratio for number of periods in the year. Bearing in mind that BarclayHedge indices have monthly frequency, for scaling purposes number of periods was 12, in case of quarterly returns – 4 would be used, etc. (Peterson 2014).

Table 5.1.1: Annualized Returns, Deviations and Sharpe Ratios of BH Strategy Indices

Strategy:	Annualized Returns	Annualized Std. Dev.	Annualized Sharpe (Rf=0%)
Convertible Arbitrage	0.0535	0.0664	0.8055
Distressed Securities	0.0678	0.0715	0.948
Emerging Markets	0.0812	0.1164	0.6978
Equity Long Bias	0.0692	0.101	0.6854
Equity Long Short	0.051	0.0515	0.9902
Equity Market Neutral	0.0346	0.0254	1.3617
Event Driven	0.068	0.0617	1.1019
Fixed Income Arbitrage	0.0449	0.0518	0.8656
Global Macro	0.0539	0.0484	1.1137
Multi Strategy	0.0613	0.0452	1.3568

Emerging Market strategy performed the best in terms of annualized return, but on the other hand it has the highest annualized standard deviation and second lowest annualized Sharpe ratio. Convertible Arbitrage and Fixed Income Arbitrage yielded to similar performance in terms of risk/return tradeoff, although Convertible Arbitrage exhibited higher return, while Fixed Income Arbitrage has lower standard deviation and therefore higher Sharpe ratio. Among equity oriented strategies, Long Bias has highest annualized return, but also the highest annualized standard deviation and together with Emerging Markets, the lowest Sharpe ratio among all strategies. On the other hand, the best risk/return tradeoff is offered by Market Neutral strategy, having annualized Sharpe ratio of 1.36, while Long/Short has Sharpe ratio close to 1, bearing in mind that annualized standard deviation is almost equal to annualized return. Multi Strategy offered second best annualized Sharpe ratio after Market Neutral – 1.35, while Global Macro also has annualized Sharpe ratio higher than 1, more precisely 1.11. All other strategies have Sharpe ratio lower than 1.

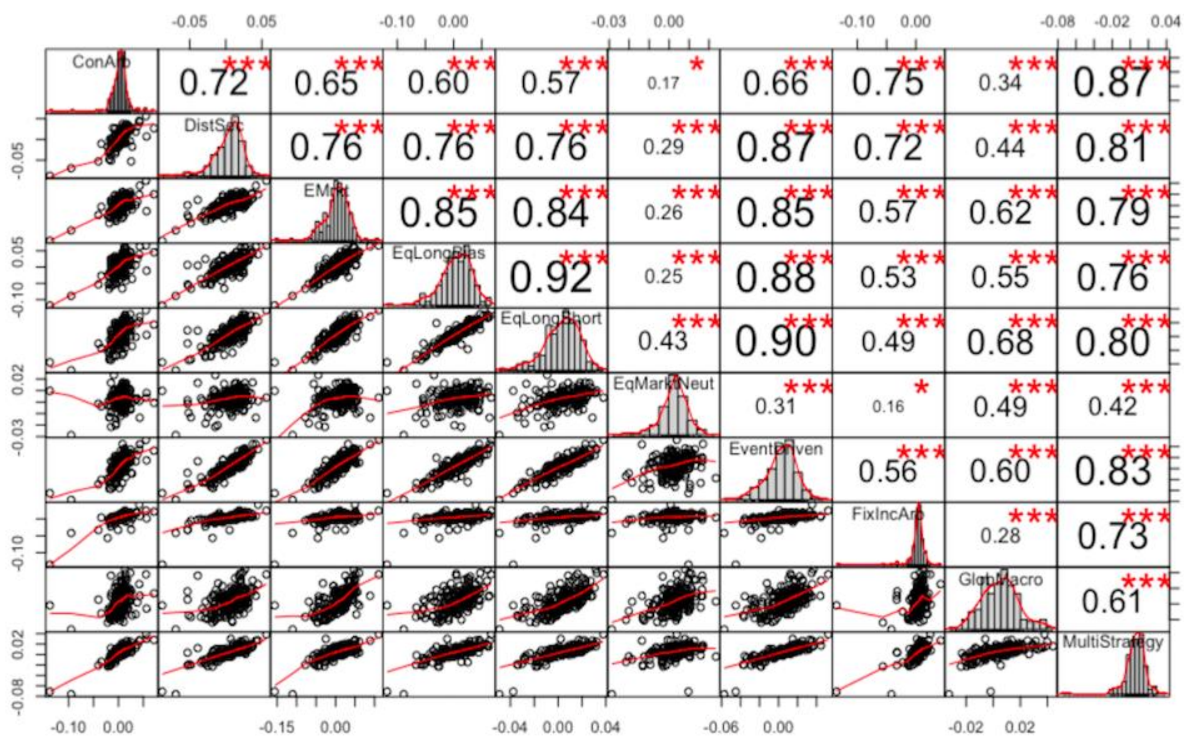

Figure 5.1.2: BH Strategy Indices' returns distributions and correlation coefficients among strategies

Figure 5.2 depicts strong and positive correlation coefficients among the strategies, apart from Market Neutral, which could be explained by the fact that all strategies share common exposure to broader market risk. Interestingly, Event Driven is extremely strongly correlated to all other strategies apart from Market Neutral while Fixed Income Arbitrage appears to be strongly correlated only to Convertible Arbitrage and Distressed Securities, having in mind similar investment approaches and underlying investments. Multi Strategy is strongly correlated to all others apart from Market Neutral. Global Macro Strategy appears to be moderately correlated with others, while intuitively the highest correlation coefficient was documented between Long/Short and Long Bias.

By looking at returns' distributions, it is observable that most strategies apart from Global Macro strategy have negative skewness and long left tails, as elaborated by Agarwal and Naik (2000). In case of normally distributed data skewness would be 0, while positive/negative skewness indicates asymmetry in returns' distributions. Negative or left skewness could indicate small frequent gains and non-frequent extreme losses.

Table 5.1.2: Risk and Distribution statistics of BH Strategy Indices

Strategy:	Monthly Std. Dev.	Skewness	Kurtosis	Downside Deviation
Convertible Arbitrage	0.0192	-2.6175	23.0213	0.0141
Distressed Securities	0.0206	-1.2299	5.9007	0.0141
Emerging Markets	0.0336	-0.9398	6.1611	0.0229
Equity Long Bias	0.0291	-0.83	4.5383	0.0197
Equity Long Short	0.0149	-0.6679	3.6002	0.0094
Equity Market Neutral	0.0073	-0.9122	5.4494	0.0045
Event Driven	0.0178	-0.5491	3.6243	0.0109
Fixed Income Arbitrage	0.015	-5.1029	44.909	0.0125
Global Macro	0.014	0.2296	3.0409	0.0072
Multi Strategy	0.013	-2.4768	16.2902	0.0091

Fixed Income Arbitrage, Convertible Arbitrage and Multi Strategy exhibited the highest negative skewness - 5.10, -2.61 and -2.47 respectively, while skewness for other strategies is within the range starting from -0.55 (Event Driven) until -1.23 (Distressed Securities), with exception of Global Macro strategy which is the only one with positive skewness of returns of 0.23 and appears to have close to normal distribution of returns. Another indicator to observe is kurtosis, which indicate how the peak and tail differ from normal distribution. In case of normal distribution, kurtosis test would have value of 3; in case of positive kurtosis test would have value higher than 3 which indicates existence of fat tails and sharper peaks which further implies that there is a higher probability for extreme outcomes; in case of negative kurtosis, test would have value lower than 3 which implies lighter tails and flatter peaks. As depicted by Figure 5.2 and Table 5.2, Fixed Income and Convertible Arbitrage have highest kurtosis by far of 23.02 and 44.91 respectively, followed by Multi Strategy with kurtosis of 16.29. Important indicator in measuring downside risk is downside deviation, which eliminates positive returns from the analysis when assessing risk levels, since investors are more concerned by downside possible loss than upside possible profit (Peterson 2014). Equity Market Neutral strategy demonstrated the lowest downside deviation of 0.0045, followed by Global Macro, Multi Strategy and Equity Long/Short with downside deviations of 0.0072, 0.0091 and 0.0094 respectively, while the highest downside deviations are observed among Emerging Market, Long Bias and Fixed Income Arbitrage Strategies of 0.0229, 0.0197 and 0.0125 respectively.

Additional indicator which is broadly used by investors when assessing hedge fund risk is Value at Risk (VaR) which indicates the maximum expected loss for a given confidence level over a specified time horizon. However, since traditional approach assumes normal Gaussian distribution of the data, Cornish-Fisher modified VaR is more appropriate, since the analysis showed that most of the strategies have negative skewness and positive kurtosis. As an extension of traditional approach, modified VaR adjusts traditional VaR for skewness and kurtosis of the distribution:

$$\mathrm{modVaR} = W[\mu - \left(z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2\right)\sigma] \qquad (5.1)$$

where W stands for asset's weight, μ for mean return, z_c for chosen confidence level, S for skewness, K for kurtosis and σ for standard deviation (Favre and Galeano 2002). Another risk indicator commonly used for hedge funds' risk assessment is Expected Shortfall. It measures the magnitude of the average losses exceeding the traditional VaR (Peterson 2014):

$$\mathrm{ES}_\alpha(X) = E[X|X \geq \mathrm{VaR}_\alpha(X)] \qquad (5.2)$$

where X is random variable denoting the loss of a given portfolio and $\mathrm{VaR}_\alpha(X)$ is traditional VaR at $(1-\alpha)$ confidence level. This indicator is also known as "beyond VaR", "tail VaR" and Conditional VaR (Yamai and Yoshiba 2002).

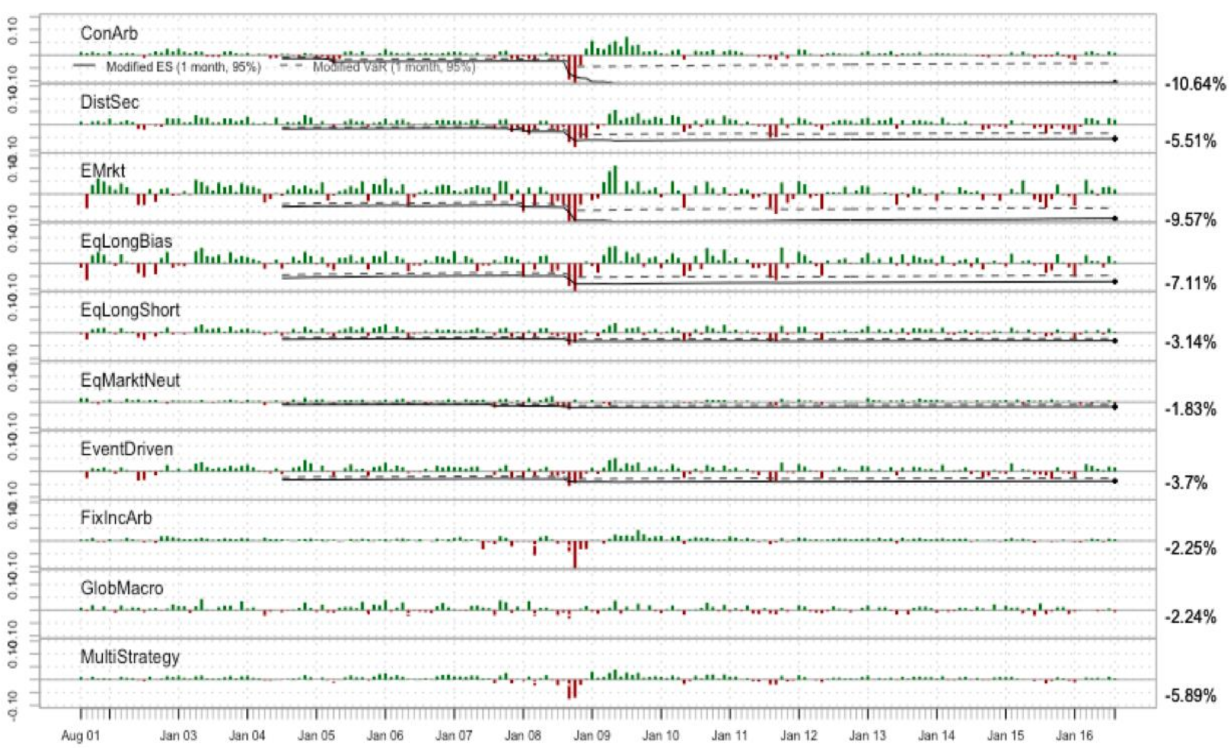

Figure 5.1.3: BH Strategy Indices' Modified Value at Risk and Expected Shortfall per strategy

Expected Shortfall (ES) could be described as the expected value of the portfolio loss, given that a Value at Risk exceedance has occurred. As depicted by Figure 5.3, in case of extreme loss which would exceed traditional Value at Risk, Convertible Arbitrage and Emerging Markets strategies have the highest possible losses of 10.64% and 9.57% of their portfolios respectively. Distressed Securities and Multi Strategy would lose more than 5% of their portfolios, while the lowest ES in case of extreme events is expected for Equity Market Neutral Strategy of -1.83%, followed by Global Macro and Fixed Income Arbitrage strategies: -2.24% and -2.25%.

5.2 Correlation and Principal Component Analysis

5.2.1 Empirical Design and Theoretical overview

In previous section, significant correlation was documented among different hedge funds strategies as well as certain level of commonality in terms of drawdowns, particularly during financial crisis in 2008/09. This could be explained by the fact that some strategies share similar investment techniques and underlying investments. Therefore, in the next step matrices of correlation coefficients between hedge fund strategies' returns and each group of external market risk proxies described in Chapter 4 (interest rates, bonds and option – adjusted spreads, equity and volatility indices, Fama – French portfolio factors, Fund–Hseih trend following factors) will be constructed. Correlation matrices were constructed in R, by calling "cor" function and using "Pearson" method, available under Performance Analytics package developed by Peterson, 2014.

Following Fung and Hsieh (2004) and Bussière et al. (2014) approaches, in the next stage the Principal Component Analysis has been applied on risk proxies' dataset. As a data reduction technique, PCA transforms the original data set into a new set of independent variables called Principal Components – PCs*.* Principal Component represent a linear combination of original variables with maximum variance. By maximizing variance of its principal components, PCA provide information regarding the fraction of variance in the original dataset explained by each of the components. Bearing this in mind, first principal component has the highest variance and captures the largest portion of variation of in original dataset. Second principal component accounts for second largest portion of variance explained and so forth. The calculation is done through computing eigenvectors on the correlation matrix, by using "princomp" function in R. The result of running PCA is matrix of variable eigenvectors – "loadings", which indicate how strong is each risk factor related to each principal component. However, as discussed by Bussière et al. (2014), it is important to point out that components' "loadings" do not provide any interpretation and economic reasoning, while signs of the columns of the loadings and scores are arbitrary, and so may differ between different programs for PCA, and even between different builds of R[27].

5.2.2 Empirical findings

5.2.2.1 Correlation Analysis Results

Correlation analysis for interest rates proxies and BH strategy indices showed that all coefficients are very weak and mostly positive, with an exception of the spread of 1–Year T–bill against Federal Funds rate (X1YTBMFR), which share mainly negative coefficients with the performances of BH indices. Short term interest rate proxy exhibits very weak and positive correlation to Emerging Markets, Equity Market Neutral, Global Macro and Multi Strategy. Long term interest rate proxy has, likewise short term interest rate, very weak and positive correlation to the same strategies, which incorporate different investment techniques and invest in variety of different asset classes and instruments: Macro, Multi and

[27] http://stat.ethz.ch/R-manual/R-devel/library/stats/html/princomp.html

Emerging Markets, together with Event Driven. Spread of 3-month T–bill against Federal Funds rate has weak or very weak and positive correlation to strategies which implement arbitrage investment technique like Convertible Arbitrage, Distressed Securities and Fixed Income Arbitrage. Spread of 1-Year T-bill against Federal Funds rate have weak and negative correlation coefficient to Equity Market Neutral, Global Macro and Multi Strategy:

Table 5.2.1: Correlation coefficients matrix for interest rates proxies and BH Strategy Indices

	X3MTB	X10YTCM	X3MTBMFR	X1YTBMFR
Convertible Arbitrage	-0.0175	0.0387	0.1940	-0.0653
Distressed Securities	0.0899	0.1853	0.2147	0.0230
Emerging Markets	0.1526	0.1860	0.0703	-0.0193
Equity Long Bias	0.0635	0.1097	0.0794	0.0202
Equity Long Short	0.0781	0.1087	0.1243	-0.0010
Equity Market Neutral	0.1121	0.0784	0.0572	-0.1214
Event Driven	0.0938	0.1328	0.1384	0.0051
Fixed Income Arbitrage	-0.0291	0.0290	0.2355	-0.0133
Global Macro	0.1385	0.1425	-0.0818	-0.1801
Multi Strategy	0.1264	0.1275	0.1146	-0.1543

By looking at the correlation coefficients of bond and option adjusted spreads and BH strategy indices, at the first glance it is obvious that correlation is strictly negative. Moreover, it seems that strategy indices have stronger correlation to option adjusted spreads of bonds against T-bill, than to simple returns on bonds. Only Fixed Income Arbitrage exhibits moderate negative correlation to both, while all other strategies in most of the cases have weak correlation coefficients to bond returns and moderate correlation to option adjusted spreads. Interestingly, Convertible Arbitrage demonstrated weak correlation coefficients to bond proxies which is counterintuitive bearing in mind strategies' features. Global Macro strategy has the lowest correlation to bond oriented factors, while Fixed Income

Arbitrage and Distressed Securities strategies have the strongest correlation coefficients.

Table 5.2.2: Correlation coefficients matrix for BofAML bond and option adjusted spreads and BH Strategy Indices

	ABOND	AOPSP	BBOND	BOPSP	CBOND	COPSP
Convertible Arbitrage	-0.1576	-0.2454	-0.1852	-0.1867	-0.1467	-0.1489
Distressed Securities	-0.2137	-0.4871	-0.3915	-0.4606	-0.3567	-0.4238
Emerging Markets	-0.1084	-0.3801	-0.2894	-0.3770	-0.2472	-0.3301
Equity Long Bias	-0.1665	-0.3500	-0.3478	-0.3904	-0.3118	-0.3535
Equity Long Short	-0.1399	-0.3191	-0.3062	-0.3532	-0.2695	-0.3144
Equity Market Neutral	-0.0970	-0.2409	-0.1444	-0.1898	-0.1436	-0.1857
Event Driven	-0.1282	-0.3278	-0.3020	-0.3561	-0.2603	-0.3124
Fixed Income Arbitrage	-0.3452	-0.4901	-0.4406	-0.4362	-0.4270	-0.4269
Global Macro	0.0016	-0.1717	-0.0729	-0.1427	-0.0595	-0.1236
Multi Strategy	-0.1627	-0.3815	-0.2953	-0.3513	-0.2606	-0.3142

Similar correlation coefficients are documented when analyzing emerging market bonds factors, while it seems that hedge funds prefer investing in high grade rather than below grade emerging market bonds, bearing in mind that "emerging" feature itself increases the risk and additionally downgrades bonds' rating:

Table 5.2.3: Correlation coefficients matrix for Emerging BofAML bond and option adjusted spreads and BH Strategy Indices

	EMHGBOND	EMHGOPSP	EMBGBOND	EMBGOPSP
Convertible Arbitrage	-0.1921	-0.2270	-0.1097	-0.1165
Distressed Securities	-0.2973	-0.4790	-0.3741	-0.3991
Emerging Markets	-0.1908	-0.3936	-0.2595	-0.2977
Equity Long Bias	-0.2365	-0.3550	-0.3103	-0.3201
Equity Long Short	-0.1940	-0.3112	-0.2707	-0.2820
Equity Market Neutral	-0.1255	-0.2291	-0.1529	-0.1670
Event Driven	-0.1951	-0.3290	-0.2903	-0.3091
Fixed Income Arbitrage	-0.4226	-0.4736	-0.3931	-0.3811
Global Macro	-0.0268	-0.1744	-0.1057	-0.1426
Multi Strategy	-0.2365	-0.3811	-0.2624	-0.2871

When it comes to equity oriented risk factors, documented correlation coefficients are strictly strong or in some cases very strong and positive, while volatility proxy is strictly negatively correlated to strategy indices and mostly moderately, apart to Convertible Arbitrage, Equity Market Neutral and Global Macro strategies. Interestingly, strategies like Convertible Arbitrage, Distressed Securities and Fixed Income Arbitrage exhibit strong correlation to equity oriented risk factors. The strongest coefficients were documented among Equity Long Bias and Long/Short, while the weakest correlation was in case of Equity Market Neutral strategy.

Table 5.2.4: Correlation coefficients matrix for MSCI Equity Indices, VIX and BH Strategy Indices

	MSCIDM	MSCIEM	VIX
Convertible Arbitrage	0.5568	0.5791	-0.2008
Distressed Securities	0.7105	0.6642	-0.4401
Emerging Markets	0.8344	0.9535	-0.3852
Equity Long Bias	0.9125	0.8401	-0.3912
Equity Long Short	0.8609	0.8181	-0.3635
Equity Market Neutral	0.1522	0.2022	-0.1955
Event Driven	0.8257	0.8063	-0.3591
Fixed Income Arbitrage	0.5141	0.4717	-0.4011
Global Macro	0.5254	0.5932	-0.1005
Multi Strategy	0.6946	0.7143	-0.3499

When analyzing Fama – French portfolio risk factors, it is straightforward that excess return on market relative to Treasury bill rate (Mkt.RF) as a measure of overperformance on broader market, has the strictly positive and strong correlation coefficients to all strategies (apart from Equity Market Neutral), especially to strategies like Emerging Markets, Long Bias, Long Short and Event Driven. “Small Minus Big” factor as a measure of overperformance of small cap stock against large cap, has also strictly positive but moderately strong correlation coefficients, while “High Minus Low” factor as a measure of overperformance of value investing strategy over growth investing, has rather very weak correlation to all strategies apart from Distressed Securities, where coefficient is still weak but much stronger than in for other strategies. “Robust Minus Weak” factor as measure of overperformance of stocks with robust operating profitability against stocks with weak operating profitability, has rather very weak and negative correlation coefficients, apart from Long Bias, Long Short and Event Driven. “Conservative Minus Aggressive” exhibited moderately strong (apart from Distressed Securities, Market Neutral and Global Macro) and strictly negative correlation.

Table 5.2.5: Correlation coefficients matrix for Fama – French portfolio risk factors and BH Strategy Indices

	Mkt.RF	SMB	HML	RMW	CMA
Convertible Arbitrage	0.5662	0.2417	0.0623	-0.1632	-0.4041
Distressed Securities	0.7159	0.2910	0.2265	-0.2761	-0.2850
Emerging Markets	0.8414	0.2508	0.0921	-0.2732	-0.4448
Equity Long Bias	0.9133	0.2088	0.0499	-0.4781	-0.3759
Equity Long Short	0.8679	0.2847	0.0439	-0.4365	-0.3786
Equity Market Neutral	0.1637	0.2460	-0.0157	0.1082	-0.0555
Event Driven	0.8325	0.3051	0.1108	-0.3970	-0.3783
Fixed Income Arbitrage	0.5194	0.1780	0.0225	-0.1308	-0.3475
Global Macro	0.5335	0.1863	-0.0056	-0.1221	-0.2680
Multi Strategy	0.7028	0.2942	0.0111	-0.2096	-0.4565

Fung and Hseih trend following risk factors exhibited almost strictly negative and either very weak or in some instances weak correlation coefficients. The strongest correlation coefficients for all strategies are documented for lookback straddles on bonds and interest rates. Counterintuitively, equity oriented strategies like Equity Long Bias, Equity Long/Short and even Event Driven have very weak correlation to lookback straddle on stocks. Lookback straddles on currencies is only to some extent relevant for Convertible Arbitrage in terms of correlation, while lookback straddles on commodities has strongest correlation coefficient to Equity Market Neutral strategy.

Table 5.2.6: Correlation coefficients matrix for Fund – Hseih trend following factors and BH Strategy Indices

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK
Convertible Arbitrage	-0.2580	-0.2237	-0.1592	-0.1948	-0.1353
Distressed Securities	-0.2020	-0.1323	-0.0976	-0.1873	-0.1443
Emerging Markets	-0.1801	-0.0131	-0.0966	-0.1420	-0.1504
Equity Long Bias	-0.1964	-0.0364	-0.0731	-0.1757	-0.1146
Equity Long Short	-0.1511	-0.0357	-0.0819	-0.1763	-0.0883
Equity Market Neutral	-0.0521	-0.1808	-0.1846	-0.1950	-0.0011
Event Driven	-0.2030	-0.0813	-0.1151	-0.1886	-0.1372
Fixed Income Arbitrage	-0.2120	-0.0876	-0.0425	-0.1922	-0.1047
Global Macro	-0.0808	0.0052	-0.1208	-0.0486	0.0973
Multi Strategy	-0.2195	-0.1560	-0.1465	-0.2192	-0.1184

5.2.2.2. Principal Component Analysis Results

The results of running PCA on market risk factors dataset indicate that there are 27 principal components, while first three components alone explain 59.92% of variation in data set, whereas first component accounts for 36.2 % of variation, second 13.47% and third 10.25%. In addition, as described in theoretical overview, first component has highest standard deviation of 3.1263, second has 1.9073 and third 1.6639

Table 5.2.7: Importance of PCs in terms of explained variance

Importance of components:	PC1	PC2	PC3
Standard Deviation	3.1263	1.9073	1.6639
Proportion of Variance	0.362	0.1347	0.1025
Cumulative Proportion	0.362	0.4967	0.5992

Explanatory power of principal components other than first three diminishes, bearing in mind that fourth principal component accounts for only 7.5% of variation in data set, fifth for only 6.4% and sixth for only 4.5% and so forth. Therefore, only first three components are included in further analysis.

Table 5.2.8: Risk factors' loadings to Principal Components

Loadings:	PC1	PC2	PC3
X3MTB		-0.467	
X10YTCM		-0.435	-0.158
X3MTBMFR		0.325	-0.106
X1YTBMFR		0.215	-0.131
ABOND	0.201	-0.354	-0.154
AOPSP	0.286		
BBOND	0.302	-0.100	-0.115
BOPSP	0.304	0.118	
CBOND	0.300		-0.145
COPSP	0.304	0.114	
EMHGBOND	0.253	-0.251	-0.164
EMHGOPSP	0.283	0.167	
EMBGBOND	0.287		-0.128
EMBGOPSP	0.274	0.208	
MSCIDM	-0.172		-0.444
MSCIEM	-0.136		-0.478
VIX	0.291		
Mkt.RF	-0.171		-0.448
SMB			-0.128
HML		-0.127	
RMW			0.242
CMA			0.226
PTFSBD			0.143
PTFSFX		-0.131	
PTFSCOM		-0.104	0.148
PTFSIR	0.113	-0.244	
PTFSSTK			0.123

(Note: Loadings lower than 0.10 are omitted from the table)

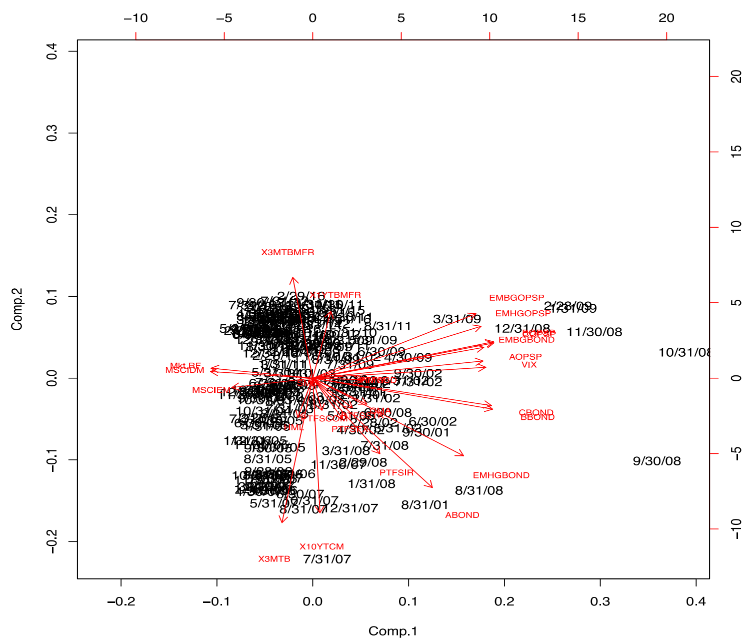

Figure 5.2.1: PCA Biplot

Note: Biplots represent graphical visualization of PCA, plotting variables as vectors and observations as points on the same graph. Angle between vectors indicate correlation between the variables, while the length of vectors indicates the strength of impact.

By looking at the table above, it is straightforward that the first principal component (which accounts for 36.2 % of variation in risk proxies' dataset) is primarily dominated by bond oriented factors and to some extent by equity factors, while second principal component is mainly driven by interest rate proxies. Lastly, third principal component is dominated by equity risk factors together with Fama – French portfolio factors.

By looking at the Biplot depicted on Figure 5.2.1, several risk factors are grouped together, indicating similar strength and direction of their corresponding impacts on PCs. First group is composed from emerging market below grade bonds, their option adjusted spreads together with VIX, "CCC", "BB", "a" and emerging market high grade option adjusted spreads. Second group is composed from "CCC" and "BB" bonds which are almost identical, while emerging market high grade bonds and "a" bonds are rather unique in terms of their impact on PCs. Short and Long term interest rates have opposite effects on PCs when compared with interest rates spreads, while equity indices together with excess return on market compose last group of factors with similar impact on PCs.

5.3 Stepwise regression

5.3.1 Theoretical overview and Empirical design

Large pool of candidate variables for inclusion in the model describing the impact of external market risk factors on hedge funds' returns imposes a variable selection problem, whereas it would be fairly difficult to choose between many possible combination outcomes. Following up on Bussière et al. (2014), a stepwise regression is applied. As an automated technique for a variable selection, a stepwise regression in each iteration includes and excludes market risk factors based on t-statistic of their corresponding estimated beta coefficients, retaining only those which showed statistical significance. Therefore, a stepwise regression searches for the optimal forecasting model with the best "fit". There are two alternative fit measures discussed in the literature: Akaike Information Criterion – AIC, and Bayesian (also known as Schwarz) Information Criterion:

$$\mathrm{AIC(K)} = ln\left(\frac{\mathrm{e'e}}{\mathrm{n}}\right) + \frac{2\mathrm{K}}{\mathrm{n}} \tag{5.3}$$

$$\mathrm{BIC(K)} = ln\left(\frac{\mathrm{e'e}}{\mathrm{n}}\right) + \frac{\mathrm{K}ln\mathrm{n}}{\mathrm{n}} \tag{5.4}$$

where K represents number of parameters, n stands for number of observations, while e is vector of least square residuals. The main goal of stepwise regression is to select models which minimize these two criterions. Both measures improve (decline) as R^2 increases (decreases), but, everything else constant, degrade as the model size increases. These measures place a premium on achieving a given fit with a smaller number of parameters per observation, K/n. Both prediction criteria have their virtues, and neither has an obvious advantage over the other. The Schwarz criterion, with its heavier penalty for degrees of freedom lost, will lean toward a simpler model. All else given, simplicity does have some appeal. (Greene 2012)

Stepwise regression is conducted in R under the "MASS" package (version 2016) developed by Brian Ripley (2002), by calling "stepAIC" function. Stepwise regression has three options: (1) start with no variable and add one additional variable each time to form a model with the best information criteria; (2) start with all variables and delete one additional variable each time, forming a model with the best information criteria; and (3) combination of the above two options (Zhou 2013). In this analysis, third option was used, therefore in code specification, direction mode was set up to "both". When conducting stepwise regression based on BIC criterion, degrees of freedom are set up to be equal to log of number of observation - "k = log (n)", as proposed by author.

Following Bussière et al. (2014), to perform risk modeling of strategies, stepwise regression was conducted by regressing monthly returns R_t^i, for each of the 10 strategies i = {1,…,10} as a dependent variables, starting from August 2001 until August 2016, t = {1,…,181}, on 27 risk factors described in section 4.2 as explanatory variables:

$$\begin{aligned} R_t^i = {} & \alpha + \beta_t^1 XTMTB + \beta_t^2 X10YTCM + \beta_t^3 X3MTBMFR + \beta_t^4 X1YTBMFR + \beta_t^5 ABOND \\ & + \beta_t^6 AOPSP + \beta_t^7 BBOND + \beta_t^8 BOPSP + \beta_t^9 CBOND + \beta_t^{10} COPSP \\ & + \beta_t^{11} EMHGBOND + \beta_t^{12} EMHGOPSP + \beta_t^{13} EMBGBOND \\ & + \beta_t^{14} EMBGOPSP + \beta_t^{15} MSCIDM + \beta_t^{16} MSCIEM + \beta_t^{17} VIX + \beta_t^{18} Mkt.RF \\ & + \beta_t^{19} SMB + \beta_t^{20} HML + \beta_t^{21} RMW + \beta_t^{22} CMA + \beta_t^{23} PTFSBD \\ & + \beta_t^{24} PTFSFX + \beta_t^{25} PTFSCOM + \beta_t^{26} PTFSIR + \beta_t^{27} PTFSSTK + \varepsilon_t \end{aligned} \tag{5.5}$$

5.3.2 Empirical Findings

Tables with estimated beta coefficients of risk factors are available in Appendix A. Tables A.1 – A.6 refer to stepwise models based on Akaike Information Criterion, while tables A.7 – A.12 refer to stepwise models based on Bayesian Information Criterion. As elaborated in theoretical part, BIC based models excludes all insignificant variables and either increases significance of other variables or adds fewer variables with high significance instead. Both AIC and BIC based models seem to be overconfident in terms of p – value with high explanatory power in terms of adjusted R^2.

When it comes to models' structures, Akaike and Bayesian Information Criterions are pretty much aligned with regards to strategies like Distressed Securities, Fixed Income Arbitrage and Multi Strategy, while they significantly deviate when it comes to variable selection for Emerging Markets, Equity Market Neutral and Global Macro models. Furthermore, both criterions are in line when it comes to selecting spread of 1–Year T-bill against Federal Funds rate as representative of interest rate risk and Fama–French portfolio factors, especially excess return on market and "Small

Minus Big", as proxies of equity markets' performance. On the other hand, BIC seems to be more restrictive when it comes to inclusion of bond oriented factors.

Estimated coefficients also differ, while AIC tends to have higher values of coefficients, BIC is more moderate for most of the risk factors. Lastly, estimated coefficients of bonds and their corresponding option adjusted spreads always have opposite signs, which indicates that if return on bonds increased, corresponding spread decreases. In addition, coefficients of option adjusted spreads are always higher than coefficients of corresponding bonds, which indicates that hedge funds are mostly involved in trading of bonds with embedded callable/puttable option.

5.3.2.1 AIC and BIC models

Convertible Arbitrage

When it comes to interest rate proxies, both AIC and BIC models for Convertible Arbitrage strategy indicate that these hedge funds favor increase in spread of 3-month T-bill against Federal Funds rate, while they get penalized for increase in spread of 1–Year T-bill against Federal Funds rate. When it comes to bond oriented risk proxies, both AIC and BIC models indicate that returns on "a" grade bonds and "CCC" option adjusted spreads are most important positive drivers, while opposite is true for option adjusted spreads of "a" grade bonds, return on "CCC" in addition to return on high grade emerging market bonds. From equity factors, both criterions include excess return to market and "Small Minus Big" factor as positive drivers. In general, BIC model yields to similar results as AIC, although estimated coefficients are lower, and it includes "BB" option adjusted spread and "Conservative Minus Aggressive" as additional factors with negative coefficient, while all insignificant variables included in AIC are excluded from the BIC model.

Distressed Securities

For this strategy, AIC and BIC models are almost identical when it comes to risk factors selection, their coefficients' signs and significance levels, with only distinction that BIC model excluded all insignificant variables and have slightly different values of coefficients. Increase in interest rates, both short and long term, has positive impact on returns of hedge funds which implement this strategy, while returns on "BB" and high grade emerging bonds have negative impact. Coefficients of "BB" option adjusted spread, return on "CCC" bonds, developed markets equity index and "Small Minus Big" factors are all positive and highly significant.

Emerging Markets

Here BIC model yields to more intuitive results, as it includes only returns and option adjusted spreads on emerging market bonds, while AIC model also includes more general proxies, option adjusted spreads of "BB" and "CCC" grade bonds. Moreover, AIC model includes long term interest rate. Furthermore, BIC model includes solely emerging markets equity index together with "Small Minus Big" factor as highly significant, while AIC model includes all equity indices together with all Fama–French factors.

Equity Long Bias

Like Emerging Markets, BIC model for Equity Long Bias yields to fewer explanatory factors, and contrary to AIC model, which includes all interest rate proxies, BIC doesn't include any. When it comes to bond oriented proxies, both models have estimated similar coefficients in terms of sign, while as in previous cases, BIC coefficients are more moderate. Return on "a" bonds and "BB" and emerging market high grade option adjusted spreads have negative, while option adjusted spread of "a" grade bond and return on "CCC" bond have positive estimated coefficients. Both criterions find performance of developed market equities together with “Small Minus Big” factor to have positive, while “High Minus Low” and “Robust Minus Weak” to have negative coefficients among equity and Fama–French factors.

Equity Long/Short

For this strategy, both AIC and BIC models indicate negative impact of spread of 1–Year T-bill against Federal Funds rate on strategy performance. However, when it comes to bond oriented factors, BIC considers only “BB” bond returns and “CCC” bond returns and option adjusted spreads, while AIC includes almost all bond factors apart from emerging markets ones. When it comes to equity factors, both models incorporate only Fama–French portfolio factors, more precisely excess return on market, “Small Minus Big” with positive, and “High Minus Low” with negative coefficients.

Equity Market Neutral

While AIC model doesn’t incorporate any interest rate, BIC model includes spread of 1–Year T-bill against Federal Funds rate with negative coefficient. On the other hand, while AIC includes bond oriented factors, BIC is neglecting all of those, and placing “Small Minus Big” factor as most significant one, together with “Robust Minus Weak” and excess return on market, all with positive coefficients, while AIC includes all Fama–French factors together with performance of developed market equites.

Event Driven

In this case, BIC again appears to be much more restrictive when it comes to variable inclusion than AIC. While BIC neglects interest rate factors, AIC includes all interest rates proxies except 3–Month T-bill. Furthermore, BIC only incorporates return on “BB” bonds and option adjusted spread on emerging markets below grade bonds with negative and return on “CCC” bonds with positive coefficients, while AIC includes majority of bond oriented proxies. On the other hand, when it comes to equity oriented factors, Fama – French excess return on market and “Small Minus Big” are incorporated by both criterions as highly significant with positive coefficients.

Fixed Income Arbitrage

For this strategy, both criterions are in line. Same as for Convertible Arbitrage, this strategy favors increase in spread of 3–month T-bill against Federal Funds rate, while it gets penalized for increase in spread of 1–Year T-bill against Federal Funds rate as well as for increase in 3-month T–bill. Coefficients of bond proxies are also in line in terms of sign and size, while they slightly vary in terms of significance. Only distinction is that BIC eliminates option adjusted spread on emerging high grade bonds.

Global Macro

Here AIC and BIC deviate one from another significantly. While AIC incorporates at least 3 variables from each risk factor category, BIC incorporates 3 factors in total. AIC criterion includes all interest rates factors apart from 3 – month T-bill, while BIC only accounts for spread of 1 – year T-bill against Federal Funds rate as relevant. Interestingly, AIC includes “a” bond returns, “CCC” bond returns and option adjusted spreads as well as emerging bonds, while BIC neglected the impact of bonds on Global Macro strategy’s performance. Moreover, while AIC incorporate both emerging equity index and majority of Fama–French factors, BIC relays solely on emerging market equity index, assigning it extremely high significance. Third factor which appears to be highly significant per both criterions is lookback straddle on stocks, although estimated coefficient in both cases is low.

Multi Strategy

Similarly to Fixed Income Arbitrage and Distressed Securities, for this strategy both criterions are in line with regards to model's structure. Both include spread of 1–year T-bill against Federal Funds rate with negative and spread of 3–month T-bill against Federal Funds rate with positive coefficients and similar values. Moreover, both incorporate returns on "a" bonds and emerging high grade bond, and all option adjusted spreads apart from emerging markets ones. With regards to Fama- French factors, only "High Minus Low" was excluded by both criterions.

5.4 Bayesian Model Averaging

5.4.1 Theoretical framework and empirical design

To overcome variable selection problem, in previous part a stepwise regression approach was implemented. However, overconfidence in terms of p – values and extremely high adjusted R^2 of all stepwise models indicate spurious results. Due to the large number of risk factors, these models could be degraded and lead to false inference. To address model uncertainty and variable selection problems, Bayesian Model Averaging was implemented in the next step, following approaches of Zhou (2013) and Havránek and Žigraiová (2015). BMA computes many regressions with different subset combinations of explanatory variables, whereas there are 2^K possible models, where K represents number of explanatory variables, in this case risk factors. BMA results give number of most promising "best models" constructed based on different combinations of explanatory variables and to each of those models is given a weight which is analog to adjusted R^2, capturing each models' fit. Moreover, BMA reports Posterior Inclusion Probability (PIP) for each explanatory variable, representing a probability for that variable to be incorporated into the "right" model describing dependent variable. Additionally, BMA gives posterior mean values and posterior standard deviations of regression parameters based on weighted averages from the checked models.

Following Zhou (2013), to perform Bayesian Model Averaging on risk modeling of BarclayHedge strategy indices' monthly returns, following model is specified:

$$\mathrm{R}^{\mathrm{i}} = \alpha^{\mathrm{i}} + \beta_{\mathrm{k}}^{\mathrm{i}} \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathbf{X_k} + \varepsilon^{\mathrm{i}} \tag{5.5}$$

where R^{i} stands for performance of hedge fund strategy $\mathrm{i} = \{1,\ldots,10\}$; α^{i} is return for i-th hedge fund strategy after stripping off the contribution from risk factors, $\mathrm{k}=\{1,\ldots,27\}$ stands for the number of risk factors; $\beta_{\mathrm{k}}^{\mathrm{i}}$ represents exposure of i-th hedge fund strategy to k-th risk factor, $\mathbf{X_k}$ is matrix composed from performances of k risk factors and ε^{i} is idiosyncratic return of i-th hedge fund strategy.

Following Havránek and Žigraiová (2015) approach, Bayesian Model Averaging is done in R, by calling "bms" function available under bms package for R developed by Feldkircher and Zeugner, 2009, which employs the Monte Carlo Markov Chain algorithm to go through the most promising of the potential models. The number of iterations is set to 1 million, number of "burn in" iterations is 500000 (i.e. throwing away some iterations at the beginning of Monte Carlo Markov Chain), the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of data) are additionally specified in R code.

5.4.2 Empirical findings

Results of BMA are summarized in figures and tables depicting the best candidate variables. Figures show full list of variables which are sorted by Posterior Inclusion Probabilities in descending order. Blue color indicates positive, while red color indicates negative estimated sign of coefficient of a variable. No color indicates that variable is not included into the model. The horizontal axis measures the cumulative posterior model probabilities, the models that are the most successful in explaining hedge funds returns are placed on the left. Tables contains either: 1) all candidate variables with PIP > 0.5; or 2) first five candidate variables with highest PIP.

Convertible Arbitrage

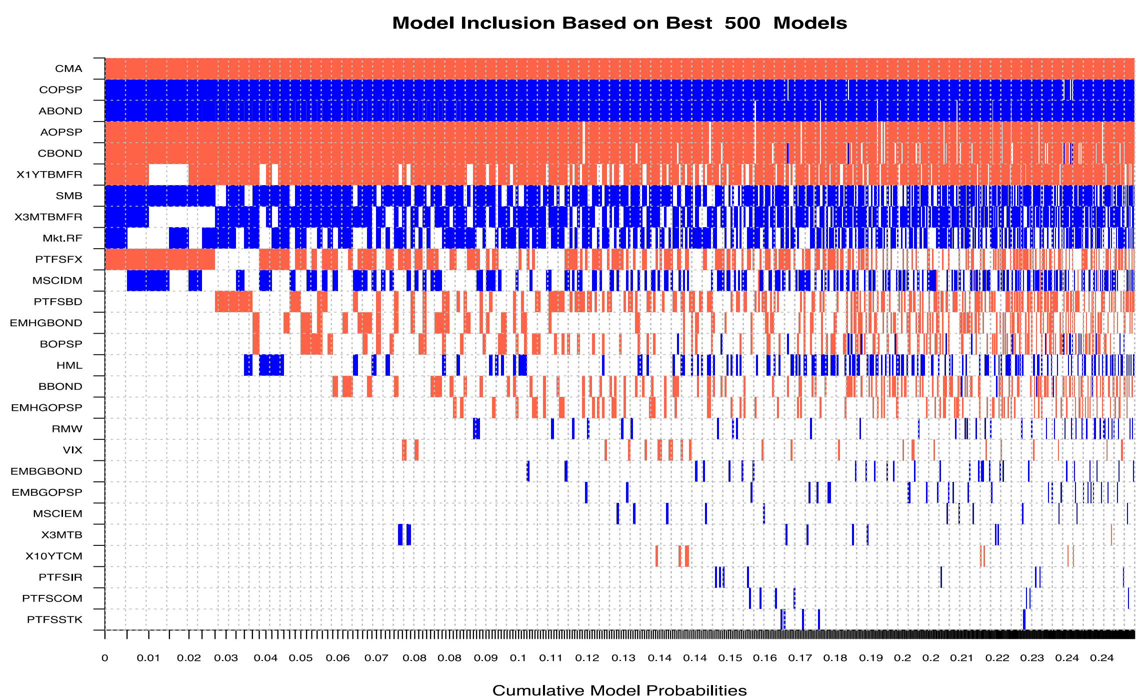

Figure 5.4.1: Convertible Arbitrage – BMA Risk factors proxies

As depicted by Figure 5.4.1, most promising candidate variables included in best models for describing Convertible Arbitrage strategy's performance are "Conservative Minus Aggressive", option adjusted spread on "a" grade bonds, return on "CCC" grade bonds, spread of 1–Year T-bill against Federal Funds rate with negative estimated coefficients; and option adjusted spread on "CCC" grade bonds, return on "a" grade bonds, "Small Minus Big" factor and spread of 3–Month T-bill against Federal Funds with positive estimated coefficients. In addition, another Fama–French factor with positive estimated coefficient and PIP value higher than 0.5 is excess return on market.

Table 5.4.1: Convertible Arbitrage – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
CMA	1.0000	-0.2747	0.0865
COPSP	0.9942	6.3517	2.0401
ABOND	0.9922	6.4193	1.7759
AOPSP	0.9796	-7.3407	2.1826
X1YTBMFR	0.9490	-5.7292	2.1987
CBOND	0.8337	-1.1981	0.7261
X3MTBMFR	0.7707	0.1301	0.0901
SMB	0.7145	1.3911	1.0705
Mkt.RF	0.5819	0.1047	0.1101

The strongest risk factors driving returns of funds following this strategy are intuitively bonds and option adjusted spreads. Interestingly, by looking at the grading of the bonds it seems that these funds invest in the bonds with the lowest grading and hedge their positions by investing in the bonds with the highest rating, or vice versa. Second highest coefficient with negative sign is documented for spread of 1–Year T-bill against Federal Funds rate, which implies that performance of this strategy is negatively affected by increase in interest rates, confirming the first hypothesis regarding the positive (negative) impact of interest rate decline (rise) on hedge funds performance. Negative coefficient of "Conservative Minus Aggressive" implies that in case of overperformance of conservative investments (i.e. oil or chemical) against aggressive investments (i.e. tech stocks), performance of these funds decreases. Additionally, "Small Minus Big" factor has relatively strong and positive coefficient, which altogether implies that these funds are rather exposed to securities which offer high growth potential.

In comparison with BIC model, BMA model excludes return on "BB" and emerging market high grade bonds and assigns different coefficients, especially for interest rates proxies.

Distressed Securities

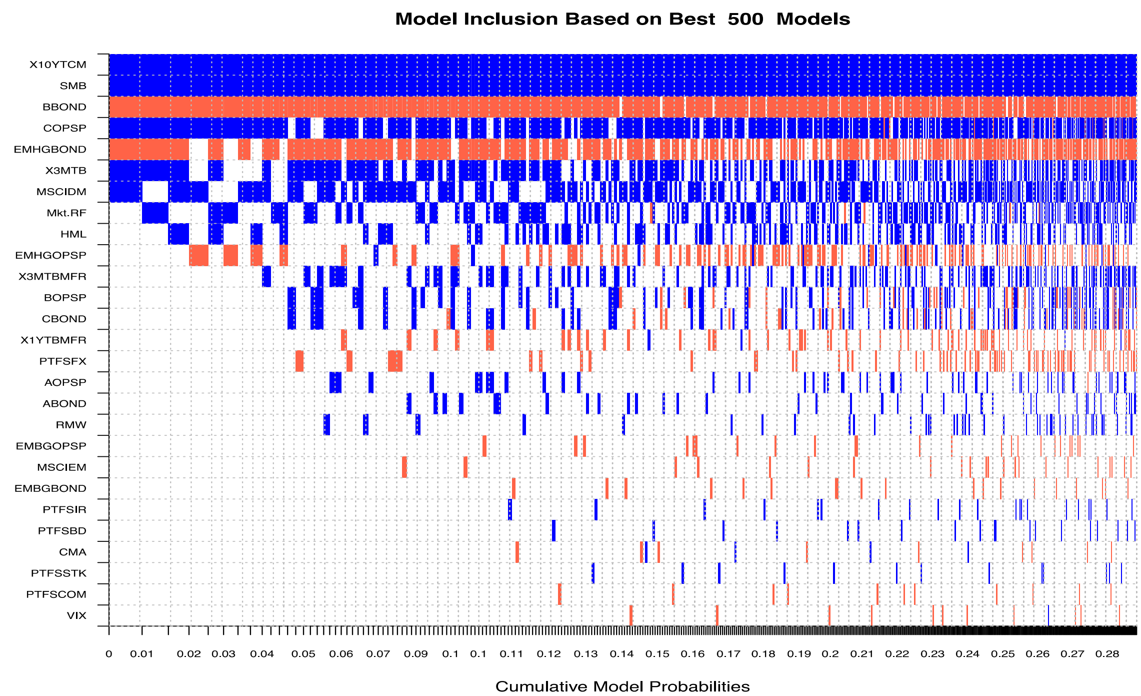

Figure 5.4.2: Distressed Securities – BMA Risk factors proxies

Figure above implies that long term interest rates, "Small Minus Big", option adjusted spread on "CCC" grade bonds together with short term interest rates and performance of equites on developed markets are most promising candidate variables with positive coefficients, while returns on "BB" and emerging high grade bonds are most promising candidate variables with negative estimated coefficients. The strongest regressors are long term interest rate and option adjusted spread on "CCC" grade bonds with positive, and "BB" grade bond with negative impact and emerging market high grade bond with negative impact. Moderate positive impact is documented among equity factors, such as performance of developed market equities and Fama-French "Small Minus Big" factors.

Table 5.4.2: Distressed Securities – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
X10YTCM	1.0000	1.8628	0.5932
SMB	1.0000	0.2459	0.0554
BBOND	0.9586	-1.3265	0.9867
COPSP	0.8517	1.0010	0.9282
EMHGBOND	0.7279	-0.8651	0.6353
X3MTB	0.5950	0.2283	0.2254
MSCIDM	0.5883	0.1501	0.1312

It could be argued that increase in interest rates creates investment opportunities for funds following this strategy, since consequently has repercussions on companies who issued debt. Therefore, increase in interest rates might be a trigger for creating more of distressed situations in debt oriented securities on the market, hence having a positive impact on performance of the funds following Distressed Securities strategy. Moreover, positive coefficients of interest rates might indicate a trading strategy where these hedge funds hold positions in puttable bonds, so increase in interest rates is used for reallocation of the funds under higher interest rate, therefore receiving higher values of coupons, which eventually yields to higher performance. By the grading of selected bond oriented proxies, it is obvious that this strategy is focused on lower graded or "distressed" bonds.

This model is more restrictive than the one based on BIC criterion, since it assigns PIPs <0.5 to short term interest rates, return on "BB" bonds, while instead of return on "CCC" bond, it selected corresponding option adjusted spread which confirms hypothesis that hedge funds give primate to derivative investing rather than investing in traditional securities. In addition, estimated coefficients obtained by this model are more moderate than those obtain by BIC, while the signs of coefficients are aligned.

Emerging Markets

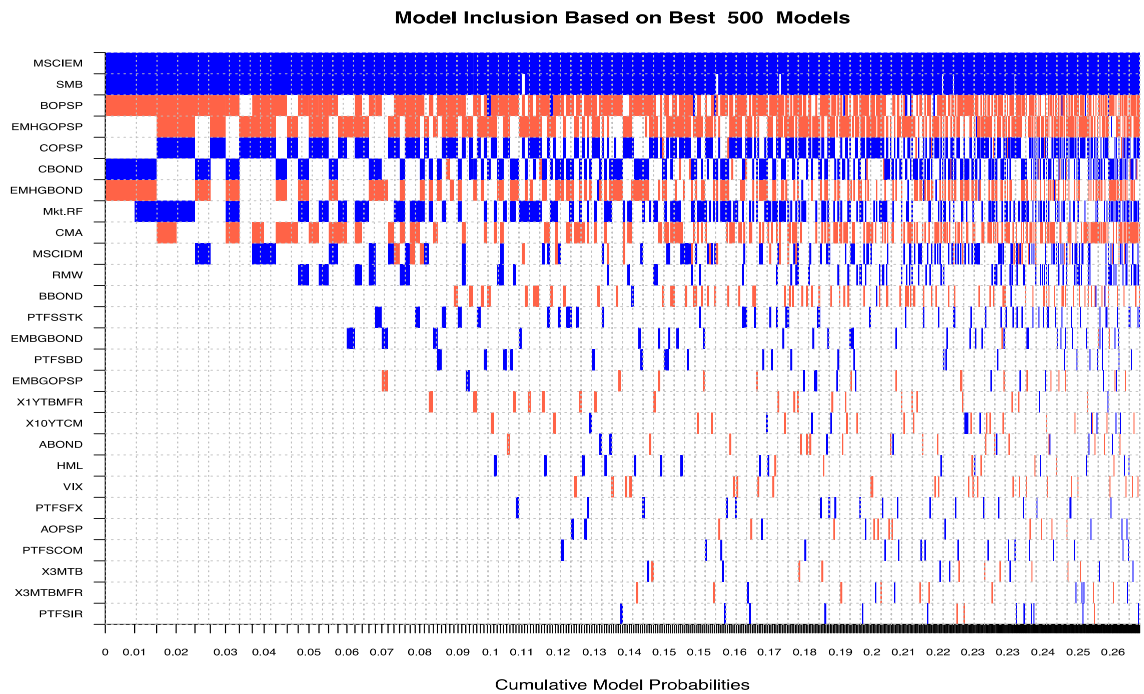

Figure 5.4.3: Emerging Markets – BMA Risk factors proxies

When analyzing Emerging Markets strategy, performance of emerging market equites together with "Small Minus Big" and option adjusted spreads on "CCC" grade bonds proved to be the most promising explanatory variables with positive coefficients, while option adjusted spreads on "BB" grade and emerging high grade bonds seems to be most promising explanatory variables with negative estimated coefficients.

Table 5.4.3: Emerging Markets – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
MSCIEM	1.0000	0.4241	0.0329
SMB	0.9905	0.1542	0.0461
BOPSP	0.7460	-0.3909	0.2977
EMHGOPSP	0.6236	-0.4506	0.3824
COPSP	0.5541	0.3244	0.3841

When compared with results obtained by BIC criterion, it is notable that BIC selects strictly bonds and spreads with "emerging" feature, while BMA model in addition to emerging high grade, adds option adjusted spreads on "BB" and "CCC" bonds. Both methods are strongly aligned when it comes to evaluating the impact of emerging market equites and "Small Minus Big" factors.

Equity Long Bias

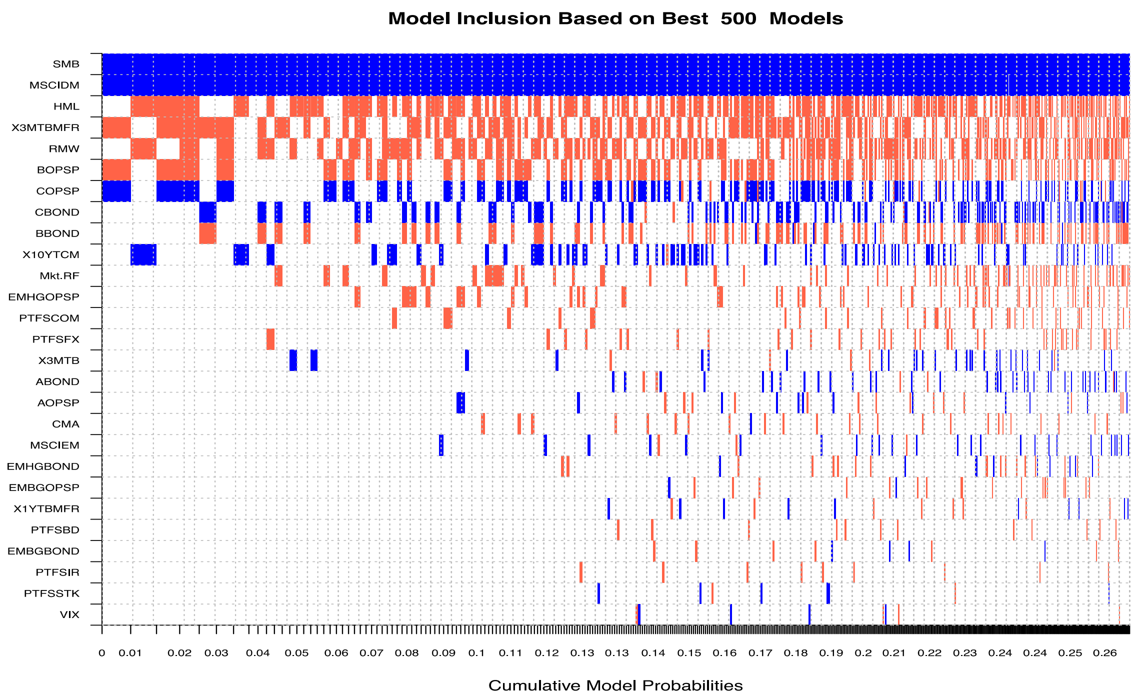

Figure 5.4.4: Equity Long Bias – BMA Risk factors proxies

Situation for Equity Long Bias is similar to Emerging Markets, whereas performance of developed market equities together with "Small Minus Big" factors are most promising explanatory variables with positive impact on hedge funds' returns following this strategy, while 2 Fama–French factors: "High Minus Low" and "Robust Minus Weak" together with spread of 3–Month T-bill are most promising explanatory variables (according to their corresponding PIPs) with negative sign of estimated coefficients.

Table 5.4.4: Equity Long Bias – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	0.3410	0.0527
MSCIDM	0.9990	0.6433	0.2423
HML	0.5737	-0.0676	0.0692
X3MTBMFR	0.5121	-0.4536	0.5136
RMW	0.4933	-0.0745	0.0888

Majority of negative impact is attributed to spread of 3–Month T-bill. It could be argued that increase in interest rate spread increases interest payments for those funds who extensively use leverage, therefore having negative impact on performance. Compared to BIC model, BMA approach appears to be more restrictive and intuitive, since BIC model assign high coefficient to numerous bond oriented factors, however when it comes to estimating coefficients for "Small Minus Big" factor and performance of developed market equites, both methods are pretty much aligned.

Equity Long/Short

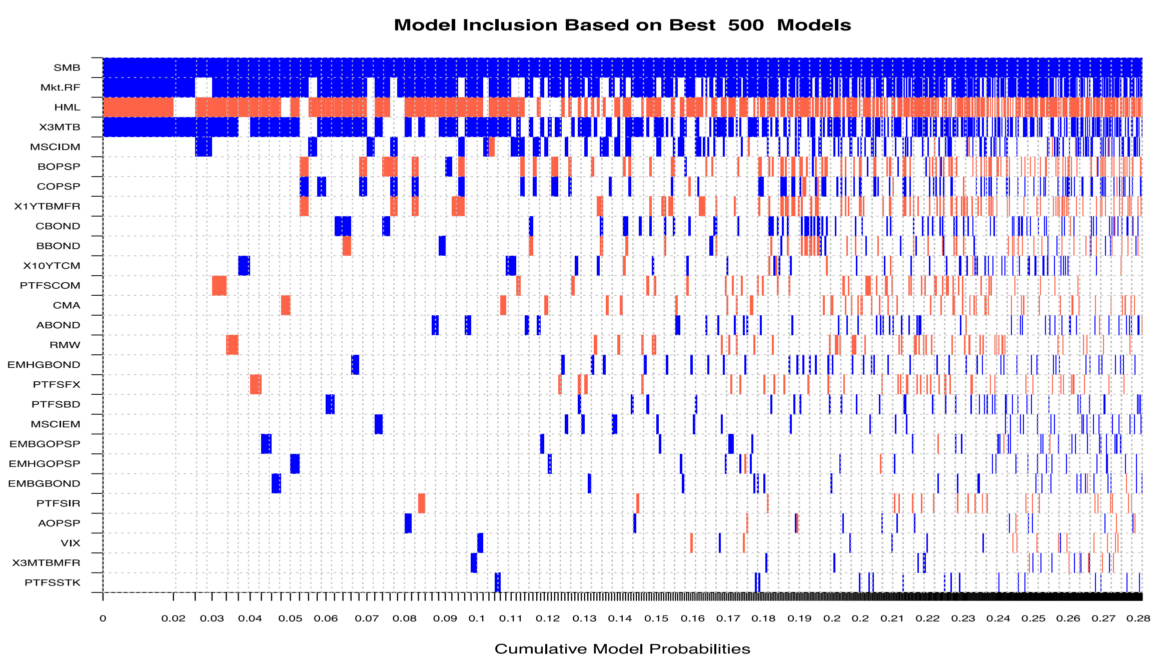

Figure 5.4.5: Equity Long/Short – BMA Risk factors proxies

Figure above indicates that Fama-French factors are best candidates for describing Equity Long/Short strategy returns. "Small Minus Big" and excess return on market have positive, while "High Minus Low" has negative signs of estimated coefficients. These coefficients imply that Long/Short funds prefer growth investing rather than value investing, which is riskier, eventually confirming hypothesis regarding risk seeking attitude of hedge funds. Moreover, short term interest rates appear to be additional explanatory variable with positive estimated coefficient, although it has small impact. This could mean that hedge funds pursuing this strategy are well aware of their exposure to short term interest rate risk, and they are doing a good job in hedging it, so in a long run they even have small benefits from the increase in interest rate. Coefficients of performance of developed market equities and excess return to market indicate exposure to broader market risk, therefore neglecting second hypothesis.

Table 5.4.5: Equity Long/Short – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	0.2288	0.0312
Mkt.RF	0.7824	0.2192	0.1194
HML	0.7204	-0.0551	0.0424
X3MTB	0.6271	0.0568	0.0515
MSCIDM	0.2315	0.0594	0.1181

BMA is again more restrictive towards bond oriented proxies, which have very low Posterior Inclusion Probabilities, than model proposed by BIC. In addition, Bayesian Model averaging approach finds small but positive impact of short term interest rates, while Bayesian Information Criterion selected spread of 1–Year T-bill against Federal Funds rate as negative contributor with much higher estimated coefficient. Estimated coefficient of Fama-French factors are again aligned.

Equity Market Neutral

Table 5.4.6: Equity Market Neutral – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	0.9991	0.1174	0.0317
RMW	0.7962	0.0977	0.0634
X1YTBMFR	0.7554	-0.3129	0.2271
PTFSCOM	0.5394	-0.0047	0.0051
PTFSIR	0.5225	-0.0026	0.0029

With regards to this strategy, Fama-French factors again take primate as "Small Minus Big" and "Robust Minus Weak" are most promising explanatory variables with positive sign of estimated coefficients. The most promising explanatory variable with negative coefficient is spread of 1–Year T-bill against Federal Funds Rate, which has the strongest coefficient among all proposed variables. Extremely weak coefficients with negative sign are documented for lookback straddles on interest rates and commodities.

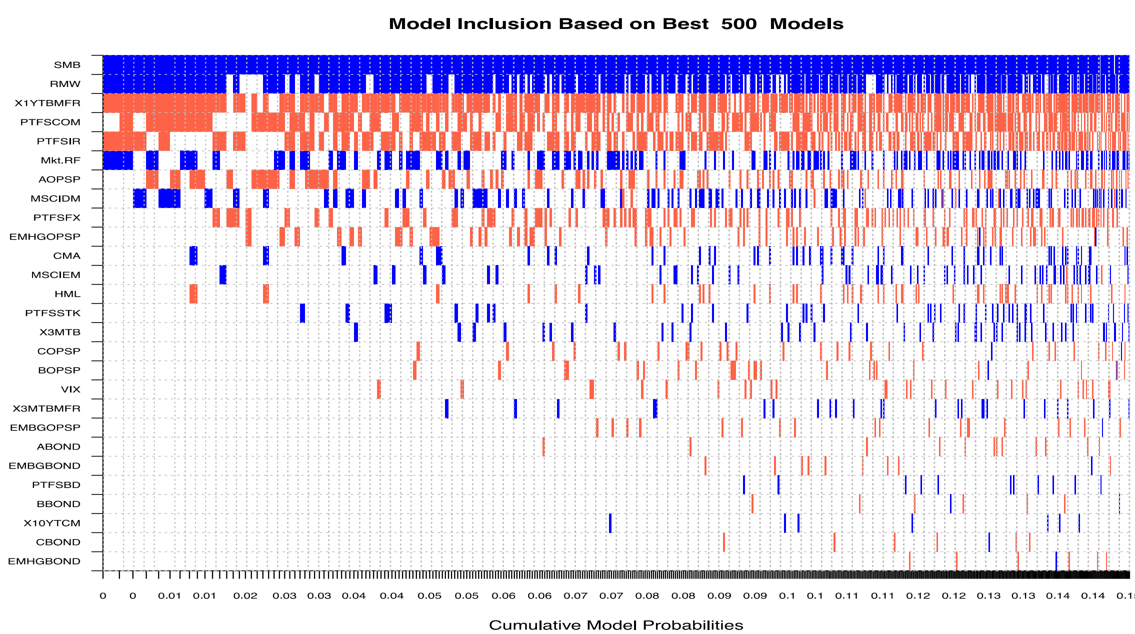

Figure 5.4.6: Equity Market Neutral – BMA Risk factors proxies

Bayesian Model Averaging approach slightly differs in comparison with the model offered by BIC. Fama-French factors appear to be robust explanatory variables, since both methods give very similar estimated coefficients. Both methods selected the spread of 1–Year T-bill against Federal Funds Rate as explanatory variable representing the negative impact of interest rates and in both cases, the highest estimated coefficient among all factors was given, while BMA gave more moderate estimation. Nevertheless, both methods confirmed hypothesis regarding the impact of interest rates on hedge funds' performance.

Event Driven

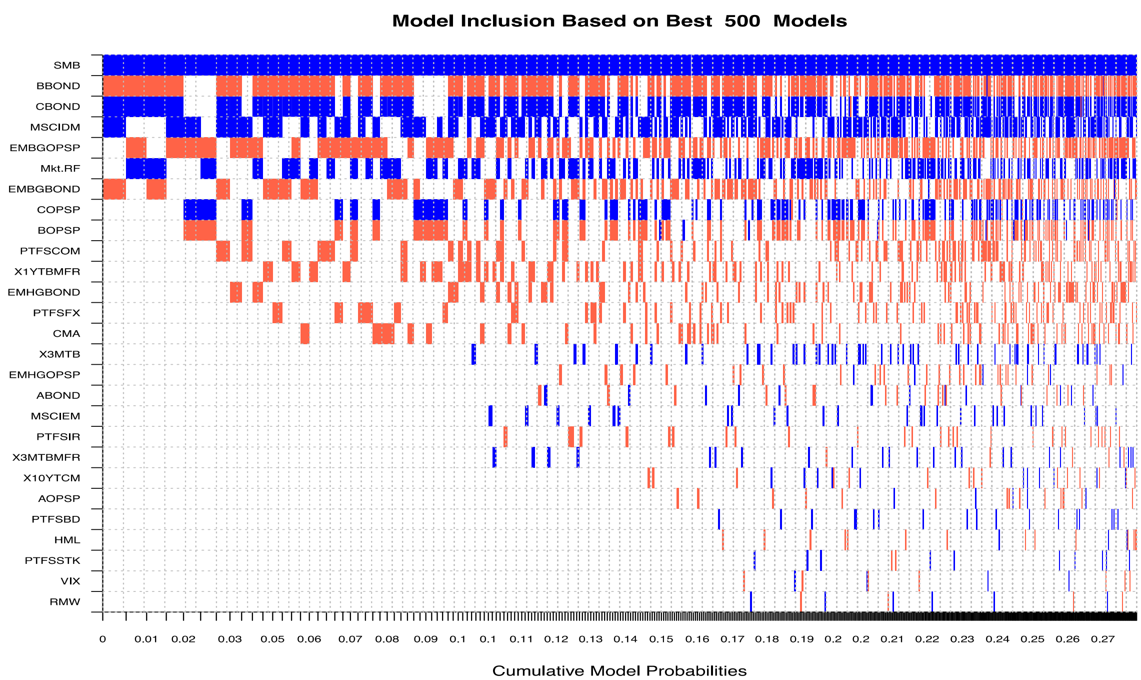

Figure 5.4.7: Event Driven – BMA Risk factors proxies

Figure above indicate that in case of Even Driven strategy, "Small Minus Big" again stands as most promising explanatory variable and together with return on "CCC" bond and performance of developed market equites have positive signs of estimated coefficients, while return on "BB" bonds and option adjusted spread of emerging below grade bonds have negative estimated coefficients.

Table 5.4.7: Event Driven – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	0.2745	0.0394
BBOND	0.7014	-0.5912	0.4288
CBOND	0.6994	0.6474	0.4678
MSCIDM	0.5667	0.1702	0.1518
EMBGOPSP	0.5413	-0.0392	0.0417

These results are in line with BIC model in terms of selected variables and signs of coefficients, while they only differ in terms of strength of coefficients.

Fixed Income Arbitrage

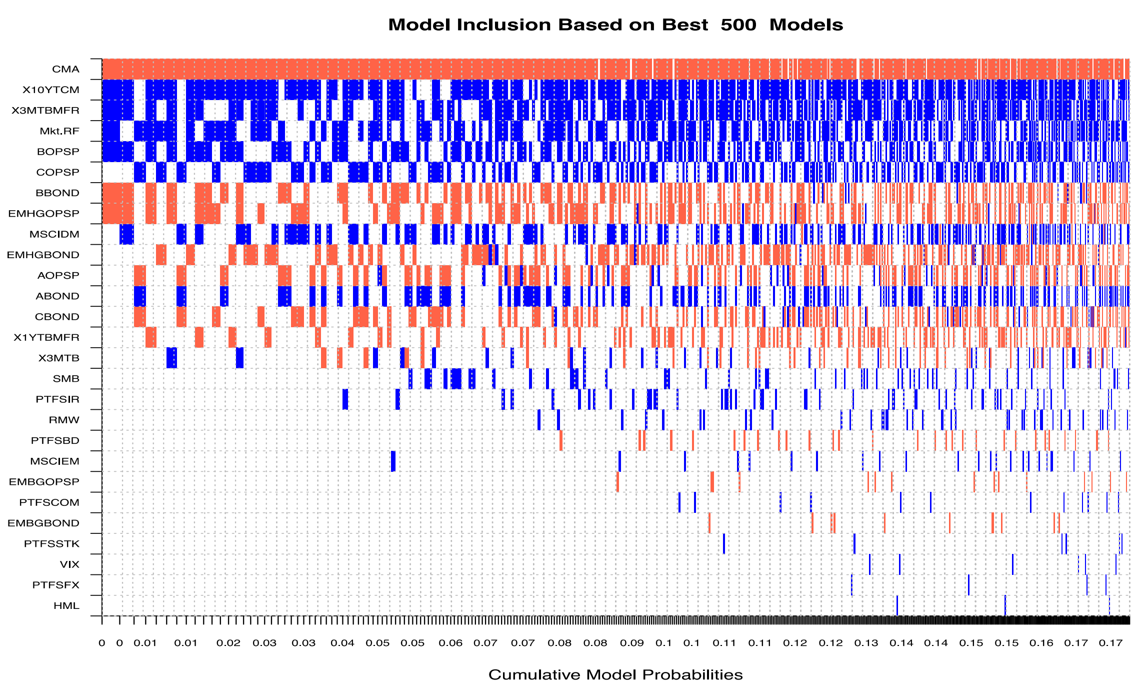

Figure 5.4.8: Fixed Income Arbitrage – BMA Risk factors proxies

As depicted on above figure, "Conservative Minus Aggressive" is most promising explanatory variable with negative sign of estimated coefficient, while all other with PIPs higher than 0.5 have positive signs of estimated coefficients. Long term interest rates together with the spread of 3-Month T-bill against Federal Funds rate both have relatively strong and positive coefficients. In addition, strong and positive coefficient is documented for option adjusted spread on "BB" bonds, while excess return on market has small positive impact on Fixed Income Arbitrage strategy's performance.

Table 5.4.8: Fixed Income Arbitrage – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
CMA	0.9587	-0.1641	0.0655
X10YTCM	0.7793	0.9127	0.6231
X3MTBMFR	0.6361	0.8018	0.7800
Mkt.RF	0.5806	0.0584	0.0613
BOPSP	0.5164	0.9519	1.3740

The presence of "Conservative Minus Aggressive" factor confirms arbitrage nature of this strategy. Negative sign of estimated coefficient indicates that funds pursing this strategy are mostly invested in more volatile securities. Similarly to Distressed Securities strategy, it could be argued that increase in interest rates creates investment opportunities for these funds, therefore estimated coefficients of interest rate proxies have positive sign. Coefficient of option adjusted spreads on "BB" grade bonds indicate that these funds prefer moderately risky investments.

Obtained BMA results differ when compared to BIC model, mainly in selection of interest proxies. While BMA finds long term interest rate to be the most relevant, BIC select all others except long interest rates. In addition, BMA model is more restrictive when it comes to inclusion of bond proxies with PIP higher than 0.5.

Global Macro

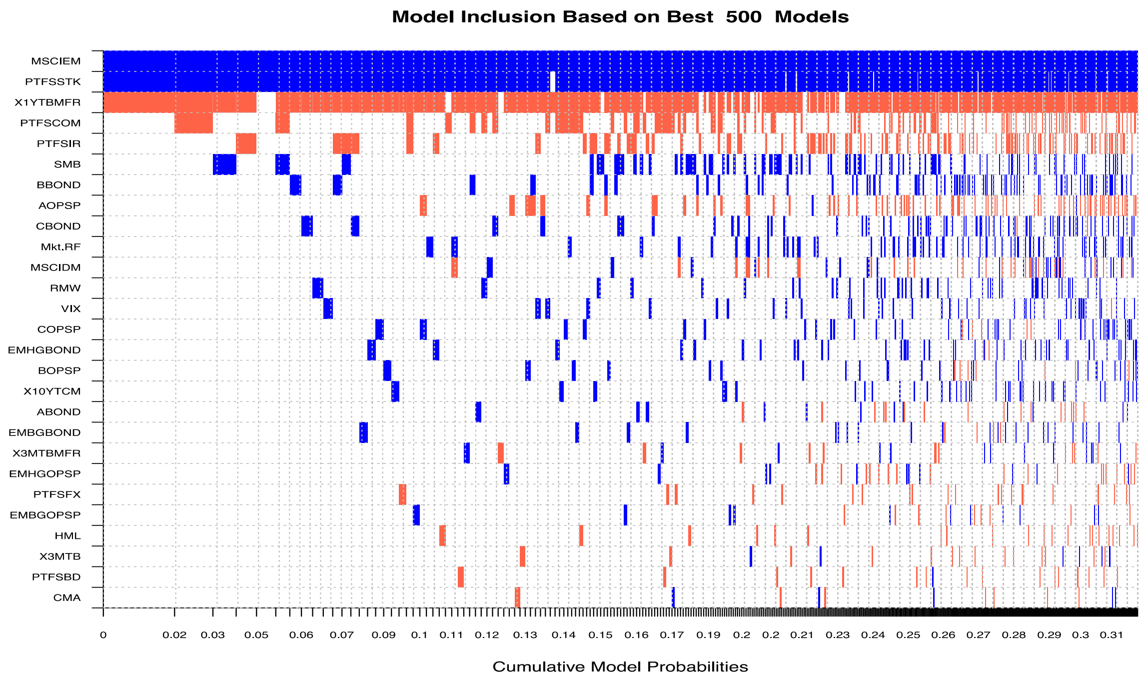

Figure 5.4.9: Global Macro – BMA Risk factors proxies

Similarly to BIC model for Global Macro strategy, BMA confirms explanatory robustness of the performance of emerging market stocks as obtained positive coefficient is equal to the one obtained by BIC. In addition, one of the most promising variable with negative estimated coefficient is spread of 1–Year T–bill against Federal Funds rate, whereas estimated coefficients obtained by both approaches are the same.

Table 5.4.9: Global Macro – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
MSCIEM	1.0000	0.1304	0.0178
PTFSSTK	0.9832	0.0192	0.0065
X1YTBMFR	0.9089	-0.6550	0.3112
PTFSCOM	0.2395	-0.0025	0.0052
PTFSIR	0.2074	-0.0013	0.0029

Multi Strategy

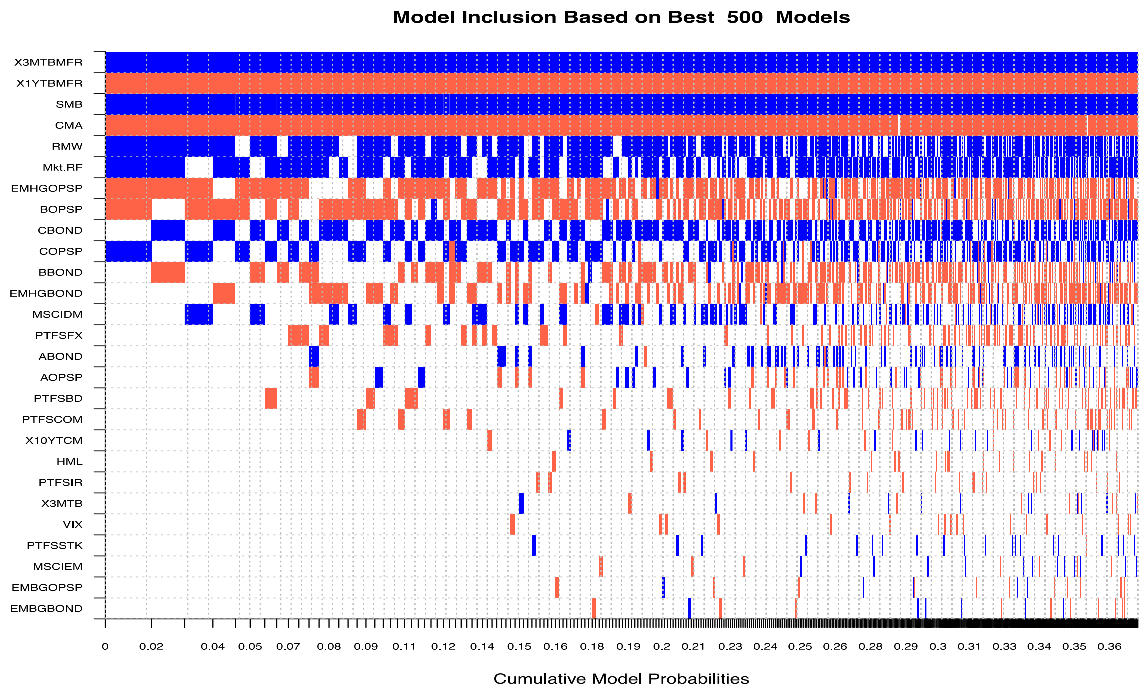

Figure 5.4.10: Multi Strategy – BMA Risk factors proxies

Results obtained for Multi Strategy indicate that spread of 3–Month T-bill against Federal Funds rate, "Small Minus Big", "Robust Minus Weak", excess return to market and return on "CCC" bond are most promising explanatory variables with positive sign of estimated coefficients, whereas interest rate spread and bond proxies are the strongest regressors. On the other hand, spread of 1–Year T-bill against Federal Funds rate, "Conservative Minus Aggressive", option adjusted spreads on "BB" and emerging market high grade bonds are most promising explanatory variables with negative estimated coefficients, among which interest rate spread and option adjusted spread demonstrated the strongest impact. Coefficients of interest rate proxies indicate that these hedge funds favor increase in spread of 3-month T-bill against Federal Funds rate, while they get penalized for increase in spread of 1–Year T-bill against Federal Funds rate.

Table 5.4.10: Multi Strategy – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
X3MTBMFR	1.0000	1.3845	0.3417
X1YTBMFR	1.0000	-1.5057	0.2259
SMB	1.0000	0.1740	0.0329
CMA	0.9955	-0.1366	0.0388
RMW	0.7761	0.0904	0.0620
Mkt.RF	0.7254	0.1297	0.0884
EMHGOPSP	0.6635	-0.2544	0.2343
BOPSP	0.6272	-0.2888	0.3030
CBOND	0.5885	0.3394	0.3572

These results are in line when compared with BIC model with regards to interest rate proxies and Fama – French factors, whereas coefficients have similar values. However, BIC approach was more inclusive when it comes to bonds and option adjusted spreads, incorporating "a" grade bonds and option spreads, while BMA gave advantage in terms of higher inclusion probability to return on "CCC" bond than corresponding option adjusted spread.

5.4.2.1 Robustness check

Robustness check is done by taking the same BMA approach on monthly returns of 7 CISDM (Center for International Securities and Derivatives Markets) strategy indices and using the same risk proxy data set composed from 27 risk factors. In comparison with BarclayHedge indices, which are equally weighted averages of the funds incorporated in specific index, CISDM demonstrates median return of hedge funds utilizing following strategies: Convertible Arbitrage, Distressed Securities, Equity Long/Short, Equity Market Neutral, Event Driven, Fixed Income Arbitrage and Global Macro. Robustness check results are summarized in Appendix B.

In terms assigned PIPs with value higher than 0.5, obtain results are robust to large extent for Fama-French "Small Minus Big" risk factor. Moreover, result for interest rates and bond oriented factors are pretty much robust in terms of PIPs > 0.5, although there are certain discrepancies in case of Event Driven and Fixed Income strategies. Also, when it comes to equity indices and Fung-Hseih factors, assigned PIPs with value higher than 0.5 are robust.

When it comes to absolute size of coefficients and PIPs, results vary a bit from one strategy to another. However, signs of estimated coefficients are aligned.

Convertible Arbitrage

Robustness check results obtained for Convertible Arbitrage indicate that BMA on CISDM monthly returns assigns PIPs < 0.5 to return on "a" bonds and corresponding option adjusted spread, performance of developed markets equities and return on "CCC" bonds, while it incorporates the option adjusted spread on emerging market high grade bonds, whereas option adjusted spread on "CCC" bonds remains important risk factors. Aside from slightly different bonds oriented factors, the structure of the model remains the same with different values of assigned PIPs and lower estimated coefficients, while signs of coefficients match.

Distressed Securities

In case of Distressed Securities, performance of developed market equity index with positive estimated coefficient was replaced by Fama–French's excess return on market with negative coefficient. In addition, short term interest rate risk proxy was assigned with PIP lower than 0.5. Selection of bond oriented risk factors is pretty much the same, with small distinction that in case of CISDM monthly returns, higher PIP is assigned to option adjusted spread on emerging markets high grade bonds instead of simple return on these bonds. Structure of the model remains the same for the rest of the factors, with the same signs and similar sizes of estimated coefficients and slightly different PIPs.

Equity Long/Short

Robustness check result for this strategy yielded to the same structure, signs and sizes of estimated coefficients, keeping “Small Minus Big”, excess return to market, “High Minus Low” and short term interest rate as most promising explanatory variables.

Equity Market Neutral

For this strategy results are aligned when it comes to selecting lookback straddles on interest rates and commodities and spread of 1–Year T-bill against Federal Funds rate. However, when it comes to equity oriented factors, instead of “Small Minus Big” and “Robust Minus Weak”, return on developed market securities and excess return on market are incporporated.

Event Driven

When it comes to bond oriented factors, results are aligned with one distinction: instead option adjusted spread on emerging market below grade bonds, return on emerging market bond was selected. In addition, BMA assigns PIPs higher than 0.5 to the spreads of 3–Month and 1–Year T-bills against Federal Funds rate. Coefficients of matching risk factors have same signs and they just slightly vary in terms of size.

Fixed Income Arbitrage

Robustness check for this strategy aligns with original model in terms of selecting “Conservative Minus Aggressive” as most promising explanatory variable, with the same sign but stronger negative coefficient. Result is also aligned in terms of selecting excess return on market. On the other hand, while original model gives PIP higher than 0.5 to option adjusted spread on "BB" bond and interest rates oriented factors, second model gives priority to "a" and "CCC" bonds and corresponding option adjusted spreads. In addition, "High Minus Low" factor was given PIP higher than 0.5.

Global Macro

Both models are aligned when it comes to assigning the highest PIPs to performance of emerging markets stocks and look back straddles on stock as most promising explanatory variables. Slightly different results are obtained for interest rates proxies: instead of 1–Year, a 3–Month spread of T-bill against Federal Funds was prioritized. Additionally, lookback straddles on commodities and interest rates are excluded.

Chapter 6
Conclusion

Growing impact that hedge funds have been exercising on financial markets imposes necessity to closely and continuously monitor their exposures to particular markets and financial instruments. This thesis aimed to identify main driving risk factors for hedge funds' performance by analyzing BarclayHedge strategy indices. Three analytical techniques were implement: Principal Component, Stepwise regression and Bayesian Model Averaging, which yielded to somewhat similar results.

First, PCA showed that largest variation in risk proxies dataset was explained primarily by bond oriented risk factors, followed by risk interest rates factors at the second place and lastly by equity oriented risk factors. In the next step, a stepwise regression approach was implemented, following up on Bussière et al. (2014). However due to overconfidence of the obtained models reflected in p – values and extremely high adjusted R^2, results were partly neglected in terms of evaluating thesis's hypothesizes. Instead, in the next step following Zhou's (2013) and Havránek and Žigraiová (2015) approaches, Bayesian Model Averaging technique was implemented in order to provide a foundation for hypothesis evaluation. Obtained results matched to certain extent to those obtained by BIC stepwise regression, however BMA approach appeared to be more restrictive and it assigned more moderate coefficients.

With regards to first hypothesis stating importance of interest rate environment on hedge funds' performance, BMA showed that interest rates do play an important role for majority of the strategies; in some cases positive as potential investment opportunity generator while for some strategies it demonstrated negative impact, possibly due to leverage or extensive short selling of those funds.

Second hypothesis stated that different hedge fund strategies exhibit different risk exposures. As for many strategies, BMA assigned high PIPs values to the same risk factors, especially “Small Minus Big” and spread of 1-Year T-bill against Federal Funds rate, it cannot be argued that each strategy is exposed to different market risk factors. Moreover, similarly to Bussière et al. (2014), analysis showed that strategies do exhibit exposure to broader market risk, as risk factors describing market’s dynamics such as Fama-French excess return to market and MSCI indices for developed and emerging equities were most promising candidate variables for couple of strategies.

Regarding third hypothesis which is emphasizing extensive usage of options, judging by obtained BMA coefficients, it could be argued that this is only true for bonds with embedded call/put option. Regarding other asset classes, like options on stocks, commodities and currencies, this hypothesis cannot be accepted, since lookback straddles demonstrated poor explanatory potential, contrary to findings of Fung and Hseih (2001, 2004).

Last hypothesis emphasized risk seeking nature of hedge funds. Since in most cases, grading of the bonds and their corresponding option adjusted spreads marked as most promising ones, was either “BB” or “CCC” - it could be argued that in search of higher returns, hedge funds invest in riskier assets. Moreover, “Small Minus Big” factor always had positive, while other factors which favored less risky investments, like “Robust Minus Weak” and “Conservative Minus Aggressive” in majority of cases had negative coefficients, additionally advocating higher risk appetite of hedge funds.

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Fung and Hseih trend following factors: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

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Appendix A: Tables and figures

Table A.1: Interest rates risk factors beta coefficients across strategies – AIC Stepwise regression

	Intercept	X3MTB	X10YTCM	X3MTBMFR	X1YTBMFR
Convertible Arbitrage	-	-	-	***1.938*** ***0.004***	***(1.733)*** ***6.90e-05***
Distressed Securities	-	***0.541*** ***0.001***	***2.532*** ***2.03e-07***	*0.822* *0.056*	-
Emerging Markets	***0.012*** ***0.003***	-	***0.436*** ***0.039***	-	(0.349) 0.103
Equity Long Bias	-	***0.607*** ***0.016***	***2.177*** ***0.001***	***(1.372)*** ***0.012***	***0.967*** ***0.0304***
Equity Long Short	-	-	-	*0.535* *0.095*	***(0.607)*** ***0.004***
Equity Market Neutral	***(0.522)*** ***0.0005***	-	-	-	-
Event Driven	-	-	***0.676*** ***0.048***	*0.71* *0.094*	***(0.768)*** ***0.005***
Fixed Income Arbitrage	*0.008* *0.081*	***(0.347)*** ***0.008***	-	***2.018*** ***0.0005***	***(1.041)*** ***0.008***
Global Macro	-	*(0.388)* *0.072*	***(1.172)*** ***0.032***	-	***(1.297)*** ***7.23e-05***
Multi Strategy	-	-	-	***1.354*** ***0.0002***	***(1.516)*** ***2.62e-10***

Table A.2: Bond and option adjusted spreads beta coefficients across strategies – AIC Stepwise regression

	ABOND	AOPSP	BBOND	BOPSP	CBOND	COPSP
Convertible Arbitrage	***7.914*** ***2.96e-05***	***(7.519)*** ***8.31e-05***	6.350 0.15	(7.191) 0.104	***(12.915)*** ***0.023***	***13.837*** ***0.013***
Distressed Securities	-	-	***(2.799)*** ***2.76e-06***	***1.936*** ***9.60e-05***	***1.061*** ***0.0003***	-
Emerging Markets	0.422 0.131	-	-	***(0.815)*** ***0.002***	-	***1.072*** ***6.31e-05***
Equity Long Bias	***(3.936)*** ***7.63e-05***	***4.652*** ***4.62e-05***	-	***(0.985)*** ***0.0003***	***1.085*** ***5.07e-05***	-
Equity Long Short	***(1.317)*** ***0.048***	***1.535*** ***0.037***	***(0.435)*** ***0.006***	-	***1.794*** ***0.008***	***(1.410)*** ***0.028***
Equity Market Neutral	*(1.261)* *0.066*	*1.261* *0.095*	-	-	***1.295*** ***0.05***	*(1.289)* *0.0515*
Event Driven	-	***0.677*** ***0.031***	***(0.959)*** ***8.91e-06***	-	***3.555*** ***2.92e-05***	***(2.326)*** ***0.002***
Fixed Income Arbitrage	***3.739*** ***0.0001***	***(4.096)*** ***0.0008***	***(3.290)*** ***0.0003***	***3.398*** ***0.0002***	-	-
Global Macro	***(1.001)*** ***0.002***	-	-	-	***1.679*** ***0.005***	***(1.396)*** ***0.018***
Multi Strategy	***1.691*** ***0.009***	***(1.538)*** ***0.028***	-	***(0.491)*** ***0.012***	-	***0.669*** ***0.0004***

Table A.3: Emerging Markets bonds and option adjusted spreads beta coefficients across strategies – AIC Stepwise regression

	EMHGBOND	EMHGOPSP	EMBGBOND	EMBGOPSP
Convertible Arbitrage	***(1.41) 0.002***	-	*0.099 0.095*	-
Distressed Securities	***(1.047) 1.73e-06***	-	-	-
Emerging Markets	***(1.200) 9.96e-05***	-	***0.299 0.034***	*(0.265) 0.056*
Equity Long Bias	-	***(0.936) 0.004***	-	-
Equity Long Short	-	-	-	-
Equity Market Neutral				-
Event Driven	***(3.282) 0.001***	***2.473 0.006***	-	***(0.089) 0.014***
Fixed Income Arbitrage	-	***(0.609) 0.039***	-	-
Global Macro	***0.88 0.009***	-	-	***(0.134) 0.004***
Multi Strategy	***(1.626) 0.01***	0.98 0.111	-	-

Table A.4: Equity indices and Fama – French portfolio risk factors beta coefficients across strategies – AIC Stepwise regression

	MSCIDM	MSCIEM	VIX	Mkt.RF	SMB	HML	RMW	CMA
Convertible Arbitrage	-	-	-	***0.168*** ***2.33e-08***	*0.117* *0.055*	*0.124* *0.083*	0.112 0.161	***(0.268)*** ***0.002***
Distressed Securities	***0.259*** ***< 2e-16***	-	-	-	***0.269*** ***1.78e-06***	*0.097* *0.064*	-	-
Emerging Markets	*(0.543)* *0.070*	***0.377*** ***< 2e-16***	***(0.041)*** ***0.049***	***0.645*** ***0.034***	***0.115*** ***0.014***	0.069 0.158	***0.111*** ***0.046***	***(0.142)*** ***0.015***
Equity Long Bias	***1.142*** ***0.001***	-	-	*(0.586)* *0.087*	***0.395*** ***5.46e-12***	***(0.115)*** ***0.013***	***(0.128)*** ***0.042***	-
Equity Long Short	-	-	-	***0.281*** ***< 2e-16***	***0.225*** ***5.91e-13***	***(0.066)*** ***0.023***	-	-
Equity Market Neutral	(0.348) 0.111	-	-	*0.401* *0.066*	***0.12*** ***0.0006***	***(0.098)*** ***0.009***	***0.128*** ***0.0019***	***0.131*** ***0.0021***
Event Driven	-	-	-	***0.306*** ***< 2e-16***	***0.255*** ***1.09e-10***	-	-	-
Fixed Income Arbitrage	-	-	-	***0.091*** ***1.56e-05***	-	-	-	***(0.174)*** ***0.002***
Global Macro	-	***0.075*** ***0.009***	-	***0.109*** ***0.015***	***0.103*** ***0.042***	0.068 0.157	***0.15*** ***0.026***	-
Multi Strategy	-	-	-	***0.181*** ***< 2e-16***	***0.177*** ***9.12e-08***	-	***0.109*** ***0.014***	***(0.119)*** ***0.001***

Table A.5: Fung and Hseih trend following factors beta coefficients across strategies – AIC Stepwise regression

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK
Convertible Arbitrage	*(0.013) 0.054*	-	-	-	-
Distressed Securities	0.009 0.139	(0.009) 0.053	-	-	-
Emerging Markets	-	*0.007 0.055*	-	-	*0.009 0.063*
Equity Long Bias	-	-	(0.008) 0.088	-	-
Equity Long Short	-	-	-	-	-
Equity Market Neutral	-	*(0.005) 0.064*	***(0.009) 0.011***	***(0.005) 0.011***	***0.008 0.026***
Event Driven	-	-	*(0.008) 0.05319*	-	-
Fixed Income Arbitrage	-	-	-	*0.005 0.091*	-
Global Macro	-	-	***(0.014) 0.012***	(0.005) 0.13	***0.024 9.59e-05***
Multi Strategy	-	(0.004) 0.138	-	-	-

Table A.6: AIC Stepwise regression models summaries:

	Ajd. R sqrd.	P-value
Convertible Arbitrage	0.588	2.20E-16
Distressed Securities	0.707	2.20E-16
Emerging Markets	0.934	2.20E-16
Equity Long Bias	0.89	2.20E-16
Equity Long Short	0.831	2.20E-16
Equity Market Neutral	0.27	7.07E-09
Event Driven	0.81	2.20E-16
Fixed Income Arbitrage	0.509	2.20E-16
Global Macro	0.479	2.20E-16
Multi Strategy	0.731	2.20E-16

Table A.7: Interest rates risk factors beta coefficients across strategies – BIC Stepwise regression

Strategy:	Intercept	X3MTB	X10YTCM	X3MTBMFR	X1YTBMFR
Convertible Arbitrage	-	-	-	***2.164 0.002***	***(1.659) 0.0002***
Distressed Securities	-	***0.412 0.007***	***2.472 3.93e-07***	-	-
Emerging Markets	***0.010 9.08e-05***	-	-	-	-
Equity Long Bias	***0.012 0.012***	-	-	-	-
Equity Long Short	-	-	-	-	***(0.325) 0.023***
Equity Market Neutral	***0.002 3.24e-05***	-	-	-	***(0.453) 0.003***
Event Driven	*0.005 0.0629*	-	-	-	-
Fixed Income Arbitrage	-	***(0.33) 0.011***	-	***1.519 0.005***	***(1.049) 0.009***
Global Macro	***0.005 3.15e-07***	-	-	-	***(0.656) 0.00542***
Multi Strategy	***0.008 0.002***	-	-	***1.504 4.18e-05***	***(1.545) 1.27e-10***

Table A.8: Bond and option adjusted spreads beta coefficients across strategies – BIC Stepwise regression

Strategy:	ABOND	AOPSP	BBOND	BOPSP	CBOND	COPSP
Convertible Arbitrage	***6.404*** ***6.53e-06***	***(6.556)*** ***7.78e-05***	-	***(0.978)*** ***0.005***	***(5.231)*** ***0.0003***	***6.534*** ***5.44e-06***
Distressed Securities	-	-	***(2.792)*** ***2.88e-06***	***1.747*** ***0.0004***	***1.255*** ***1.16e-05***	***-***
Emerging Markets	-	-	-	-	-	-
Equity Long Bias	***(1.021)*** ***0.003***	***1.851*** ***0.002***	-	***(0.893)*** ***0.0008***	***0.906*** ***0.0006***	-
Equity Long Short	-	-	***(0.425)*** ***0.007***	-	***0.492*** ***0.0008***	***(0.091)*** ***0.016***
Equity Market Neutral	-	-	-	-	-	-
Event Driven	-	-	***(0.827)*** ***4.50e-05***	-	***0.867*** ***6.63e-06***	-
Fixed Income Arbitrage	***4.359*** ***2.43e-06***	***(5.295)*** ***5.51e-07***	***(3.786)*** ***1.48e-05***	***3.829*** ***1.86e-05***	-	-
Global Macro	-	-	-	-	-	-
Multi Strategy	***0.735*** ***9.96e-05***	***(0.438)*** ***0.0009***	-	***(0.621)*** ***0.0009***	-	***0.775*** ***2.86e-05***

Table A.9: Emerging Markets bonds and option adjusted spreads beta coefficients across strategies – BIC Stepwise regression

Strategy:	EMHGBOND	EMHGOPSP	EMBGBOND	EMBGOPSP
Convertible Arbitrage	***(1.081)*** ***0.011***	-	-	-
Distressed Securities	***(1.148)*** ***2.45e-07***	-	-	-
Emerging Markets	***(0.532)*** ***1.38e-07***	-	***0.498*** ***4.44e-08***	***(0.423)*** ***9.68e-09***
Equity Long Bias	-	***(0.835)*** ***0.005***	-	-
Equity Long Short	-	-	-	-
Equity Market Neutral	-	-	-	-
Event Driven	-	-	-	***(0.061)*** ***0.0003***
Fixed Income Arbitrage	-	-	-	-
Global Macro	-	-	-	-
Multi Strategy	***(0.733)*** ***0.0006***	-	-	-

Table A.10: Equity indices and Fama – French portfolio risk factors beta coefficients across strategies – BIC Stepwise regression

Strategy:	MSCIDM	MSCIEM	VIX	Mkt.RF	SMB	HML	RMW	CMA
Convertible Arbitrage	-	-	-	***0.171*** ***1.45e-10***	***0.153*** ***0.0104***	*0.124* *0.083*	-	***(0.220)*** ***0.001***
Distressed Securities	***0.256*** ***< 2e-16***	-	-	-	***0.271*** ***1.00e-06***	-	-	-
Emerging Markets	-	***0.466*** ***< 2e-16***	-	-	***0.164*** ***6.76e-05***	-	-	-
Equity Long Bias	***0.548*** ***< 2e-16***	-	-	-	***0.331*** ***2.45e-11***	***(0.109)*** ***0.0209***	***(0.169)*** ***0.008***	-
Equity Long Short	-	-	-	***0.277*** ***< 2e-16***	***0.224*** ***4.34e-13***	***(0.070)*** ***0.0151***	-	-
Equity Market Neutral	-	-	-	***0.036*** ***0.005***	***0.123*** ***6.73e-05***	-	***0.133*** ***0.001***	-
Event Driven	-	-	-	***0.305*** ***< 2e-16***	***0.262*** ***3.73e-11***	-	-	-
Fixed Income Arbitrage	-	-	-	***0.088*** ***3.47e-05***	-	-	-	***(0.166)*** ***0.0034***
Global Macro	-	***0.134*** ***< 2e-16***	-	-	-	-	-	-
Multi Strategy	-	-	-	***0.178*** ***< 2e-16***	***0.17*** ***2.68e-07***	-	***0.115*** ***0.009***	***(0.125)*** ***0.0009***

Table A.11: Fung and Hseih trend following factors beta coefficients across strategies – BIC Stepwise regression

Strategy:	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK
Convertible Arbitrage	-	-	-	-	-
Distressed Securities	-	-	-	-	-
Emerging Markets	-	-	-	-	-
Equity Long Bias	-	-	-	-	-
Equity Long Short	-	-	-	-	-
Equity Market Neutral	-	-	-	***(0.005)*** ***0.002***	-
Event Driven	-	-	-	-	-
Fixed Income Arbitrage	-	-	-	-	-
Global Macro	-	-	-	-	***0.018*** ***0.001***
Multi Strategy	-	-	-	-	-

Table A.12: BIC Stepwise regression models summaries:

Strategy:	Ajd. R sqrd.	P-value
Convertible Arbitrage	0.564	2.20E-16
Distressed Securities	0.693	2.20E-16
Emerging Markets	0.93	2.20E-16
Equity Long Bias	0.883	2.20E-16
Equity Long Short	0.827	2.20E-16
Equity Market Neutral	0.1762	2.19E-07
Event Driven	0.789	2.20E-16
Fixed Income Arbitrage	0.4944	2.20E-16
Global Macro	0.408	2.20E-16
Multi Strategy	0.727	2.20E-16

Table A.13: Summary of Convertible Arbitrage BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
11.4822	1000000	500000	2.514999	400579
Modelspace 2^K	**% visited**	**% Topmodels**	**Corr PMP**	**No. Obs.**
130000000	0.3	25	0.9911	181
	Model Prior	**g-Prior**	**Shrinkage-Stats**	
	uniform / 13.5	UIP	Av=0.9945	

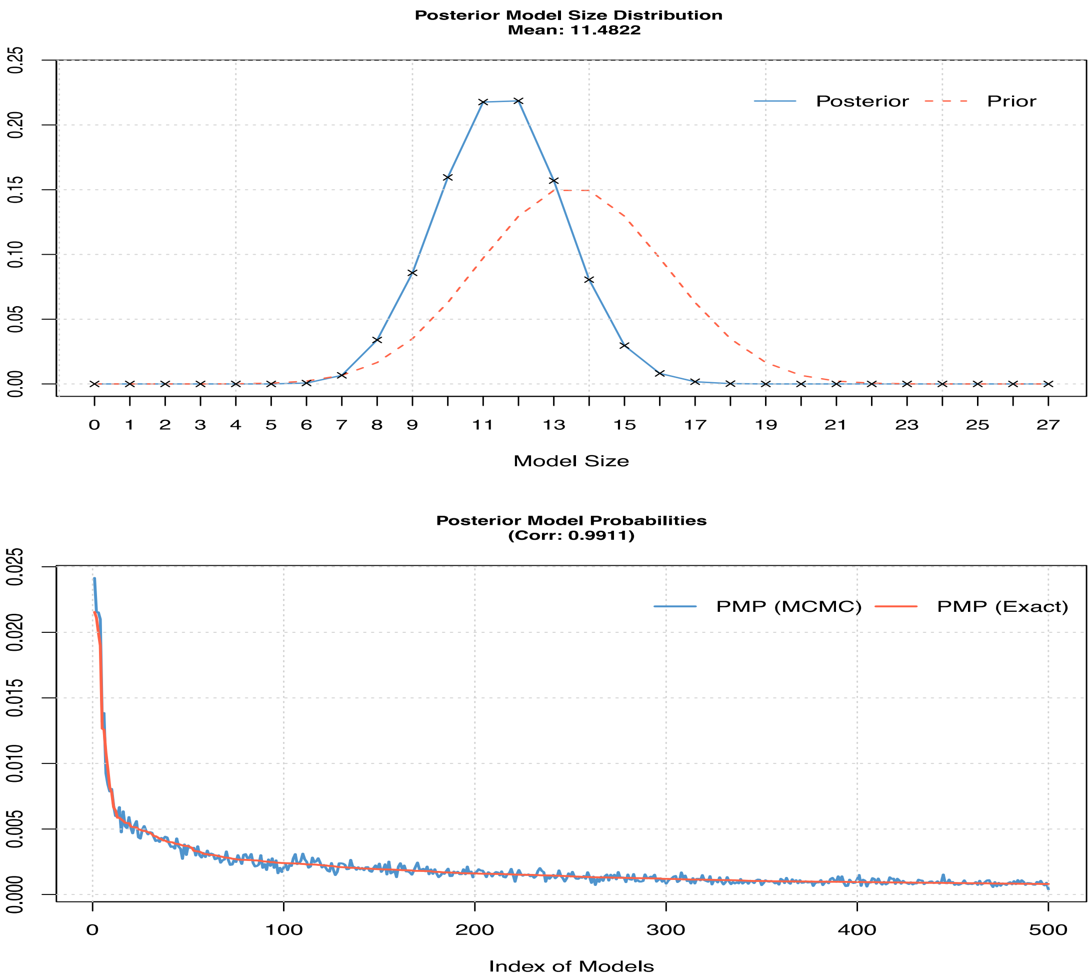


Figure A.1: Convertible Arbitrage BMA – Model Size and Convergence

Table A.14: Summary of Distressed Securities BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
9.581	1000000	500000	2.256615 mins	349553
Modelspace 2^K	**% visited**	**% Topmodels**	**Corr PMP**	**No. Obs.**
130000000	0.26	29	0.9925	181
	Model Prior	**g-Prior**	**Shrinkage-Stats**	
	uniform / 13.5	UIP	Av=0.9945	

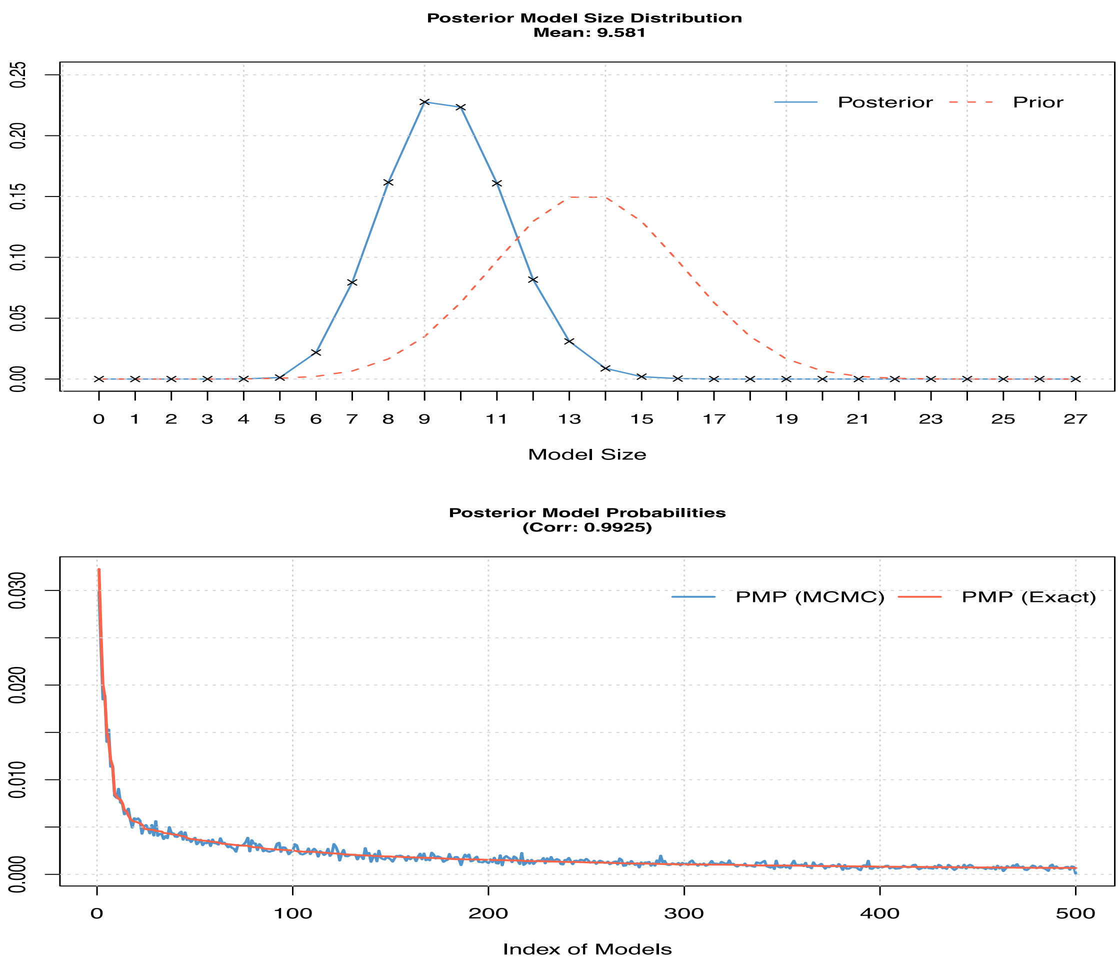


Figure A.2: Distressed Securities BMA – Model Size and Convergence

Table A.15: Summary of Emerging Markets BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
8.202	1000000	500000	2.403292 mins	390173
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.29	27	0.9939	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	

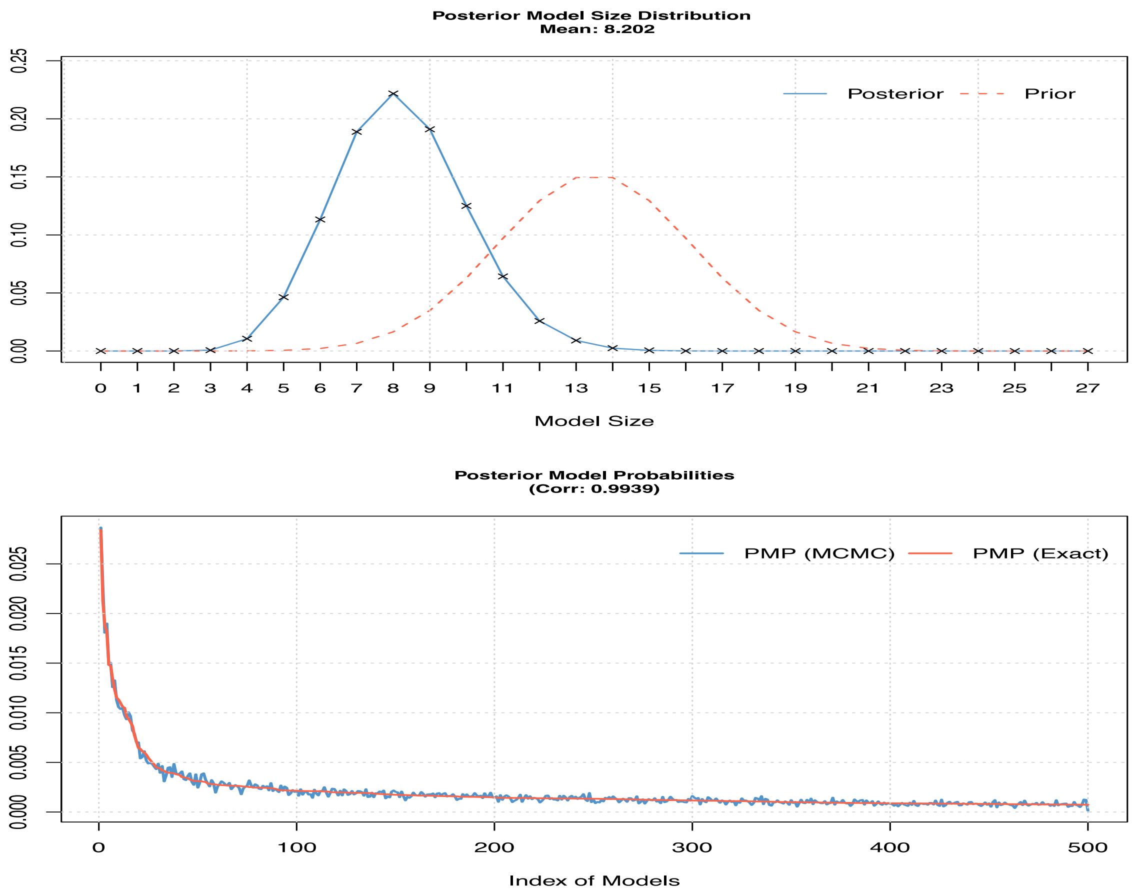


Figure A.3: Emerging Markets BMA – Model Size and Convergence

Table A.16: Summary of Equity Long Bias BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
7.2586	4096	500000	2.353585 mins	410342
Modelspace 2^K	**% visited**	**% Topmodels**	**Corr PMP**	**No. Obs.**
130000000	0.31	27	0.9939	181
	Model Prior	**g-Prior**	**Shrinkage-Stats**	
	uniform / 13.5	UIP	Av=0.9945	

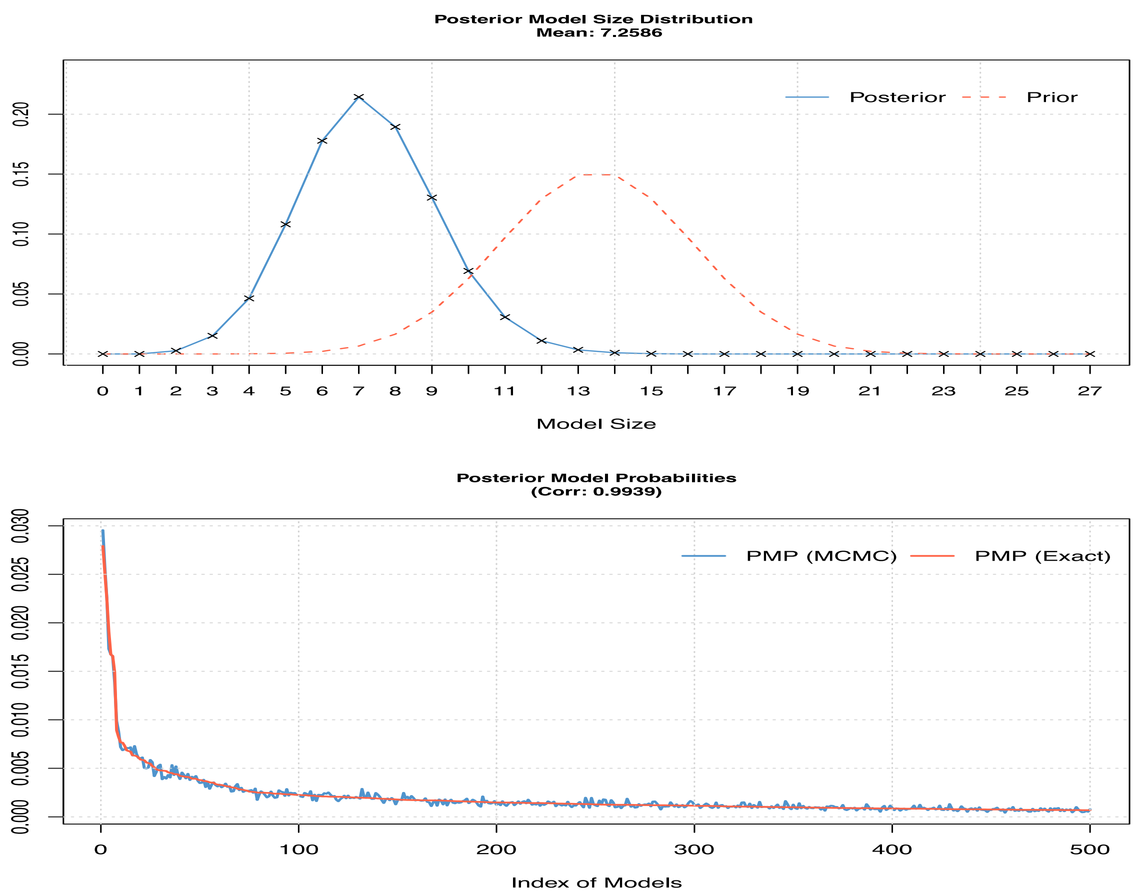


Figure A.4: Equity Long Bias BMA – Model Size and Convergence

Table A.17: Summary of Equity Long Bias BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
6.3796	1000000	500000	2.357666 mins	386767
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.29	28	0.9968	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	

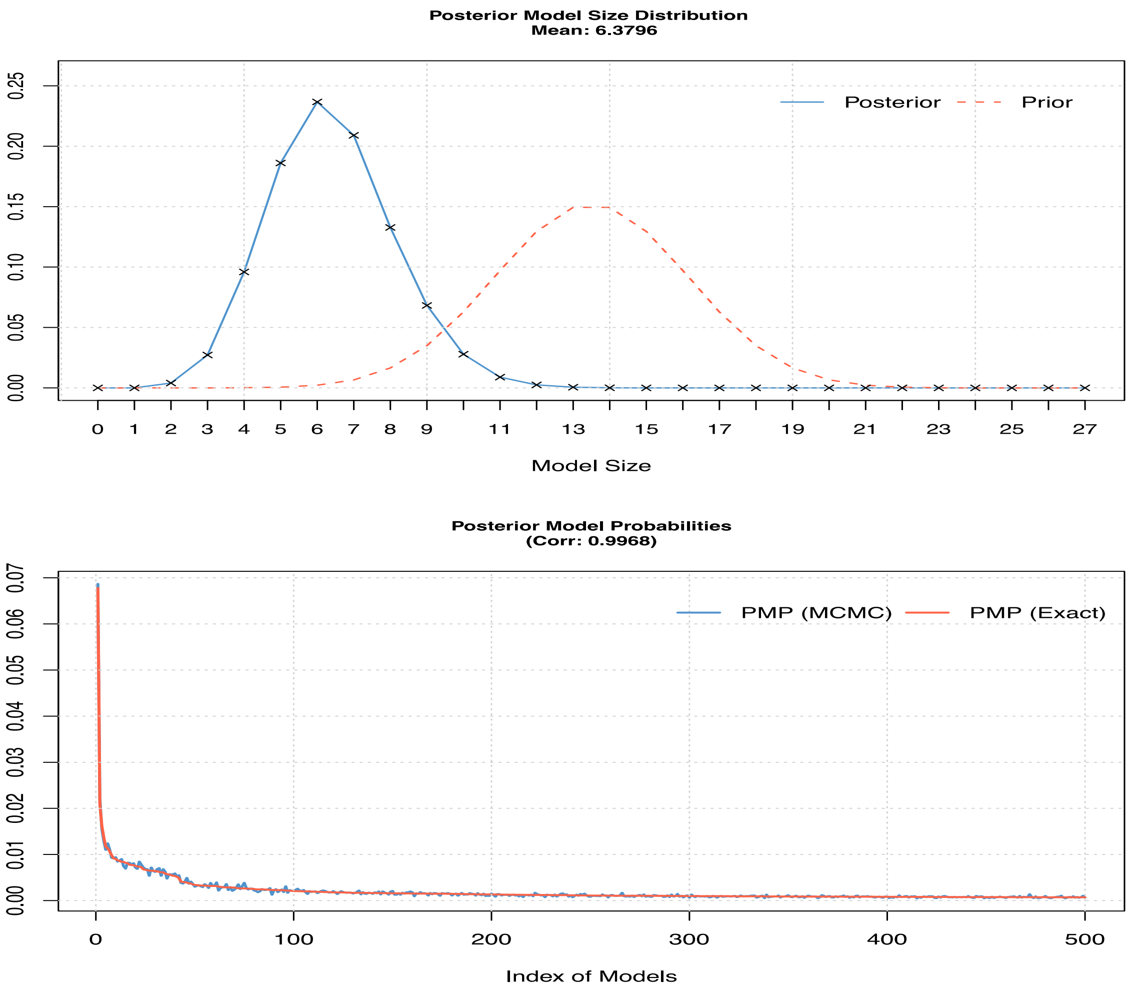
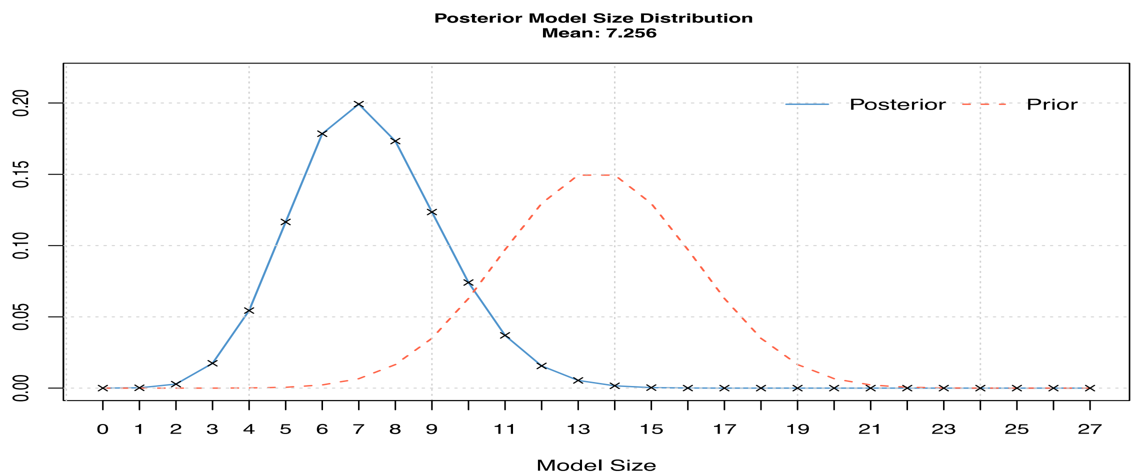


Figure A.5: Equity Long/Short BMA – Model Size and Convergence

Table A.18: Summary of Equity Market Neutral BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
7.256	1000000	500000	2.717721 mins	499266
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.37	15	0.9789	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	



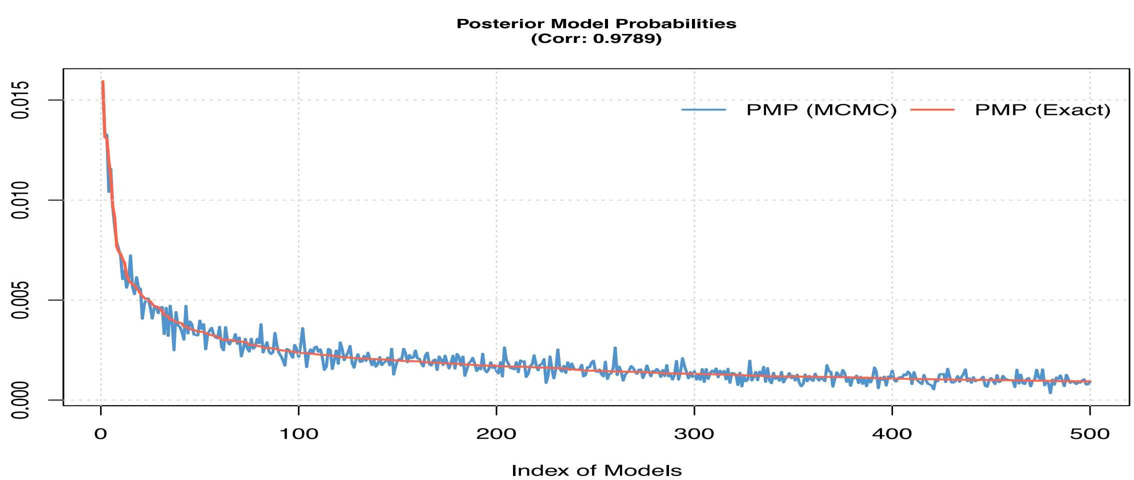


Figure A.6: Equity Market Neutral BMA – Model Size and Convergence

Table A.19: Summary of Equity Market Neutral BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
7.7689	1000000	500000	2.384449 mins	346892
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.26	28	0.9922	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	

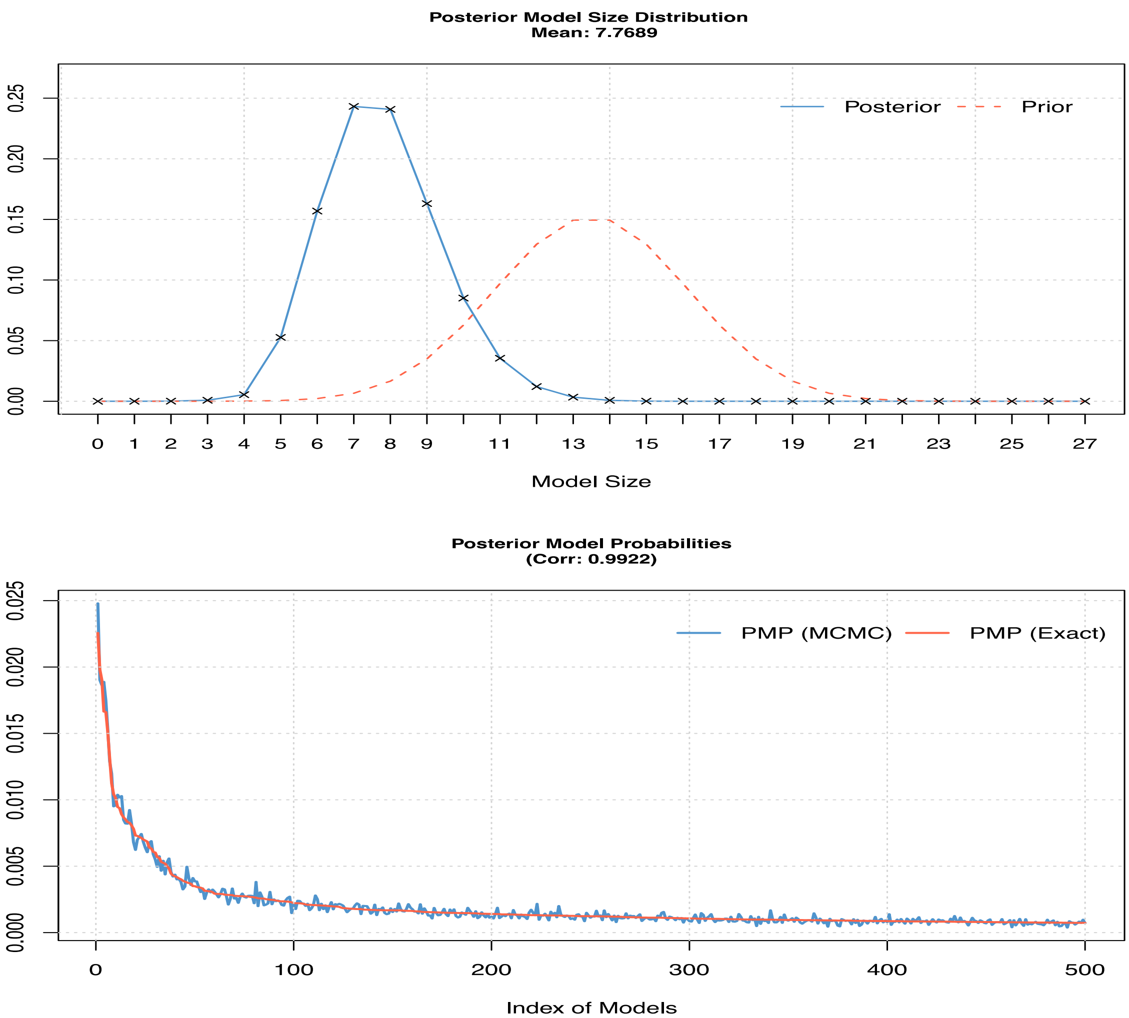
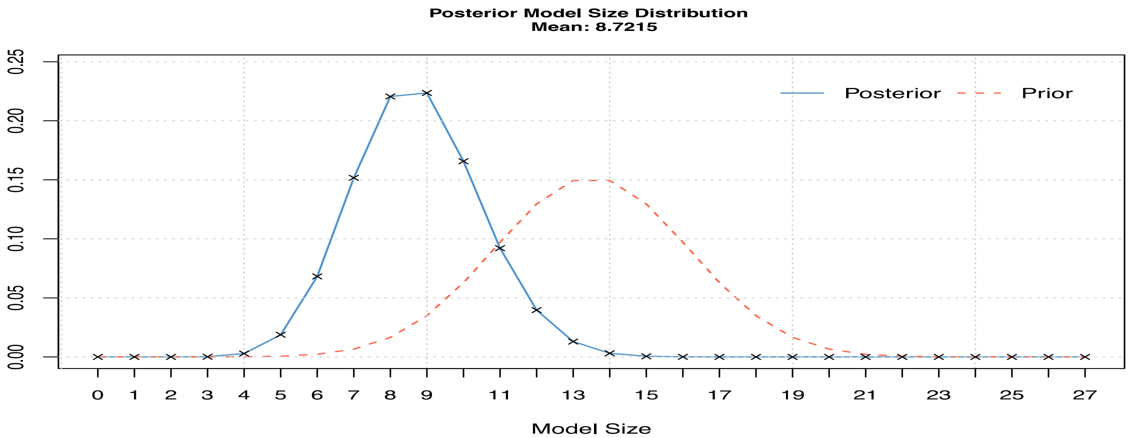


Figure A.7: Event Driven BMA – Model Size and Convergence

Table A.20: Summary of Fixed Income Arbitrage BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
8.7215	1000000	500000	2.249182 mins	392080
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.29	17	0.9723	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	



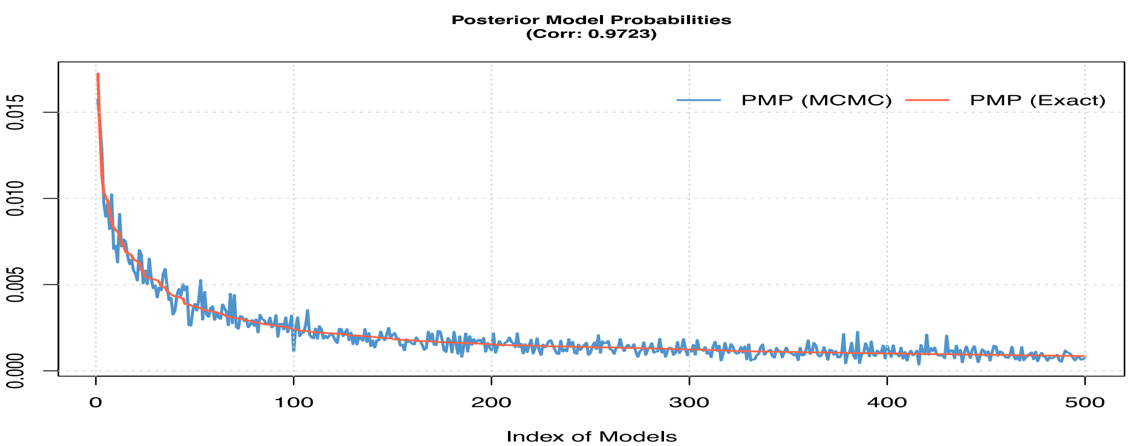


Figure A.8: Fixed Income Arbitrage BMA – Model Size and Convergence

Table A.21: Summary of Global Macro BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
6.5041	1000000	500000	2.475338 mins	417080
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.31	32	0.9982	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	

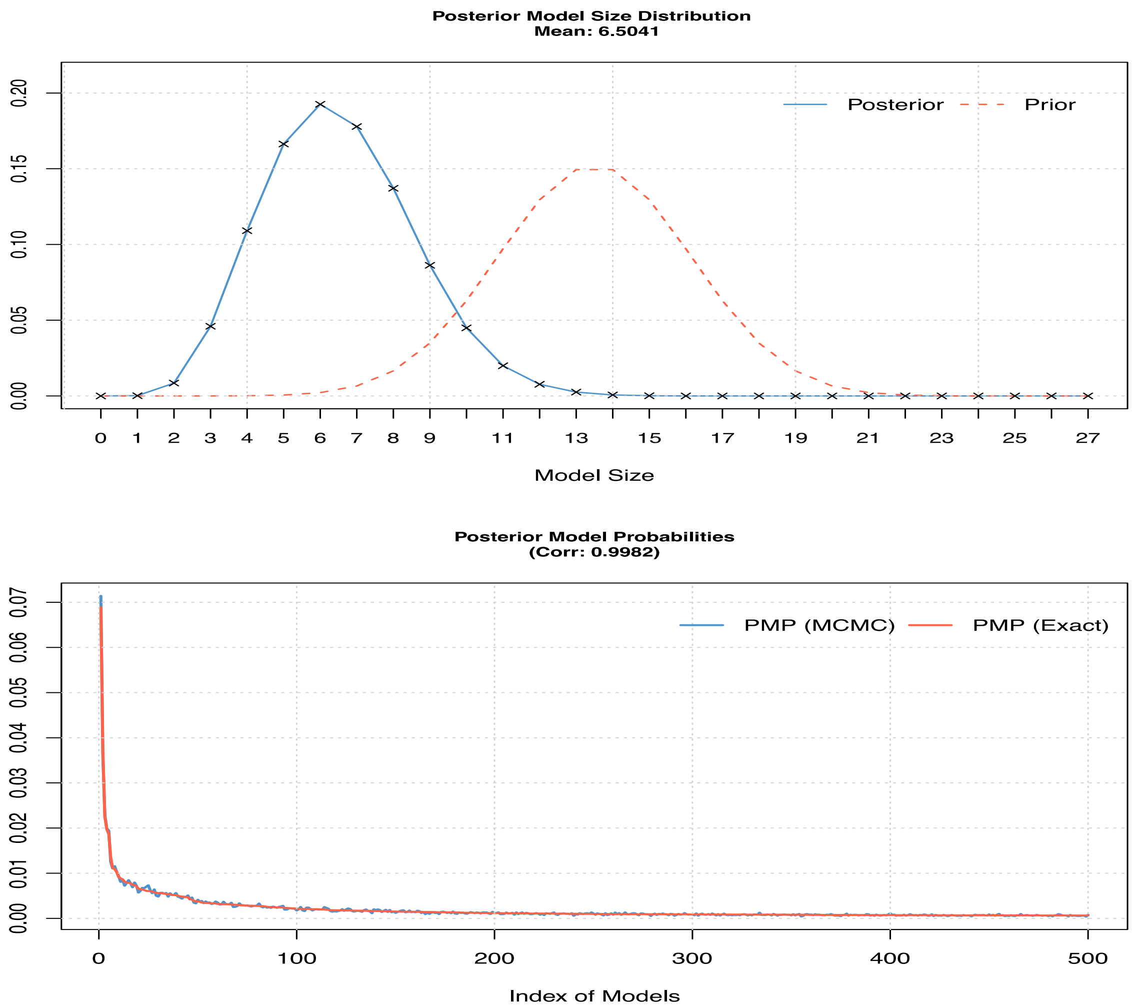


Figure A.9: Global Macro BMA – Model Size and Convergence

Table A.22: Summary of Global Macro BMA

Mean no. regressors	Draws	Burnins	Time	No. models visited
10.75	1000000	500000	2.173253 mins	301959
Modelspace 2^K	% visited	% Topmodels	Corr PMP	No. Obs.
130000000	0.22	37	0.9928	181
	Model Prior	g-Prior	Shrinkage-Stats	
	uniform / 13.5	UIP	Av=0.9945	

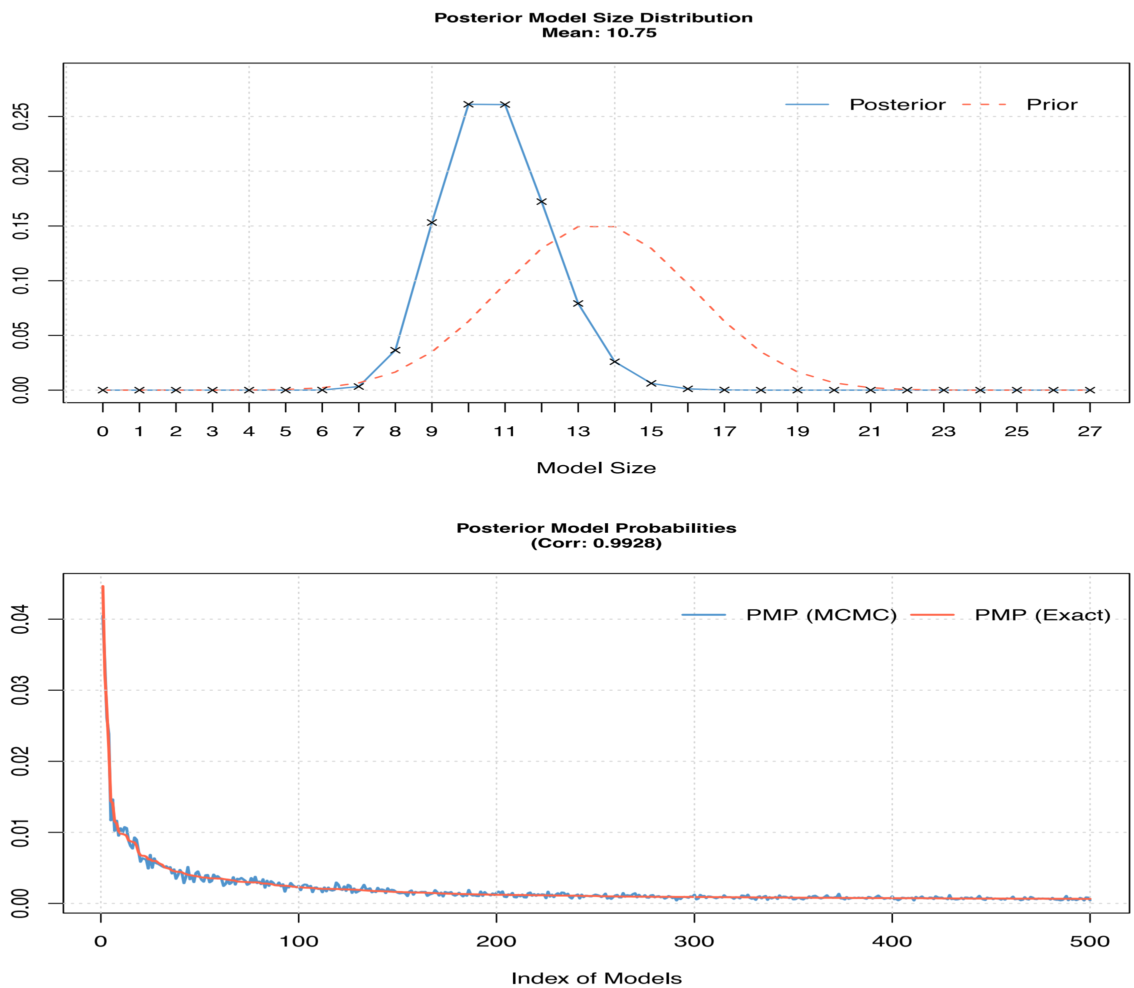


Figure A.10: Multi Strategy BMA – Model Size and Convergence

Appendix B: Robustness Check

Table B.1: Convertible Arbitrage – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
X1YTBMFR	1.0000	-1.8050	0.4051
X3MTBMFR	0.9772	1.8784	0.6308
COPSP	0.8313	0.9783	1.1259
EMHGOPSP	0.7414	-0.5455	0.4726
SMB	0.7339	0.1046	0.0785
Mkt.RF	0.7050	0.1544	0.1343
CMA	0.5768	-0.0854	0.0873

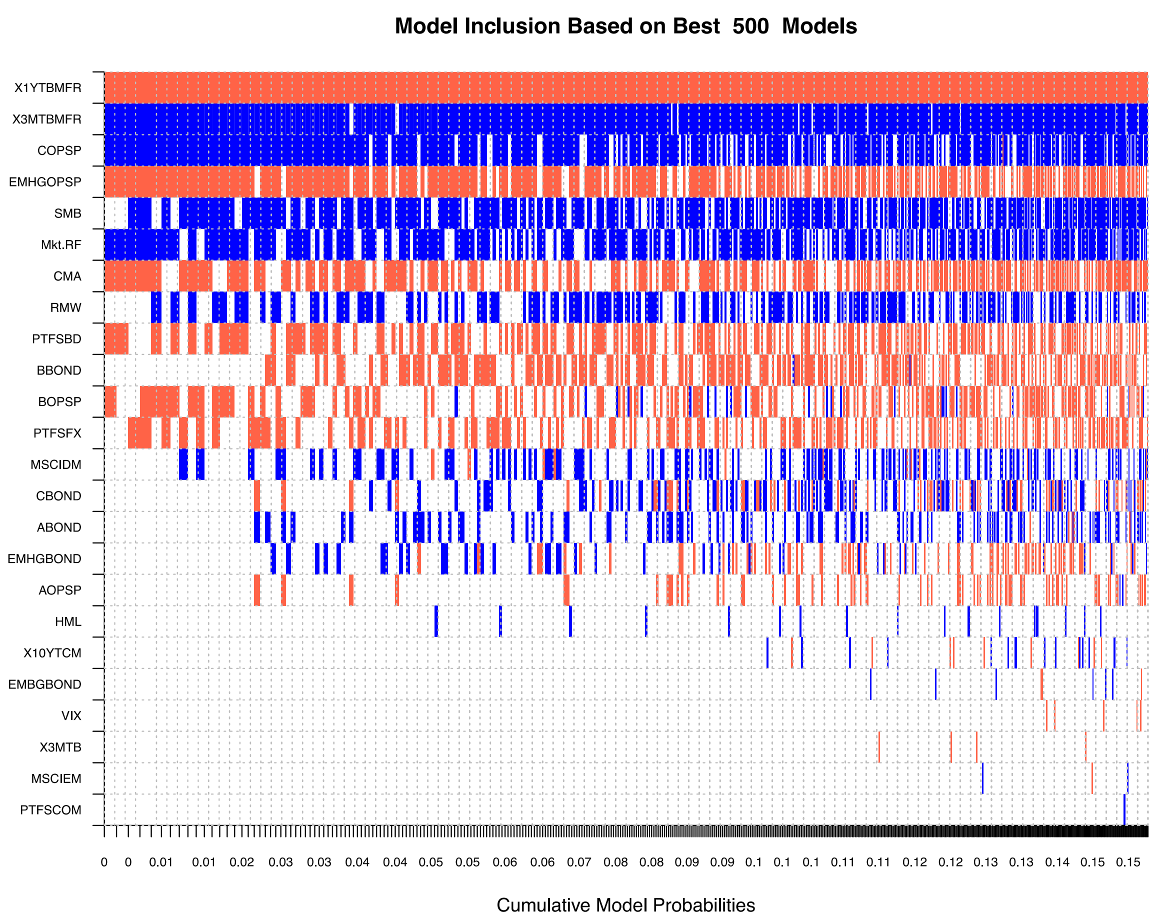


Figure B.1: Convertible Arbitrage – BMA Risk factors proxies

Table B.2: Distressed Securities – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	1.8628	0.5932
COPSP	0.8142	0.2459	0.0554
BBOND	0.7096	-1.3265	0.9867
X10YTCM	0.7090	1.0010	0.9282
Mkt.RF	0.6412	-0.8651	0.6353
EMHGOPSP	0.5400	0.2283	0.2254

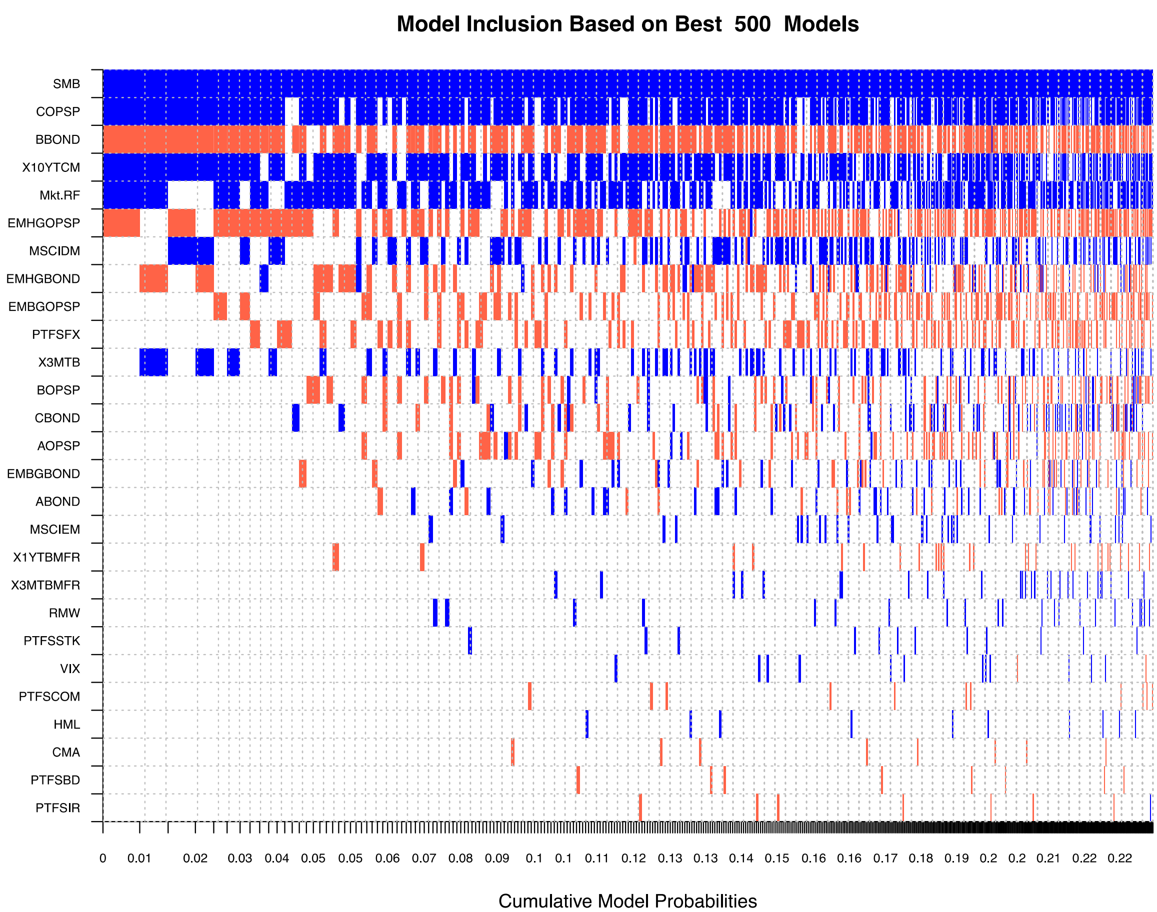


Figure B.2: Distressed Securities – BMA Risk factors proxies

Table B.3: Equity Long/Short – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	0.2288	0.0312
Mkt.RF	0.7824	0.2192	0.1194
HML	0.7204	-0.0551	0.0424
X3MTB	0.6271	0.0568	0.0515

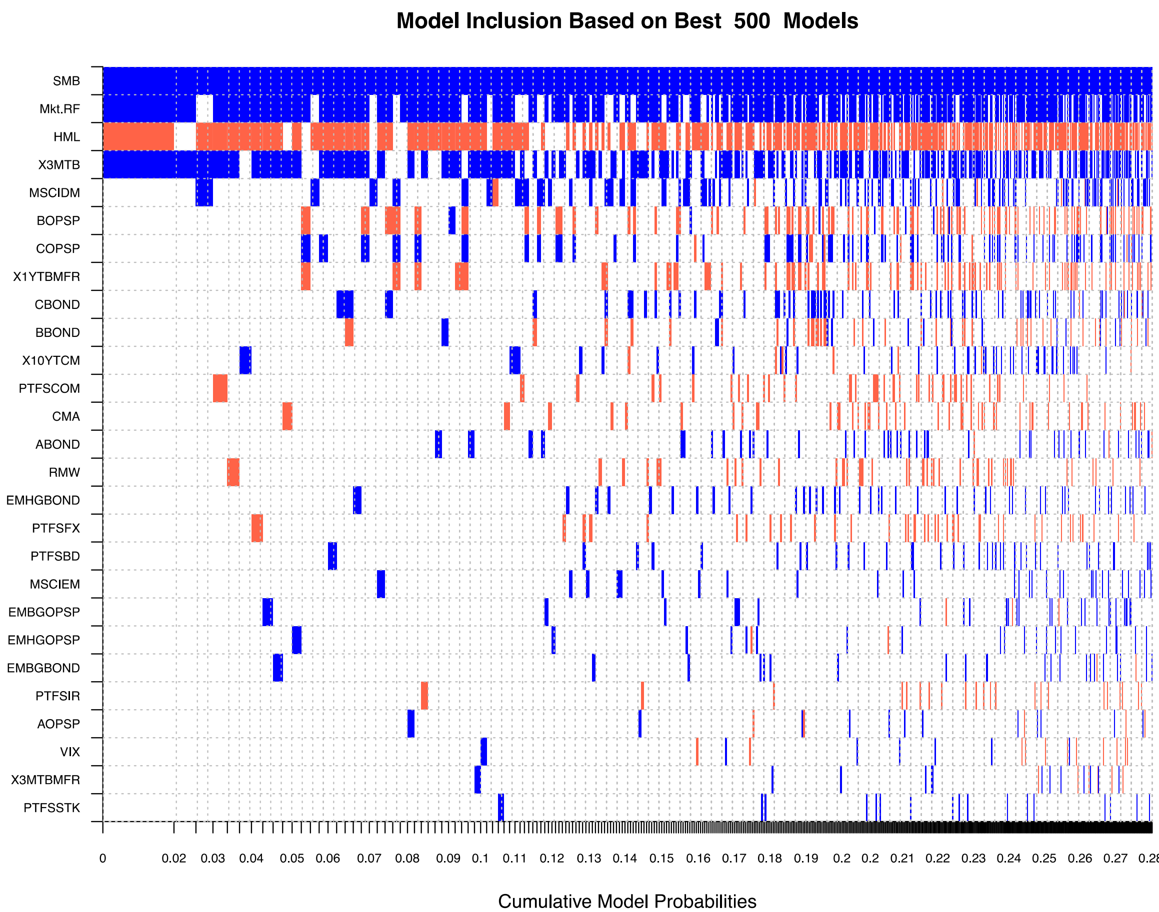


Figure B.3: Equity Long/Short – BMA Risk factors proxies

Table B.4: Equity Market Neutral – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
MSCIEM	0.5990	0.0236	0.0219
Mkt.RF	0.4246	0.0284	0.0492
X1YTBMFR	0.4092	-0.1231	0.1820
PTFSCOM	0.5394	-0.0047	0.0051
PTFSIR	0.5225	-0.0026	0.0029

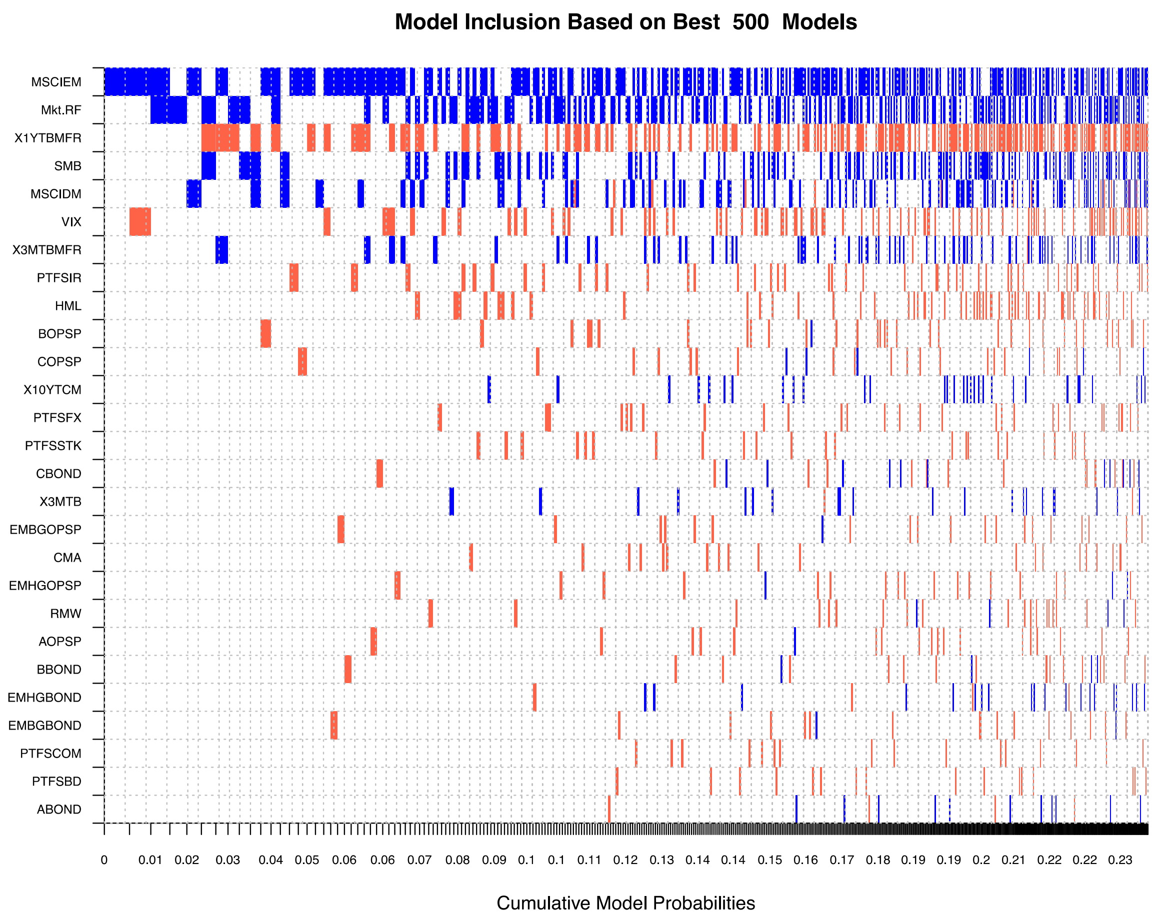


Figure B.4: Equity Market Neutral – BMA Risk factors proxies

Table B.5: Event Driven – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
SMB	1.0000	0.2081	0.0377
MSCIDM	0.8398	0.2261	0.1060
X1YTBMFR	0.7564	-0.6640	0.4577
X3MTBMFR	0.6809	0.8251	0.6616
EMHGBOND	0.5971	-0.4562	0.4914
CBOND	0.5936	0.5335	0.5093
BBOND	0.5922	-0.4677	0.4444

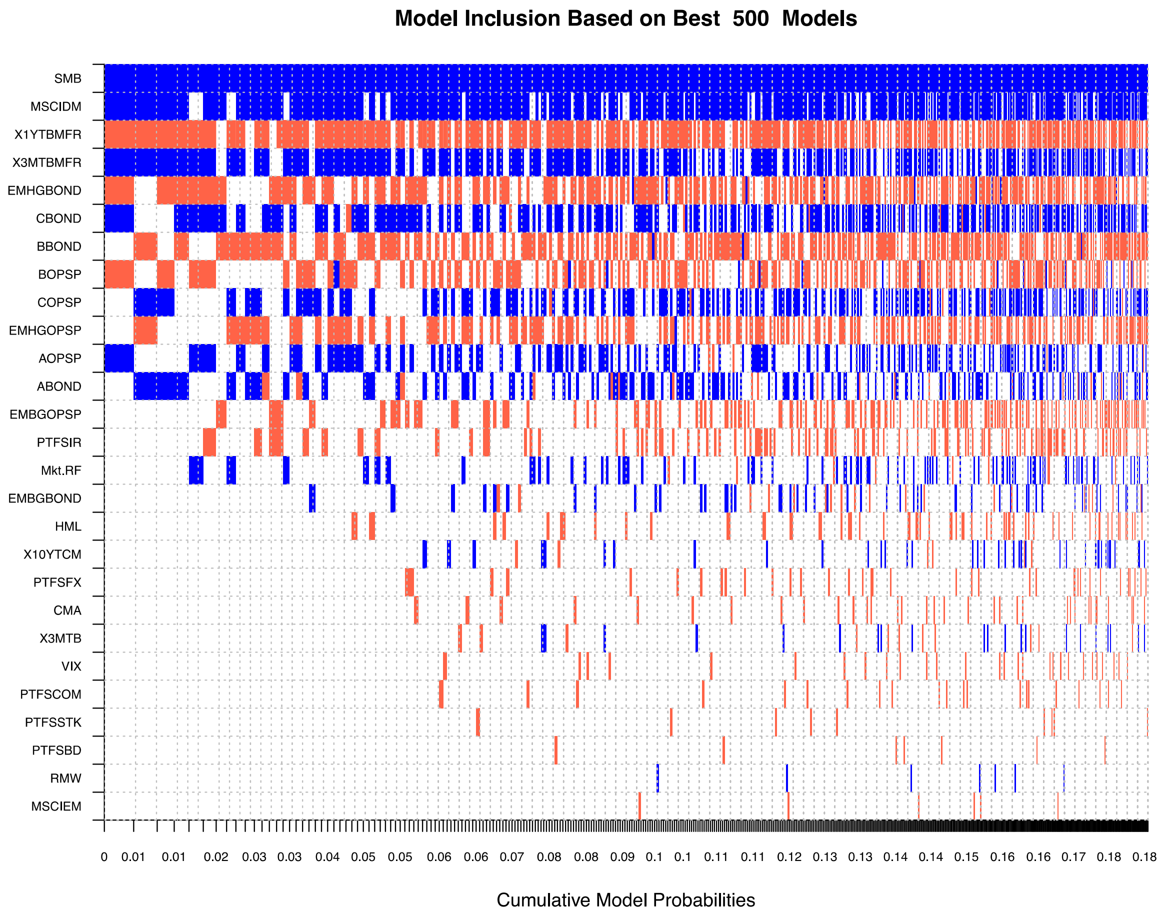


Figure B.5: Event Driven – BMA Risk factors proxies

Table B.6: Fixed Income Arbitrage – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
CMA	1.0000	-0.2922	0.0618
ABOND	0.9961	4.6210	1.1452
AOPSP	0.9800	-5.1164	1.4038
COPSP	0.9698	4.2477	1.3590
CBOND	0.9490	-4.0784	1.3758
HML	0.9287	0.1347	0.0606
Mkt.RF	0.6498	0.0750	0.0877

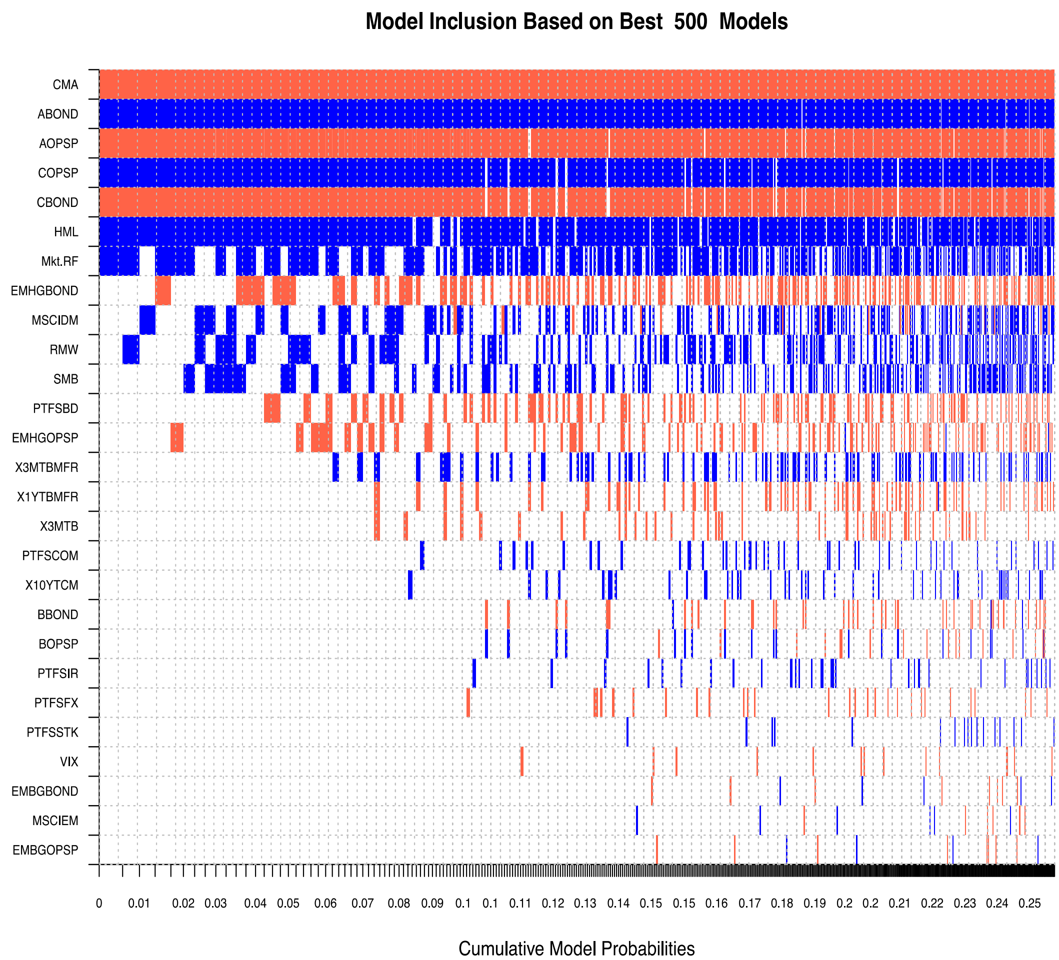


Figure B.6: Fixed Income Arbitrage – BMA Risk factors proxies

Table B.7: Global Macro – BMA Risk factors proxies' coefficients

	PIP	Post Mean	Post SD
MSCIEM	1.0000	0.0664	0.0108
PTFSSTK	0.7234	0.0086	0.0066
X3MTBMFR	0.4484	-0.2732	0.3504

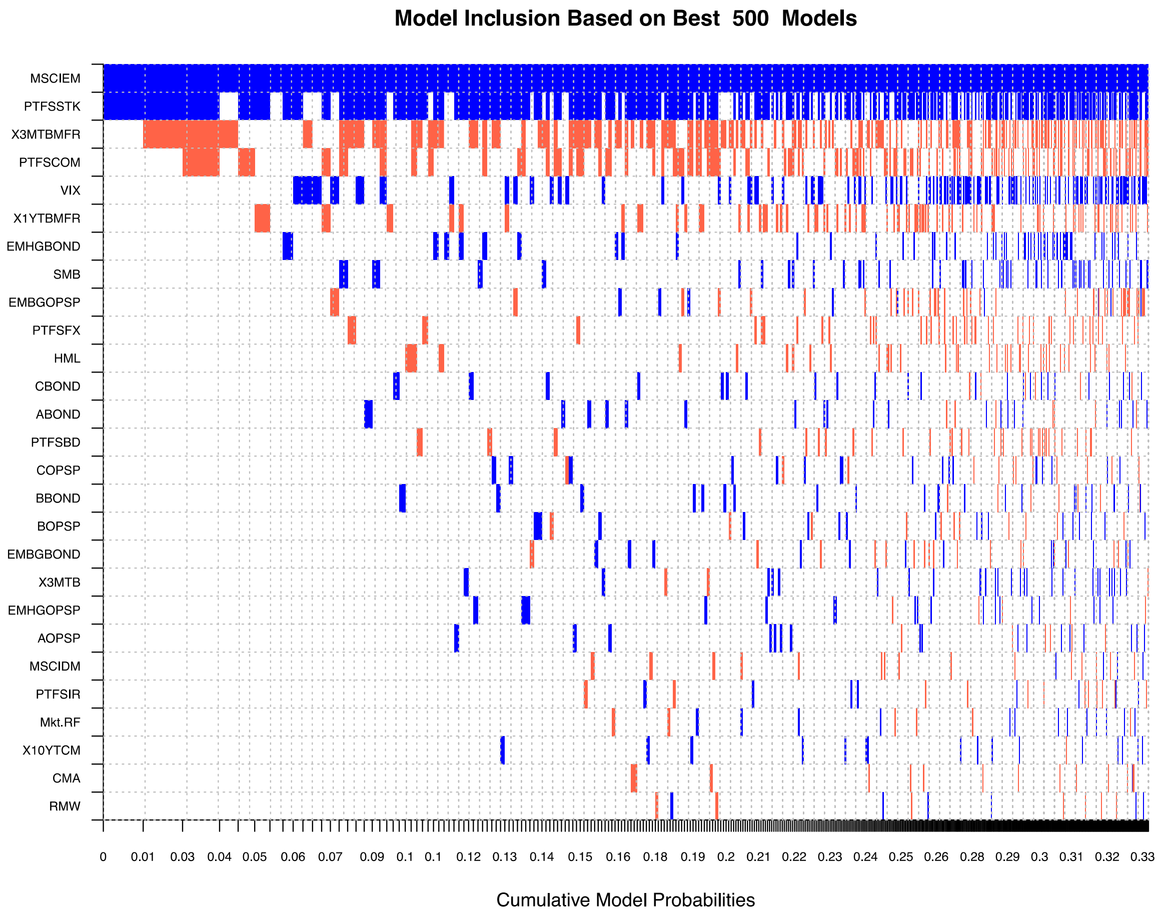


Figure B.7: Global Macro – BMA Risk factors proxies

Appendix C: Content of Enclosed DVD

There is a DVD enclosed to this thesis which contains empirical data and R source code.

- Folder 1: Source codes
- Folder 2: Empirical data