Master Thesis

The search for alpha continues. Estimating time-varying risk premia of hedge funds with a conditional model.

Lund University School of Economics and Management

Authors: Henrik Dyrssen (860830-0318)
Jakob Gloner (861127-T530)

Supervisors: Hossein Asgharian & Björn Hansson

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ABSTRACT

Numerous past studies investigating the performance of hedge funds suffer from two distinct problems: unreliable and biased return data inherent in virtually all databases and the use of static asset-pricing models. Using "indexes of indexes" for our hedge fund returns, both free of biases and highly representative, we investigate which risk factors investors are exposed to and whether hedge fund managers are able to consistently yield abnormal returns during the period February 1997 to January 2011. To measure abnormal returns, we focus on three different asset-pricing models. We argue that the static CAPM and Fama-French Three-Factor model are ill suited to benchmark hedge fund returns over time. The introduced time-varying five-factor model adds market timing and a proxy for left-tail events to the traditional Fama-French factors. The combination of the presented risk factors and business cycle proxies, used as instruments, has not previously been studied. The conditional model presented in this thesis is able to capture time-variations in business cycles and therefore proves to be superior to the static models examined. We find that around 50% of investigated strategies earn significant abnormal returns. In addition, we show that investors require a risk premium for the exposure to left tail events. Whether hedge fund managers possess a positive market timing ability is debatable and subject to further research.

Keywords:
Abnormal Returns, Conditional Model, Hedge Funds, Principal Components, Default Spread, Gold Price, Market Timing, PUT Write Index, TED Spread, Term Spread, VIX Index

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Lund, 25 May 2011

Henrik Dyrssen **Jakob Gloner**

“We simply attempt to be fearful when others are greedy and to be greedy only when others are fearful.”

- **Warren Buffet -**

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1. INTRODUCTION

This chapter introduces the reader to the area of research of this thesis. In addition, we provide some background information on hedge funds and a general discussion on the current state of research. Before presenting the outline, we closer specify the problem and purpose of this thesis.

At the time when Alfred W. Jones created the first (market neutral) "Hedge Fund" in 1949, by investing in *undervalued* assets, and at the same time selling short *overvalued* assets, no one could have imagined the scope and importance the hedge fund industry would undergo in the following six decades up to this date (Anson, 2006). With currently around $2.2 trillion in assets under management, the global hedge fund industry quickly recovered from the financial crisis and is soon expected to reach pre-crisis heights (Fletcher, 2011).

Alternative investments and especially hedge funds have received great attention, during the past two decades, partly due to their low systematic risk and modest correlation with other traditional securities (Liang, 1999). Whereas hedge funds have been characterized by offering outstanding risk-return relationships during the 1990s, successful performance has lately been attributed to excessive risk taking by greedy hedge fund managers with dubious ethics on a quest to always beat the market.

With the ultimate goal of reducing risk and yielding positive (absolute) returns regardless of the overall state of the market, hedge funds invest in miscellaneous assets employing numerous different investment strategies. The nature of this alternative asset class, which enjoyed very little regulation until recently, is highly dynamic. By combining leverage and short selling with investments in derivatives, commodities, currencies as well as traditional asset classes, hedge funds are generally able to quickly adapt to and benefit from changing market conditions.

The fast growth of the hedge fund industry throughout the 1990s and the first decade of the new millennium resulted in a tremendous amount of research and publications. We present a short overview of contrasting findings below.

Whereas a very large body of researchers (e.g. Liang, (1999); Brown et al., (1999)) proposes the superior return performance of hedge funds, Malkiel and Saha (2005, p.87) argue that "hedge funds have returns lower than commonly supposed" (due to hedge fund's fee structure and biases in return data). The question whether hedge fund managers are able to earn abnormal returns is as inconclusive as the overall performance of hedge funds. Kat and Miffre (2003) use a conditional multifactor model and find that more than 80% of the investigated funds yield positive abnormal returns. Other researchers claim that abnormal returns are rather unlikely (Edwards & Caglayan, 2001). Another question that has kept academics and researchers busy for years is which risk factors influence hedge fund returns. A wide consensus exists that hedge funds are exposed to multiple risk sources (e.g. liquidity risk, default risk or volatility risk) (Edhec, 2011). Other investigated factors, yet without common accord, include the risk premium associated with the exposure to left tail events (see Agarwal & Naik (2000); Mitchell & Pulvino (2000) and Lo (2001)) and whether hedge fund managers possess a positive market timing ability (see Fung et al., (2002); Cerrahoglu et al. (2003); and Chen and Liang (2007)).

Given the numerous inconclusive findings on whether hedge fund managers can add value and which risk factors actually do affect hedge fund returns, we believe that further in-depth research is both necessary and justified.

The majority of past studies suffer from two distinct problems. Until not long ago, researchers relied upon using static asset-pricing models to study hedge fund performance. However, as has recently been shown, both the CAPM and unconditional multifactor models, such as Fama-French's Three-Factor Model, are unsuitable to benchmark hedge fund returns, since static models ignore information about the changing state of the overall economy (Bird et al., 2010). Hedge funds have a dynamic nature and are exposed to multiple risk factors. Another point of criticism is the use of unreliable and biased hedge fund data, inherent in virtually all databases.
To tackle the problem of biased return data, academics, in particular the Edhec-Risk Institute, have created a very stable, less biased, and highly representative set of alternative indexes. These indices are "indexes of indexes" which by construction are almost entirely free of biases. To overcome the problems associated with static models, the focus of academic research has shifted towards employing conditional (time-varying) models. A nowadays commonly utilized approach to capture time-variability is the use of instrumental variables in order to condition factor exposure to commonly observable information (e.g. proxies for business cycles).

Despite the shift towards conditional models, relatively little research has been conducted utilizing unbiased hedge fund return data.

As hedge funds continue growing both in size and popularity, investors are similarly interested in whether hedge fund managers are able to generate positive alphas and which specific risk factors they are exposed to.

The purpose of this thesis is to evaluate how different hedge fund strategies perform during different economic environments. Specifically, we are interested in investigating the influence of various risk factors on hedge fund returns and whether hedge funds are able to provide positive abnormal returns.

In order to investigate (abnormal) hedge fund returns, and their distributions, three different models will be employed. Besides using the static CAPM and the Fama-French Three-Factor Model, we will also investigate time-varying variables by employing a Conditional Multifactor Model using Principal Component Analysis. As proxies for the business cycle and the current/future economic outlook, we introduce the term spread, TED spread, default spread, gold price, VIX index and industrial productivity. The time period investigated is February 1997 to January 2011, capturing two major bubbles (IT & US real estate bubble) and two crisis periods affecting the global economy at large.

The following chapter will provide a broad overview of the hedge fund industry. Previous empirical findings will be discussed and a general overview of theoretical frameworks will be provided. In addition, the different asset pricing models, risk factors and instruments employed will be introduced. Chapter 3 introduces the empirical methodology used, describes the general method of work and analyses potential biases of hedge fund returns. In Chapter 4, we present and discusses in depth the empirical findings of the three different asset-pricing models employed. Chapter 5 concludes with the most important findings of this thesis and suggests directions for further studies.

2. THEORETICAL FRAMEWORK

In the following chapter, the reader will be given a broad overview of the hedge fund industry from its historical background to the impact of hedge funds during the recent financial crisis. In addition, previous empirical findings will be discussed and different asset pricing models as well as risk factors and instruments will be introduced. Furthermore, in order to be able to understand discussions of later chapters, we review statistical properties (e.g. normality, multicollinearity, heteroscedasticity) and performance measures.

2.1 HEDGE FUNDS

The following pages will provide interesting background information on hedge funds, looking at their history, strategies, fee structure, legal structure and location, regulation, risk and the impact hedge funds had on the 2008-2009 financial crisis.

2.1.1 History

Alfred W. Jones created the first Hedge Fund in 1949 striving to neutralize the effect of overall market movement (Anson, 2006). This *market neutral strategy* also known as *long / short equity* aimed at balancing out the price movements of the overall market since the gain from long positions (undervalued securities) would make up for the loss of shorted (overvalued) securities in bull markets and vice-versa for bear markets. Hence, the returns did not depend on the overall market sentiment, but rather on the investor's stock picking abilities (Lhabitant, 2007). Interest in those newly created funds rose quickly and Jones started introducing a 20% *performance fee* in 1952. The combination of using a hedged strategy and leverage, as well as sharing risk, attracted many new investors. Whereas in the 1970s, most hedge funds followed one specific strategy *(market neutral)*, the substantial growth of hedge funds in the wake of the 1990s rising stock markets led to numerous new diversified investment strategies (Ineichen, 2002).

2.1.2 Strategies

In this thesis, we closer investigate 13 different hedge fund strategies, classified into the four major types *global macro*, *directional*, *event driven* and *relative value / arbitrage*. Hedge funds typically invest in a broad range of assets following different investment strategies and combine short and long positions with leverage. Their aim is to reduce exposure to market movements and to profit from security selection

(Crowley & Purcell, 1999). According to Sadek (2010), each individual hedge fund strategy is comprised of various different factors:

Elements of Hedge Fund Strategies

Style	Four main groups: global macro, directional, event driven, relative value/arbitrage & their sub-categories
Market	Equity, Fixed Income Securities, Currencies, Commodities
Instrument	Long/short, options, swaps, futures
Exposure	Directional, market neutral, arbitrage
Sector	US, emerging markets, chemicals, automotive, precious metals
Method	• Discretionary/qualitative: manager picks individual investments • Systematic/quantitative: computer models select investments
Diversification	Multi-manager, multi-strategy, multi-fund, multi-market

Figure 2.1: Elements of Hedge Fund Strategies

Source: Sadek (2010)

Next, we will focus on the four major groups of hedge fund strategies as well as funds of hedge funds.

Global Macro

Hedge fund managers focusing on a *global macro* strategy analyse global markets for macroeconomic events. Combining leverage with large positions in different investments and several markets (equity, fixed income, currencies) makes this strategy highly flexible. Crucial for success is the proper timing of the strategy's implementation (Ineichen, 2002).

A sub-strategy within global macro is for instance *CTA (Commodity Trading Advisors) global* in which the fund invests in futures, options or swaps in commodity as well as currency markets. The *CTA global* strategy often combines long and short positions in order to profit from both market upswings and downturns (Walker, 2010).

Directional

Directional investment strategies, such as *short selling*, exploit market movements, trends or irregularities when choosing securities across different markets. These strategies are in general riskier than market neutral strategies, mainly due to the larger exposure to overall market fluctuations (Sadek, 2010).

Sub-strategies of directional strategies include among others *emerging markets*, and *long/short equity*. The latter strategy either maintains a net long (directional) or market neutral (relative value) position. Other typical investment strategies, not covered in this essay are investments in certain sector funds (e.g. healthcare) or *fundamental value* strategies investing in undervalued securities (Tran, 2006).

Event Driven

Event driven investment strategies focus on valuation inconsistencies in the market before or after a corporate event occurs, taking positions in the predicted market movements. Among these transactional events are for instance mergers and acquisitions, consolidations, divestitures, recapitalizations or liquidations. Due to the expertise, time and resources needed to properly analyse corporate events, institutional investors, especially hedge funds, rather than individual investors typically engage in *event driven* strategies (Ineichen, 2002).

Sub-categories of this specific strategy include *merger arbitrage*, *distressed securities* and *credit arbitrage* among others. It should be stressed that an *event driven* strategy focusing for instance on acquisitions yields the highest returns during bull markets, whereas investing in *distressed securities* in general is better in bear markets (Fry, 2008).

Relative Value / Arbitrage

The aim of *relative value / arbitrage* strategies is to profit from relative price frictions between securities. These frictions occur either due to overall market mispricing or due to specific mispricing of securities compared to other (closely) related securities. Since *relative value* strategies in general are rarely directionally exposed to the overall market, they are often called *market neutral strategies*. Sub-categories of *relative value / arbitrage* include *equity market neutral*, *convertible arbitrage* as well as *fixed income arbitrage*.

Funds of Hedge Funds

A *fund of hedge funds* is a special investment vehicle that invests in a range of other hedge funds. With the aim of diversifying the risk exposure, these funds invest in various investment styles and markets. Research has shown, that *funds of hedge funds* already enjoy overall reduced volatility by investing in only a few different funds. Nevertheless, most *funds of funds* invest in around 20 different funds despite rapidly decreasing incremental diversification (French et al., 2005). A major advantage of *funds of funds* is that they allow small investors with limited capital resources to invest in a range of (otherwise closed) hedge funds (Brown et al., 2004).

More detailed information on the 13 individual styles used throughout this thesis can be found in *Figure 2.2* below.

Definition of Hedge Fund Styles

Convertible Arbitrage	Investment in convertible bonds. The strategy is to buy the convertible bond & sell short the common stock of the same company.
CTA Global	CTA Global funds invest in listed financial and commodity markets as well as in currency markets all over the world. They can follow systematic or discretionary strategies & are referred as to Commodity Trading Advisors.
Distressed Securities	Involves buying back, at a low price, the securities of companies that are experiencing financial difficulties. The securities targeted may cover a wide range, from senior secured debt (lowest risk) to common stock (highest risk).
Emerging Markets	Investment in equities or bonds from emerging markets.
Equity Market Neutral	Exploits inefficiencies in the market through balanced buying of undervalued securities & selling of overvalued securities enabling either a beta or a dollar neutral approach to be obtained.
Event Driven	Investment strategy that exploits price movements related to the anticipation of events affecting the life of the company (merger, acquisition, bankruptcy, etc.).
Fixed Income Arbitrage	The investment return is based on exploiting price anomalies related to interest rate instruments.
Funds of Funds	Consists of investing in several funds that may or may not follow the same strategy.
Global Macro	Investment strategy with a strong leverage effect on market events or developments.
Long / Short Equity	Involves investing mainly in equities and derivative instruments. The manager systematically uses short selling, but takes care to maintain a permanent overall net position that is either long or neutral.
Merger Arbitrage	Merger Arbitrage funds invest in companies involved in a Merger or Acquisition process. They typically go long the targeted company & sell short the stock of the acquiring company.
Relative Value	The objective of this type of strategy is to take advantage of the relative price differentials between related instruments.
Short Selling	Maintains a net or simple short exposure relative to the market.

Figure 2.2: Definitions of Hedge Fund Styles

Source: Edhec Risk & Asset Management Research Center - Replicated from Géhin &Vaissié (2004), p. 29.

Event Driven Family: Event Driven, Distressed Securities, Merger Arbitrage
Global Macro Family: CTA Global, Global Macro
Directional Family: Emerging Markets, Long/Short Equity, Short Selling
Relative Value/Arbitrage Family: Convertible Arbitrage, Equity Market Neutral, Fixed Income Arbitrage, Relative Value

2.1.3 Fee Structure

To align interest between managers and investors, in general high net worth individuals and institutional investors, hedge funds have a special fee structure, often referred to as 2 & 20 fee (Wilson, 2010). Next to a *management fee* to cover operational costs, typically around 2% of assets under management, an *incentive fee* of around 20% (decreasing in most recent years) aiming to align the manager's interest with the fund's performance is highly common. The *incentive fee* is typically only paid after a certain *hurdle rate* (e.g. S&P 500 return) has been achieved (Wilson, 2010). In addition, most hedge funds have *high watermark provisions* under which the fund's manager is required to make up prior period losses before he is entitled to receive an incentive fee (Liang, 1999). In addition to the above-mentioned fees, certain funds charge investors a *withdrawal fee* (also called *redemption fee*) when withdrawing their investments from the fund (Liang, 1999). Rather than benefiting the fund manager, the proceeds are retained by the fund. The major reason for adding a redemption fee is to discourage high turnover and short-term investment, which would make it difficult to take positions in long-term or illiquid strategies.

2.1.4 Legal Structure & Location

A hedge fund pools money from a number of wealthy investors and invests in various assets and markets employing different investment strategies. Whereas the actual fund has no employees, a fund manager manages the portfolio. This investment manager typically is a separate body, a real firm with employees. The tax environments of the prospective hedge fund's clients as well as local regulations typically determine the legal structure (location and type of legal entity) of a specific hedge fund. In order to channel tax payments on the increase in portfolio value from the fund to investors, many hedge funds are based at offshore financial centres. Opposite to the funds domicile, hedge fund managers are usually located in the world's major financial canters (NYC, Connecticut, London) and will pay taxes on the fees they receive for managing the fund. According to Stowell (2010), around 60 per cent of hedge funds are registered offshore, with the Cayman Islands, British Virgin Islands and Bermuda taking 55%, 15% and 10% respectively. The major onshore locations are the US (65%, mostly Delaware) and Europe (31%) with a large number of funds registered in Luxembourg and Dublin.

The favourable tax treatment for *limited partnerships* in the US makes it the most commonly used legal entity for hedge funds (based in the US). Whereas individual investors are regarded as limited partners, the investment manager (or an offshore entity) is the general partner. Establishing offshore corporate funds simplifies investments for non US-investors and pension funds that would otherwise have to deal with rather complex tax issues.

In addition to the common fact that fund managers invest substantial portions of their own wealth in the fund in order to better align interests with other investors, most hedge funds follow an *open-ended structure*. This structure periodically accepts additional investments and allows its financiers to withdraw money.

2.1.5 Regulation

Hedge funds have historically been lightly regulated entities with little transparency. The *Dodd-Frank Act* passed in the United States in 2010 in the wake of the financial crisis aims to increase transparency and governmental oversight. It will most probably affect both US and international hedge fund markets once it becomes effective in July 2011. Under the new law, funds with more than 15 clients residing in the US or investors managing more than $25m will have to register with the Securities and Exchange Commission in the US.

2.1.6 General Risk

With the ultimate goal of reducing risk and yielding positive (absolute) returns on investments regardless of the overall state of the market, hedge funds invest in miscellaneous assets using numerous different investment strategies. In general, hedge funds have low systematic risk and modest correlation with other traditional securities (Liang, 1999). The low correlation with for instance bonds and equities makes hedge funds an *important diversifier*, reducing overall portfolio risk. Despite their beneficial role as a diversification tool, allocating a too large portion of overall portfolio investment into hedge fund poses certain risks. The numerous investment styles, strategies and high individuality of each fund make it extremely difficult for investors to estimate the likely risks and returns. Additionally, in contrast to Liang (1999) who proclaims hedge funds a superior return performance, research shows that hedge fund performance is considerably lower than anticipated. This is due to at least two factors. After subtracting (high) fees and adjusting for biases in return data, hedge fund performance can decline substantially (Malkiel & Saha, 2005). Furthermore, literature states that the generally low correlation of hedge funds with other assets often vanishes during market downturns, reducing the overall diversification potential of hedge funds. Despite the above-mentioned facts, it should be stressed, that hedge funds were approximately one-third less volatile than the S&P 500 index during the period 1993 to 2010 (Hennessee Group, 2010).

It is often falsely anticipated that hedge funds are resistant to market downturns. The recent financial crisis clearly revokes this idea. Hedge funds were unable to shield investors from risk, nevertheless still outperformed (despite yielding negative returns) numerous other investment classes in 2008. The S&P 500 for instance, one of the world’s most diversified equity indices fell 37%, its worst reported performance since its inception in 1957. Hedge funds mastered the crisis slightly better (-17%), nevertheless were hit much harder than in any other crisis before (Le Sourd, 2009). Morgan Stanley estimates a 37% decline in assets under management in line with 1,471 Hedge Fund closures in 2008 alone according to Hedge Fund Research (2009) and the Federal Reserve Bank of St Louis (2009).

Investors in hedge funds, under almost any jurisdiction are required to fulfil certain criteria. They need to be sophisticated, qualified investors who are not only aware of the potentially high returns of investing in hedge funds, but also, and more importantly of their (large) risks. Large minimum investments and certain wealth/income requirements are in place in order to only have the rich elite or institutional investors as a client base.

Investors also face additional risk due to the *legal structure* of hedge funds. The private entities typically have very few disclosure requirements, making the fund’s strategy and manager’s actions less transparent (López de Prado & Peijan, 2004). The increasing influence of institutional investors, together with new regulations passed in the US and Europe in the wake of the financial crisis, will require fund managers to report more information on a regular basis. This will ultimately lead to greater transparency.

Furthermore, it is being argued that the use of *leverage* in many investment funds including trading on margin not only increases potential returns, but also increases the opportunity for larger losses. In general however, hedge funds only use little leverage as compared to investment banks (Chan et al., 2005). The more leverage or other risks a hedge fund is exposed to, the higher will be the need for proper risk management. Fund managers can send *positive signals* to other investors by investing their own money into the fund, which shows the fund manager's incentive to actively engage in risk management practices (Lo, 2001).

2.1.7 Systematic Risk & Impact on the Financial Crisis

Since 2007, "greedy" investment bankers and traders, hedge fund managers, and hedge funds in general have been popular targets by the media and public when searching for reasons and explanations for the financial crisis. But do hedge funds seriously pose *systematic risk*, a risk to the overall state of the financial industry and economy?

Despite many critics falsely blaming hedge funds causing the crises, hedge funds as compared to mutual funds and investment banks are way too small to have a serious impact on systemic risk. In 2009, Ben Bernanke, the Chairman of the Federal Reserve stated that "[he] would not think that any hedge fund or private equity fund would become a systematically-critical firm individually" (House Financial Services Committee, 2009). In addition, surveys from the UK Financial Services Authority stressed that the European hedge fund industry does not "pose any significant risk to the financial system" (Armitstead, 2010)

The most recent financial crisis has been initiated in the US subprime mortgage markets rather than by hedge funds or excessive short selling. Banks and *special purpose vehicles* repackaged loans into *collateralized debt obligations (CDOs)* and sold them to market participants. These investors, mainly banks, financial institutions, hedge funds and other institutional investors relied on credit ratings provided by rating agencies. Despite their investment grade ratings, loans underlying these CDOs defaulted on a broad scale once interest rates started rising around January 2004 (see *Figure 2.3*). Eventually, large financial institutions were forced to adjust their balance sheets, incurring substantial losses. This resulted in a lack of trust combined with a greater risk aversion in the interbank market, ultimately causing illiquidity.

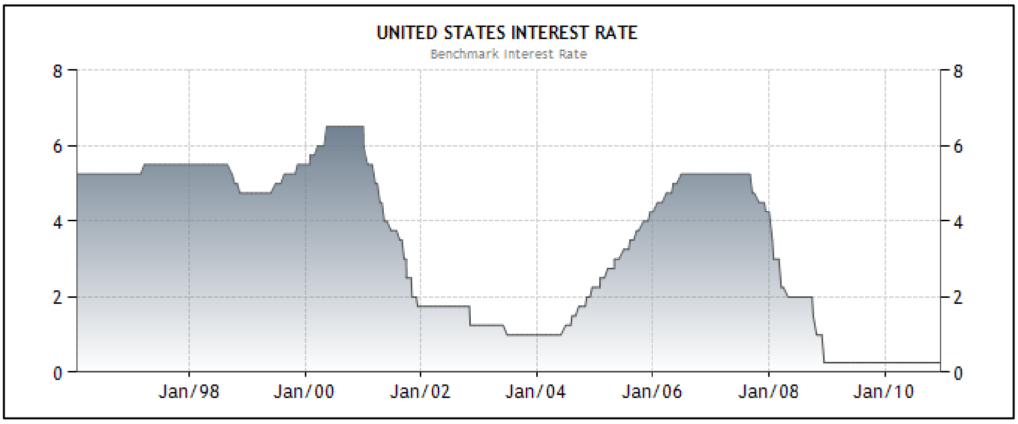

Figure 2.3: United States Interest Rate (Jan 1997 – Jan 2011)

Source: TradingEconomics.com; Federal Reserve

Overall, it has not been hedge funds that structured mortgages into CDOs. Purchasing those securities alone, does certainly not qualify hedge funds as the cause of the failure for these securities. As already mentioned above, hedge funds at large were not as severely hit by the crisis as investment banks and the overall market. A reason for this can be found in the investment philosophy of hedge funds. Next to the fund manager's distinct interest alignment with its investors (hurdle rate, high watermark) (Liang, 1999), the investment manager usually additionally is required to invest his own money in the fund. The close interest alignment and the manager's investment in his own fund led most fund managers to conduct own proprietary research and rely on individual risk assessments rather than ratings provided by Fitch, S&P or others (Shadab, 2008). This in turn enabled hedge fund managers to abandon risky CDO investments at an early stage, or alternatively, the fund themselves against adverse effects.

A further popular reasoning causing the financial crisis is ruthless *short selling*. Short selling in fact is only one of myriad different hedge fund strategies, resting on the belief of over- and undervalued securities. The fall of Northern Rock in the UK in 2007 shed a very negative light on the practice of short selling and hedge funds. Estimates say that hedge funds on aggregate gained around £1 billion by short selling Northern Rock stocks. From a theoretical and economic point of view however, one would expect short selling to rather benefit the market since it balances investor's positive and negative outlooks for securities. Culp and Heaton (2008) further provide evidence that short selling prevents markets from being irrationally overpriced. Following the collapse of Lehman Brothers, the SEC quickly banned short selling (mostly due to the large negative publicity) between 19 September and 8 October 2008. The success of this ban is still debated to date. During the 3-week ban, shares of numerous financial institutions and ETFs plummeted (as much as 40%) (Autore et al, 2009). Regarding the fact that share prices of exactly these stocks (slightly) increased after the abandonment of the ban questions the harmful nature of short selling and hedge funds following such a strategy to financial markets.

An additional factor demonstrating the actual importance of hedge funds during the most recent crisis are *credit default swaps (CDS).* A CDS is basically an insurance on the default of a security, which is designed to transfer the credit exposure of fixed income securities from one party to another. Hedge funds played a pivotal role for the stability of financial markets by providing *liquidity* being either on the up- or downside of CDSs. In line with Shadab's (2008) findings, hedge funds rather mitigated the adverse effects of market illiquidity and might have prevented even larger government bailouts and stimulus packages.

To summarize the above findings, hedge funds did not cause the most recent financial crisis and do not pose systematic risk. One might be able to blame the hedge fund industry on the demise of Northern Rock, but at large hedge funds played a crucial role for financial stability by providing liquidity and diversification, therefore ultimately contributing to a general integration of financial markets (Garbaravicius & Dierick, 2005). Nevertheless, whether stricter disclosure and reporting requirements for the hedge fund industry could have prevented certain occurrences from happening is a legitimate question subject to further research.

2.2 PREVIOUS STUDIES

The fast growth of hedge funds over the last few decades resulted in a vast amount of research and publications. Whereas a large number of researchers (e.g. Liang, 1999) attest hedge funds superior return performance, as compared to the S&P 500 or mutual funds, Malkiel and Saha (2005) and others argue that hedge fund performance is worse than originally anticipated. The authors justify their argumentation with high fees typically charged by hedge funds and the numerous biases in reported hedge fund returns (e.g. backfill or survivorship bias).

Liang (1999) analysed the risk and return relationship of hedge funds and not only found a higher standard deviation coupled with a lower beta value as compared to traditional mutual funds, but also concluded that hedge funds show superior performance. Brown et al. (1999) investigated the performance of offshore hedge funds employing an unconditional CAPM. The authors provide empirical evidence that the majority of hedge funds historically outperform the S&P 500 index. Furthermore, Liang (1999) and Fung & Hsieh (1997) show that the correlation between the market index and hedge funds is much lower than for instance the highly correlated mutual funds. In addition, they find a low correlation between different hedge fund strategies.

Many authors have started using conditional multifactor models to investigate fund performance. Kat and Miffre (2003) investigated hedge fund performance during 1990 and 2000 employing a conditional model. More than 80% of funds investigated provide a positive abnormal return. Furthermore, they find that hedge funds yield higher returns in bear markets. Edwards and Caglayan (2001) investigated the period 1990 until 1998 and discover that hedge fund returns differ considerably between investment strategies, but on average yield an excess return of 8.52% per annum. However, only one quarter of the investigated funds in the sample have significant positive alphas. Liang (1999) backs Edwards and Caglayan's (2001) findings using a static eight-factor model for the period 1992 to 1996. He concludes that different strategies have significantly different alphas, ranging from (-5.22% to 1.26%). About half of the indices in Liang's sample have positive and significant alphas.

Next to Malkiel and Saha (2005) who question the superior performance of hedge funds, Ackermann et al. (1999) find that hedge funds (when using risk adjusted or absolute returns) could not persistently beat the market (S&P 500) during 1988 and 1995. When considering gross returns, the authors show that hedge funds are indeed able to outperform the market, however the superior return is equal to the amount of management and incentive fees charged. Despite the fact that hedge funds yield approximately the same return as the market index after subtracting fees, Ackermann et al. conclude that hedge funds have a good diversification potential. Hence, it is wise for investors to include hedge funds in their portfolio.

2.3 ASSET PRICING MODELS

Factor models decompose the return of an asset into various factors. Whereas these common factors capture the risk components, the factor model measures the asset's sensitivities to these risk factors. The uses for factor models are manifold. Among the most common are:

- Estimating abnormal returns
- Estimating variance / covariance between asset returns
- Forecasting returns
- Identifying risk sensitivities

2.3.1 CAPM

The Sharpe (1964) and Lintner (1965) Capital Asset Pricing Model (CAPM) builds upon Markowitz's (1959) modern portfolio theory (mean-variance model). The CAPM rests on various simplified assumptions. The most important is that investors only look at the trade-off between expected return and risk measured as variance. Quite often, the model also assumes unlimited risk-free borrowing and lending. Other assumptions include homogenous expectations, stating that all investors share exactly the same information set i.e. agree on expected risk and returns of all assets. In addition, asset prices are said to adjust quickly to new information and contain all information publicly available. These assumptions imply that all efficient portfolios must be combinations of both the risk-free asset and a single risky tangency portfolio (Fama & French, 2004). Since all investors have homogenous expectations, they ultimately hold the same risky assets, namely the efficient market portfolio of risky assets. This portfolio must lie on the minimum variance frontier (efficient frontier) to clear the asset market (Fama & French, 2004).

Sharpe-Lintner CAPM

$$E(R_i) = R_f + \beta_{im}\left[E(R_m) - R_f\right] \quad (1)$$

The above paragraph has shown that the expected return of a risky security under the Sharpe-Lintner model equals the return of a risk-free asset (whose return is uncorrelated with the market) plus the risky asset's beta, measuring the asset's sensitivity to the market portfolio, times the market risk premium (Fama & French, 2004). Since the market portfolio is mean-variance efficient, the CAPM claims that differences in expected return are *entirely* explained by differences in market beta.
In order to test whether hedge funds are able to generate abnormal returns, we employ the following empirical model:

CAPM Regression Model

$$r_{it} - r_{ft} = \alpha_i + \beta_i\left(r_{mt} - r_{ft}\right) + \varepsilon_t \quad (2)$$

2.3.2 Fama-French Three-Factor Model

Ever since its very first days in 1964, the CAPM has empirically been tested and its findings been challenged. Research suggests that a substantial amount in the variation of expected returns is in fact unrelated to market beta. Especially ratios involving stock prices contain information market betas fail to explain. Market capitalization (size) (Banz, 1981), E/P (Basu, 1977), debt/equity (Bhandari, 1988), BE/ME (Statman, 1980 and Rosenberg et al., 1985), and past sales growth all seem to reveal shortcomings of capital asset pricing models (Fama & French, 2004). Continuing short-term returns (Jegadeesh & Titman, 1993), long-term reversal (DeBondt & Thaler, 1985), or the equity premium puzzle are further anomalies the CAPM cannot explain. Regarding all these facts, it seems obvious that beta alone, serving as a proxy for market risk fails to explain stock returns. In reality, risk stems from various sources that can hardly be captured by a single risk measuring variable.

The above findings gave rise to develop multifactor models, among them the Fama-French Three-Factor Model. Fama and French (1993) include two additional risk factors next to beta, namely size, as measured by market capitalization and the ratio BE/ME, separating stocks in either value or growth securities. They show that the predictive power of beta vanishes when firms are sorted simultaneously by BE/ME and beta or by beta and market capitalization. Their equilibrium pricing model, an empirical example of Merton's ICAPM (1993), or Ross' APT (1976), provides a good description for portfolios formed on BE/ME and size (Fama & French, 1993).

Fama-French Three-Factor Model

$$E(R_i) = R_f + \beta_{im}\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) \qquad (3)$$

The factor SMB (small minus big), measured by market equity accounts for the size premium when investing in small companies, whereas HML (high minus low), measures value risk, the premium investors require for investing in high BE/ME, so called value firms (Fama & French, 1993). The model covers most of the anomalies identified above, yet falls short in explaining the continuation of short-term effects (momentum). In more recent studies, some critics question the robustness of higher returns for small stocks or high BE/ME stocks, whereas others explain Fama-French's findings with data-snooping and other dataset biases (Black, 1993).

For empirically testing the Fama-French model and abnormal returns of hedge funds, we use the following model:

Fama-French Three-Factor Regression Model

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}\left(r_{mt} - r_{ft}\right) + \beta_{i2} SMB + \beta_{i3} HML + \varepsilon_t \qquad (4)$$

2.3.3 Conditional Factor Model

Ferson and Harvey (1999) report evidence on how both single and multi-factor models can lower the in-sample variance by using a conditional variables approach. The idea is to employ time-varying parameters as linear functions of predetermined conditioning variables, also known as instruments. The variables are supposed to work as proxies for time-varying economic phenomena. In our case we adjust the regressors with different instruments that represent the business cycle and/or the current/future economic condition. The model first proposed by Ferson and Harvey (1999) is the general framework for modelling with conditioning variables.

$$E_t(r_{i,t+1}) = a_{it} + \beta'_{it} E_t(r_{p,t+1}) \quad (5)$$
$$\beta_{it} = b_{0t} + b'_{1t} Z_t$$
$$\alpha_{it} = a_{0t} + \alpha'_{1t} Z_t$$

where:

$r_{i,t+1}$= Return on asset *i*

$r_{p,t+1}$= Vector of excess returns on the risk factor mimicking portfolio

Z_t= Vector of conditioning variables at time *t*

α_{it}= Abnormal return

b'_{1t}= Unconditional sensitivity to the conditional beta

By combining these models one obtains a multi factor model with time-varying betas.

$$r_{i,t+1} = (a_{0i} + a'_{1i} Z_t) + (b_{0i} + b'_{1i} Z_t) r_{p,t+1} + \varepsilon_{i,t+1} \quad (6)$$

According to Gupta et al. (2003) a time varying regression is particularly applicable to hedge fund data since hedge funds follow various different investment strategies, which are exposed to a large quantity of time-varying risks. Ferson and Schadt (1996) report similar findings and conclude that the nature of hedge funds is too complex to be applied to an unconditional asset-pricing model. A time varying conditional model is more likely to provide reliable results on hedge fund data.

To adjust the independent variables for long-term changes in the business cycle, we choose six potential proxies: default spread, term spread, ted spread, gold returns, the VIX Index an industrial productivity. The motivation for choosing these instrumental variables will be presented in part 2.5. Those variables are reduced to two instrumental variables by using a principal components approach. Principal component analysis will be closer explained in the next section. In addition to the risk factors that are incorporated in the Fama-French model, our conditional model introduces the *PUT Write Index* to proxy left tail events and market timing, to test for the ability of hedge fund managers to time changes in the business cycle. The regression model is presented below.

Conditional Regression Model

$$r_{it} - r_{ft} = \alpha_{i0} + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}PUT_t + \beta_{i5}MT_t + \beta'_p[z_{t-1}(r_{mt} - r_{ft})] + \beta'_p[z_{t-1}SMB_t] + \beta'_p[z_{t-1}HML_t] + \beta'_p[z_{t-1}PUT_t] + \beta'_p[z_{t-1}MT_t] + \varepsilon_t \quad (7)$$

The extended version looks as follows:

$$r_{it} - r_{ft} = \alpha_{i0} + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}PUT_t + \beta_{i5}MT_t + \beta_{i6}[PC1_{t-1}(r_{mt} - r_{ft})] + \beta_{i7}[PC1_{t-1}SMB_t] + \beta_{i8}[PC1_{t-1}HML_t] + \beta_{i9}[PC1_{t-1}PUT_t] + \beta_{i10}[PC1_{t-1}MT_t] + \beta_{i11}[PC2_{t-1}(r_{mt} - r_{ft})] + \beta_{i12}[PC2_{t-1}SMB_t] + \beta_{i13}[PC2_{t-1}HML_t] + \beta_{i14}[PC2_{t-1}PUT_t] + \beta_{i15}[PC2_{t-1}MT_t] + \varepsilon_t \quad (8)$$

2.3.4 Principal Component Analysis

The principal component analysis (PCA) method strives to convert observations of correlated variables into a set of uncorrelated variables. The method is especially helpful when one is facing a large number of variables. PCA reduces the number of variables and minimizes the loss of information in the variance/covariance matrix. The method was first introduced by Karl Pearson over a century ago, but is still widely used for empirical testing of asset pricing models.

By transforming the data into a new set of variable, which contribute with highest amount of variance, one can obtain the first principal component (PC). Additional uncorrelated PCs can be added as long as the loss of information in the covariance matrix is not too extensive (all above Gujarati, 2006).

The first principal component is given by:

$$x'_1 R_t = PC_{1t} \quad (9)$$

where:

$x_1 = (N * 1)$ vector that solves the following optimization problem:

$$\max(x'\hat{V}x)$$
$$s.t. \quad x'x = 1$$

where:
$\hat{V}$= Variance/covariance matrix

By adding one constraint to the optimization problem, one can obtain the second principal component.

$$x'_1 x = 0 \quad (10)$$

This restriction imposes orthogonality between x_1 *and* x_2.

2.4 RISK FACTORS

Next, we will motivate the reason for choosing the below risk factors that will be employed as independent variables in our conditional model.

- **MKT:** The market factor is motivated by the CAPM, which states that asset returns are entirely explained by changes in market beta.

- **SMB:** is a Fama-French (1993) risk factor. SMB is a proxy for *size risk*, as measured by market equity. Fama and French state that small firms are riskier (e.g. less transparent, stocks less frequently traded), hence yield higher returns than large firms.

- **HML:** is a Fama-French (1993) risk factor stating that high BE/ME stocks *(value stocks)* are related to higher returns.

- **PUT:** Due to the typical high level of negative skewness in the return distribution of hedge funds, we include the CBOE S&P 500 Put Write Index as proposed by Bird et al. (2010) building on the work of Agarwal & Naik (2000); Mitchell & Pulvino (2000) and Lo (2001). The S&P 500 Put Write Index is a measure for the *risk premium* received for the *exposure to tail events*.

- **MT:** The *market timing factor* $(r_m - r_f)^2$ will investigate whether hedge fund managers exhibit a market timing ability (Gupta et al., 2003). Research shows that for traditional asset classes, such as mutual funds, this ability is rather unlikely (Kon, 1983; Chang & Lewellen, 1984; Henriksson, 1984; Friesen &

Sapp, 2007). The academic literature for the market timing ability of hedge fund managers is twofold (see Fung et al., (2002); Cerrahoglu et al. (2003); and Chen and Liang (2007)). The inconclusive findings give rise to investigate the market timing ability of hedge fund managers in our conditional model.

2.5 INSTRUMENTS

The instruments presented below are crucial inputs for the conditional time-varying model and for creating our principal components. Although no academic paper has collectively tested the instruments chosen in this thesis, we believe that the chosen variables are good proxies for the general business cycle, as well as the current and future real economic activity.

- **TED**: The TED spread is an indicator of the *current* perceived *credit risk* in the general US economy. According to Frenkel et al. (2005) the TED spread is affected by: i) world political stability, ii) balance of trade, and iii) the US fiscal policy. It is a measure for the rate of return banks are charging over the risk-free T-bill rate when lending to other banks. Higher spreads show a lack of confidence combined with greater risk aversion in the interbank market. The higher the TED spread, the more likely banks perceive the risk that other banks will default. When the TED spread increases, investors prefer safe investments, since the increase is associated with an increase in default risk.

- **TERM:** In line with previous research (e.g. Harvey, 1988 or Estrella & Hardouvelis, 1991), we include the term spread, since we believe it contains information about the *future real economic activity* (future economic health) and future investment opportunities. (Petkova, 2006). The values for the term spread are typically high prior to business cycle troughs and low close to business cycle peaks (Fama & French, 1989).

- **DEFAULT:** The BAA – AAA credit spread is an indicator of the *current state of the economy*. It is used to proxy *(global) default risk* and *financing conditions*. The default spread can be regarded as a default premium investors require for investing in low(er) grade corporate bonds. Sharp increases in the default spread are usually an indicator of flights to quality, which are closely linked to decreases in the performance of various hedge fund strategies (Lowenstein, 2000).

- **GOLD:** We use the gold return as a proxy for *inflation* in the United States. We believe that an increase in inflation is linked to an increase in gold price.

- **VIX:** In line with Whaley's (2000), we include the VIX CBOE Volatility Index to measure the *market's perception of risk (investor fear).* VIX in fact measures the volatility of the US equity market and additionally, at least partially determines the amount of *liquidity* available in the market.

- **IND PROD:** Rather than using US GDP figures, which are only reported on a quarterly basis, we decided to include industrial productivity, a factor closely linked to the GDP but reported monthly, to proxy the overall market situation / business cycles in the US.

2.6 PERFORMANCE MEASURES

The following paragraphs will introduce two well-known performance measures, Jensen's alpha and the Sharpe ratio.

2.6.1 Jensen's Alpha

Michael Jensen (1968) introduced his performance index on mutual fund data. It is based on the CAPM and follows the same underlying assumptions (see part 2.3.1). The alpha is a measurement of abnormal returns and can be interpreted as a proxy for superior security picking skills of fund managers.

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) \quad (11)$$

$$\alpha_i = R_i - \left[R_f + \beta_i(R_m - R_f)\right]$$

2.6.2 Sharpe Ratio

William Sharpe introduced the Sharpe ratio, also called reward-to-variability ratio, in 1966. It is a measure of the risk premium for each unit of risk.

$$Sharpe\ Ratio = \frac{E(R_i)-R_f}{\sigma} \quad (12)$$

The main advantage of the Sharpe index is that it requires only a small amount of information. It is both applicable with systematic and idiosyncratic risks. According to López de Prado and Peijan (2004) one should be cautious when applying the Sharpe ratio on hedge fund data since it neglects the existence of third and fourth moments. Negative skewness and excess kurtosis are unfavourable to the investor and can inflate the Sharpe Ratio. For that reason we only report Sharpe ratios in the descriptive statistics part (4.1), but leave their interpretation to the reader.

2.7 STATISTICAL PROPERTIES

In order to be able to draw reliable conclusions from regression outputs and descriptive statistics, a solid knowledge of some basics in statistics is vital. When using the ordinary least squares method to estimate parameters, one should keep in mind that the OLS estimators are supposed to be BLUE (best linear unbiased estimator). If the tests reveal that the regression suffers from heteroscedasticity or autocorrelation, one needs to make adjustments in order to get a best linear unbiased estimator. If a biased estimator is incorporated in the regression, the confidence interval will shift, making hypothesis testing unreliable. One way to adjust for biased estimators is to use robust estimators. Another concept that should be carefully investigated is multicollinearity (all above Gujarati, 2006). Below, we will provide an in depth analysis of important statistical concepts

2.7.1 Skewness

When investigating the distribution of a data set, one needs to consider skewness. It measures the asymmetry of the probability distribution of a random variable. The value of the skewness can either be negative or positive. If the value is below zero it indicates that the left tail is longer, the opposite holds for positive skewness. By examining the skewness of hedge fund returns, an investor can analyse the distribution of past returns (Gujarati, 2006).

Definition:

$$\gamma_1 = E\left[\left(\frac{X-\mu}{\sigma}\right)^3\right] \quad (13)$$

where:

γ_1= Third standardized moment

X = Random variable

2.7.2 Kurtosis

Kurtosis measures the “peakedness” of the probability distribution of a random variable. One could also describe kurtosis in terms of how “fat” the tails are. High levels of kurtosis are associated with fat tails. Kurtosis is often referred to in terms of excess kurtosis, which is defined as the fourth moment around the mean divided by the squared variance minus 3.

Definition:

$$\gamma_2 = \frac{\mu_4}{\sigma^4} - 3 \quad (14)$$

where:

γ_2 = Excess kurtosis

In order for a probability distribution to be normally distributed, the kurtosis should be around three (excess kurtosis of zero). An excess kurtosis of zero gives a mesokurtic distribution. If a probability distribution demonstrates positive excess kurtosis, the distribution is said to be leptokurtic, if the excess kurtosis is negative, the distribution is platykurtic. A leptokurtic distribution has a higher peak around the mean and fat tails. Platykurtic distributions have lower peaks, are more spread around the mean and typically have thin tails (all above Gujarati, 2006).

2.7.3 Normality

In order to perform a statically valid test on the data set, returns should be normally distributed. The Jarque-Bera test for normality is widely used to investigate normal distribution. The test is based on the skewness and kurtosis parameters.

Definition:

$$JB = \frac{n}{6}\left(\gamma_1^2 + \frac{1}{4}\gamma_2^2\right) \qquad (15)$$

The JB test follows an asymptotic chi-square distribution with two degrees of freedom. When testing for normality we employ a 5% level of significance.

$$H_0: \gamma_1, \gamma_2 \neq 0$$
$$H_1: \gamma_1, \gamma_2 = 0$$

2.7.4 Heteroscedasticity

A regression is only unbiased if its residuals exhibit constant variance (homoscedastic residuals). If the random variables have different variances or show a systematic pattern, the regression might suffer from heteroscedasticity. The problem might occur both for time series and cross sectional data (Brooks, 2002). Several tests are applicable to detect the possibility of volatility clustering. We use the White's test for our dataset, since it makes a low number of assumptions about the distribution of heteroscedastic residuals (White, 1980). The general form of the test allows investigating the return distributions of hedge funds, which in general vary considerably among different strategies.

The below regression will illustrate the White test:

$$y_t = \beta_1 + \beta_2 x_{1t} + \beta_3 x_{2t} + \varepsilon_t \qquad (16)$$

We are interested in testing the residual (ε_t) for heteroscedasticity. According to the null hypothesis, the residuals are homoscedastic.

By running the auxiliary regression on the squared residuals, one obtains a new residual (v_t).

$$\hat{\varepsilon}_t^2 = \alpha_1 + \alpha_2 x_{1t} + \alpha_3 x_{2t} + \alpha_4 x_{1t}^2 + \alpha_5 x_{2t}^2 + v_t \quad (17)$$

where:

v_t is a normally distributed error term independent of ε_t

If $\alpha_2 = \cdots = \alpha_5 = 0$ the following relationship holds: $\hat{\varepsilon}_t^2 = \alpha_1 + v_t$.

From here we get:

$$\hat{\sigma}^2 = \frac{\sum \hat{\varepsilon}_t^2}{N-K} = \frac{\sum(\alpha_1 + v_t)}{N-K} = \frac{\alpha_1 N}{N-K} \quad (18)$$

where:

$\sum \alpha_1 = N\,\alpha_1$

α_1 is a constant

and $\sum \varepsilon_t = 0$

If all coefficients are equal to zero, the variance only depends on the constant and the error term. The regression is then said to be homoscedastic. If all coefficients are rejected from being zero, one can expect heteroscedastic error terms.

In order adjust for heteroscedastic residuals, White (1980) proposed a robust estimator, called “heteroscedastic-consistent covariance matrix estimator”.

$$E(\hat{\varepsilon}\hat{\varepsilon}') = diag(\hat{\varepsilon}_1^2, \hat{\varepsilon}_2^2 \ldots\ldots \hat{\varepsilon}_n^2) \quad (19)$$

where:

$\hat{\varepsilon}\hat{\varepsilon}' = \hat{\sigma}^2(n-k)$

The estimator $E(\hat{\varepsilon}\hat{\varepsilon}')$ can be derived from the general method of moments.

The “heteroscedastic-consistent covariance matrix estimator” is applied to our regressions when we observe a problem with heteroscedasticity. The estimator adjusts the p-values by making the residuals unbiased.

2.7.5 Multicollinearity

A multiple regression will suffer from multicollinearity if two or more variables are highly correlated,. The high correlation between two variables generates a systematic dependency between the affected variables, which could lead to spurious regression results. According to Westerlund (2005) a correlation exceeding 80% suffers from a multicollinearity problem. In order to detect this problem within regressions, we will present a correlation matrix between all our independent variables and instrumental variables. To correct the regression from a problem with multicollinearity, the most prominent way is to exclude the variable exhibiting the highest level of correlation.

2.7.6 Autocorrelation

In order to obtain a regression that is BLUE, the residuals need to be independent of each other. Autocorrelation describes the correlation between observations over a certain period of time. The serial correlation violates the OLS assumption of time independent residual and creates an unreliable hypothesis test. To examine the existence of autocorrelation one can use the Durbin-Watson test.

$$d = \frac{\sum(\varepsilon_t - \varepsilon_{t-1})^2}{\sum \varepsilon_t^2} \qquad 0 \leq d \leq 4 \qquad (20)$$

As rule of thumb, if the Durbin-Watson statistics is below one, the regression is said to suffer from positive autocorrelation. A test statistic exceeding three shows negative autocorrelation.

3. METHODOLOGY

In this chapter, we introduce the empirical methodology used. After providing a brief motivation, we describe the general method of work, collection of data and specify the construction of the chosen risk factors and instruments. In addition, potential biases of hedge fund return data / indices will be closer analysed. The chapter finishes with a short discussion on the limitations of our research.

3.1 MOTIVATION

The aim of this thesis is to evaluate how different hedge funds (hedge fund indices) perform during different economic environments. Specifically, we are interested in investigating which risk factors influence returns and whether hedge fund managers are able to earn positive abnormal returns. We use quantitative data, empirically testing well-known frameworks and a newly proposed conditional model using principal components. This gives our thesis a *descriptive character*. To capture crucial features of our dataset, we use a *deductive approach* by analysing our problem under various different hypothesis and models. We believe that with the help of our hypotheses we are able to prove real events.

3.2 GENERAL METHOD OF WORK

In a first step we obtained monthly (return) data for dependent, independent and instrumental variables from various data sources. The time period chosen consists of 168 monthly observations (February 1997 - January 2011). Since we are interested in investigating abnormal hedge fund returns during market bubbles and economic crises we chose this specific period in order to capture both the IT and US real estate bubble and the crises that occurred thereafter. The period chosen is divided into four subperiods (Period I: IT bubble (Feb 1997 - Aug 2000), Period II (Sep 2000 - Feb 2003), Period III: US real estate bubble (Mar 2003 - Oct 2007), Period IV (Nov 2007 - Jan 2011). The chosen subperiods are linked to the S&P 500 price movements (indicator of the overall market) as shown in *Figure 3.1* on the next page.

After collecting our (secondary) data we transformed all variables but the default spread, term spread, TED spread and the VIX CBOE Volatility Index into logarithmic returns and then ran several regressions using OLS. The factor models include the traditional CAPM, the Fama-French Three-Factor model, as well as a conditional time-varying model using principal components. For each model, we additionally tested for autocorrelation and heteroscedasticity. To adjust for heteroscedasticity, we employed the "heteroscedastic-consistent covariance matrix estimator." The regression results and descriptive statistics will be presented in part four.

Figure 3.1: S&P 500 Closing Prices (Jan 1997 – Jan 2011)

3.3 DATA

The data used in this thesis stems from various sources. They include the Edhec Risk Institute, which provides monthly return data (net of fees) for 13 different hedge funds strategies since January 1997. The returns provided on Edhec's website are indices tracking the global hedge fund industry. Despite the fact that the indices presented are so-called *non-investable indices*, they are highly representative and easily replicable. While the stated returns of (non-investable) indices might in general not be realizable due to various biases inherent in hedge fund data (see part 3.3.1), the Ehdec Risk Institute reduces those biases by creating a set of alternative indexes, which are *indexes of indexes.* "[By construction], these indices [are] less biased than the indexes they contain. Since the competing indexes are affected differently by biases, searching for the linear combination of competing indexes that implies a maximization of the variance explained (around 80%), leads to a minimization of the biases" (Amenc et al., 2003, p.10). We therefore assume that the return data used in our dataset is highly representative and virtually free of biases. Other data sources include the Kenneth R. French data library, the U.S. Federal Reserve, the Chicago Board Options Exchange (CBOE) as well as Thomson Reuters Datastream.

Below, we will show both the sources and construction of our risk factors and instruments.

RISK FACTORS

- **MKT:** The market factor MKT (r_m - r_f) is the excess return on the market obtained from the Kenneth R. French data library. It is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from the CRSP database) minus the one-month Treasury Bill rate (from Ibbotson Associates).

- **SMB:** The Fama-French (1993) factor is constructed by forming six value-weighted portfolios on size and BE/ME. SMB is the average return of the three small portfolios minus the average return on the three big portfolios.
  SMB = 1/3(Small Value + Small Neutral + Small Growth) – 1/3(Big Value + Big Neutral + Big Growth).
  Data is collected from the Kenneth R. French data library.

- **HML:** The Fama-French (1993) factor is the average return of the two value portfolios minus the average return on the two growth portfolios.
  HML = 1/2(Small Value + Big Value) – 1/2(Small Growth + Big Growth).
  The data can be found on the Kenneth R. French data library.

- **PUT:** The S&P PUT Write index strategy introduced by the Chicago Board of Exchange (CBOE) is highly negatively correlated with *left tail events* (Bird et al. 2010). It sells a sequence of one-month at-the-money S&P 500 puts and then invests the proceeds in one- and three-month Treasury Bills. Data can be collected from the CBOE Website.

- **MT:** In order to test the *market timing ability* of hedge funds, we employ Treynor and Mazuy's (1966) measure by including a quadratic term $(r_m – r_f)^2$ in the market excess return. The authors argue that if a fund manager exhibits forecasting ability, the portfolio's return will not be linearly related to the excess market return. Rather, they claim that returns are a convex function of the market returns, since managers having a market timing ability are expected to earn higher returns than the market when the return on the market is expected to rise and lose less than the market when markets are forecasted to decline.

INSTRUMENTS

- **TED:** The TED spread is calculated by subtracting the 3-month T-Bill rate from the 3-month USD LIBOR rate. Data can be obtained from the Federal Reserve website.

- **TERM:** The Term spread is measured by taking the differences between the yields of the 30-year and 3-month US treasuries. Data is available on the US Federal Reserve homepage.

- **DEFAULT:** The default spread can be calculated by subtracting Moody's Seasoned Aaa Corporate Bond Yield from Moody's Seasoned Baa Corporate Bond Yield. The included bonds have remaining maturities close to 30 years. Moody’s removes bonds once the maturities fall below 20 years, the rating changes or if the bond is subject to redemption. The bond yields are collected from Moody’s Investor Services, accessible on the homepage of the Federal Reserve.

- **GOLD:** The data for the monthly average USD price of a LBM Gold Bullion per troy ounce can be obtained from Datastream. This index shows the performance of gold prices over time per troy ounce, which is a weight measure for precious metals.

- **VIX:** The theoretical foundations underlying the VIX CBOE Volatility Index are rather technical and out of the scope of this paper. The index is basically constructed by using a weighted average of the implied volatilities of eight OEX calls and puts with an average time to maturity of 30 days (Amenc et al. 2002). Historical data can be found on the CBOE website.

- **IND PROD:** Data on US industrial productivity is reported monthly and can be found on the Federal Reserve homepage.

3.3.1 Potential Biases

In order to be able to conduct empirical testing, one requires return data for a large number of hedge funds with different strategies. Historically, it has been quite difficult to retrieve unbiased data on the performance of hedge funds. As stated by Lo (2001) hedge fund data suffers from an extensive amount of problems and biases. It is hard to measure a fund's exposure towards liquidity and credit risk, since their environment is hardly regulated. It is difficult to establish a meaningful and reliable benchmark due to the lack of transparency and regulation. The most commonly used benchmark when conducting one factor analysis is the risk-free rate. Hedge funds are dynamic investments and are exposed to a multi dimensional risk universe. Taking this as a starting point, one can question whether the risk-free rate is an appropriate benchmark for empirical testing of hedge fund data. In order to acknowledge and overcome the inaccuracy of the risk free rate as a benchmark, indices are widely used.

Even though the indices are a more precise tool when testing theory in practice, the method still suffers from a number of problems. The indices available are composed from different data and develop at different paces (Edhec, 2011). When only considering individual indices, one might face heterogeneity problems leaving the investors with unreliable results. The data used in this thesis handles that problem by combining a large number of indices to arrive at a more precise benchmark. The benchmarks are called *Edhec alternative indexes* and have the advantage of capturing a very large fraction of the information of “unadjusted” indices without suffering from major heterogeneity problems.

Investors should be aware of the problem of *time biasedness,* which often prevails in return estimates. Disclosure of return data in the hedge fund industry typically only occurs a few weeks after the end of a month. This lenient approach leaves room for hedge fund managers to publish fund performance relatively late. *Time biasedness* might potentially create an inaccurate index that can reduce the explanatory level of empirical tests. To overcome this bias some hedge funds have decided to post preliminary returns at an earlier stage. The alternative indexes used in this thesis handle the lack of timeliness in that manner and so create a more reliable index.

Fung and Hsieh (2000) as well as Malkiel and Saha (2005) discuss four additional types of biases associated with the testing of empirical hedge fund data: *i) survivorship bias*, *ii) backfill bias*, *iii) selection bias* and *iv) multi period sampling bias*.

Survivorship bias means that non-surviving funds are excluded when compiling data. Malkiel and Saha (2005) claim that without correcting for survivorship bias, returns will be overestimated by approximately 3%. To handle this problem, the return data used in this thesis are Edhec indices that do not allow for retroactive adjustments (Edhec, 2011). The number of hedge funds accounted for in the indices varies over time, since funds that close during the investigated period will be kept in the sample for the period they were “alive”.

In the same way the Edhec indices adjust for *backfill bias*. *Backfill bias* is related to *survivorship bias* and occurs when the data set is complemented with new return data as some hedge funds get closed down or merge within the observed time period. It is common that a fund manager will allow a poor performing fund to get closed down or merged in order to hide the negative impact of the total fund performance. The data set used in this thesis adjusts for this bias by only including hedge funds in the indices that disclose sufficient information. According to Edwards & Caglayan (2001) a biased and unadjusted data set is overrated by approximately 1% due to the backfill bias.

A *selection bias* might be present in hedge fund data due to the lack of regulation within the industry. Fund managers have the opportunity to disclose information infrequently. Therefore, in many cases, managers only report results when their fund is performing well, making evaluation for investors impossible and at the same time causing biases in stated returns. Edwards & Caglayan (2001) report evidence on the topic of the *selection bias* stating that successful hedge funds do not disclose any relevant information as they are already closed to new investors. This in turn might lead to an underestimation of performance when compiling hedge fund data into indices. Fung & Hsieh (2000) take a neutral position and argue that it is impossible to predict the effect of the *selection bias*, since it could affect returns both positively and negatively.

Another bias that might affect our data is the *multi sample bias*. For empirical testing, it is important that the data is reliable and can be used for future predictions. Hence, one should exclude data from hedge funds that only started reporting recently. In some cases, a newly created fund might suffer from so-called “childhood diseases”, which could affect the predictive value of the test. Ackermann et al. (1999) argue that 24 months of sufficient return data is required in order to draw reliable conclusions from empirical testing. Our data is not adjusted for the *multi sampling bias*, a fact that we have decided to disregard in accordance with Fung and Hsieh (2000), who conclude that the *multi sampling bias* hardly has any effect on average returns.

3.3.2 Limitations

In the following, we will list several limitations of our research.

Average Returns

One potential limitation is the usage of average returns. Since the nature of hedge funds is extremely dynamic, two hedge funds within the same strategy might be differently exposed to the same risk factor. Combining different hedge funds of the same strategy into an index might hence create biased average returns. In addition, the observed abnormal returns might be inaccurate since we force all funds within the same strategy to have identical factor loadings.

Non-investable indices

Using indices as a proxy for the average return within a certain strategy is beneficial in the sense that it minimizes potential biases. At the same time, the indexes provided from the Edhec Risk Institute are *non-investable indices*. One might argue using non-investable indices is not representative, given that investors cannot directly invest in these indices. We neglect this problem for two obvious reasons. We believe that the advantage of using unbiased return data by large offsets the non-investable nature of our indices. In addition, the indices presented in this thesis are easily replicable (Edhec, 2011).

Number of instruments

The conditional model used in this thesis is based on two instrumental variables. These two principal components are created from six business cycle proxies. When examining the principal components, one can conclude that they do not capture 100% of the variance in the original variables. Given the substantial number of variables we would obtain from adding further principal components, we limit this thesis to two instrumental variables.

Monthly Data

All data used throughout this thesis is monthly data. It would have been optimal to use daily or weekly observations instead, since they capture more information in the variance covariance matrix. However, given the fact that weekly/daily observations for the hedge fund return indices and several of the instruments and independent variables chosen were not observable, we decided to use monthly data.

Period IV – Crisis & Recovery

When dividing the scope of our thesis into different time periods we aimed to classify periods into either bullish or bearish market environments. At least 30 observations are needed in order to obtain valid statistical results. The recent financial crisis was one of the most severe crises for decades affecting the global economy at large. The trough of the financial crisis was reached quickly, and the recovery phase set in before the financial crisis had lasted for 30 consecutive months. For this apparent reason, we needed to include some observations capturing the after-crisis global recovery period. As a result, subperiod IV is not entirely exposed to bearish market conditions.

4. EMPIRICAL FINDINGS & DISCUSSION

In the following chapter, the empirical findings of the three different asset-pricing models employed will be introduced and discussed thoroughly. The chapter begins with an analysis of the descriptive statistics throughout the different time periods, before we will closer investigate multicollinearity, the CAPM and Fama-French Three-Factor model. The last part is devoted to examining the chosen principal components and our conditional time-varying model.

4.1 DESCRIPTIVE STATISTICS

The purpose of this chapter is to describe the descriptive statistics of the return data for the different hedge fund strategies. The scope of our thesis stretches over two bull periods and two bear periods. The first part of this chapter investigates the overall period, the second part the bullish periods and the last part covers the bearish periods.

Entire Period – Feb 1997 - Jan 2011

In our sample, the average hedge fund performs about twice as well as the equity market during the entire time period. As a proxy for the equity market we use the S&P 500 index, which yields a monthly average return of 0.326% compared with the average return of 0.668% of our hedge fund universe. According to the mean-variance theory, the portfolio yielding the highest return and the lowest variance dominates all other portfolios. The standard deviation reveals that the average hedge fund faces a lower systematic risk than the well-diversified equity index. These findings contradict the capital asset pricing model on the grounds that a higher return can theoretically only be achieved by taking larger risks.

Style	Aver. Return	Std. Dev	Skewness	Kurtosis	J-B	Sharpe-Ratio	Cumul. Returns
Convertible Arbitrage	0.703%	0.020	-2.681	19.486	2116.349	0.233	118.78%
CTA Global	0.642%	0.025	0.123	2.798	0.711	0.152	105.80%
Distressed Securities	0.869%	0.018	-1.587	8.998	324.244	0.337	146.21%
Emerging Markets	0.863%	0.037	-1.276	8.389	250.326	0.165	145.93%
Equity Market Neutral	0.584%	0.009	-2.671	20.515	2361.070	0.385	98.68%
Event Driven	0.805%	0.018	-1.687	9.000	333.729	0.309	136.05%
Fixed Income Arbitrage	0.492%	0.014	-3.641	22.938	3172.644	0.177	83.17%
Funds Of Funds	0.581%	0.018	-0.467	6.461	90.474	0.189	98.27%
Global Macro	0.757%	0.017	0.808	4.823	41.778	0.308	127.96%
Long/Short Equity	0.788%	0.022	-0.395	4.169	14.014	0.247	133.25%
Merger Arbitrage	0.671%	0.011	-1.663	9.163	345.349	0.394	113.41%
Relative Value	0.695%	0.013	-2.087	12.179	715.961	0.347	117.46%
Short Selling	0.228%	0.054	0.619	5.339	49.322	-0.004	38.61%
S&P 500	0.326%	0.049	-0.809	4.068	26.464	0.009	55.17%
Average of all Hedge Funds	**0.668%**	**0.021**	**-1.277**	**10.328**	**755.075**	**0.249**	**112.58%**

Figure 4.1: Summary Statistics – Total Period (Feb 1997 – Jan 2011)

The category Average of all Hedge Funds does not incorporate the market index (S&P 500)

It should be mentioned that the only hedge fund style yielding similar returns than the S&P 500 is *short selling*. The seemingly low performance of *short selling* most probably has its roots in its close links to the equity market. This style in general is highly negatively correlated with the market index. Since our time period includes two very distinct economic cycles, the similar returns and standard deviations of both the S&P 500 and short selling strategy seem plausible.

The distribution of hedge fund returns shows an unfavourable picture for investors. The average skewness of -1.277 is not beneficial to the investor since the left tail is predominantly larger than the right one. Investors prefer positive skewness because returns are limited on the downside and there exist potential of earning extremely high returns. All styles of hedge funds, but three, demonstrate a negative skewness. The fixed income arbitrage strategy shows the highest negative skewness (-3.641), which is in accordance with theory. The strategy is known for “picking up nickels in front of a steamroller.” It usually creates relativity small returns, but at the same time has a potential of creating huge losses (Duarte et al., 2007). The *short selling* strategy unlike the other styles exhibits a positive skewness for the overall period. The larger right tail could be viewed as a compensation for the rather low average returns where the investor benefits from having the opportunity of gaining high returns. The overall excess kurtosis demonstrates a leptokurtic distribution, which is not favourable for the investor. The only style with (almost) normally distributed returns is *CTA global*.

The Jarque-Bera Test is based on both skewness and kurtosis. The critical value at 5% significance is approximately 5.99. Due to the extreme test statistics we observe, the test for normality is proven to be non-significant, for all but *CTA global*. The result is not just a proof for the non-normal distribution of hedge funds, but also could be seen as evidence that the time period investigated might be too long and should be segregated into bullish and bearish market environments.

Bullish Market Environments: Period I & III

By looking at *Figure 7.1* and *7.3* provided in the appendix, one can conclude that the *average monthly return* is higher for the S&P 500 (Period I: 1.53%, Period III: 1.091%) than for the average hedge fund during bull markets (Period I: 0.923%, Period III: 0.734%). The third period, also the longest period with 56 observations, demonstrates an average return only slightly above the total period average (0.668%). It seems that hedge funds on average are yielding lower returns (as compared to the S&P 500) during bullish market environments.

By taking a closer look at the different styles, *long/short equity* has a very specific pattern. The strategy shows the highest returns among all in Period I (1.644%) and also has one of the highest returns in Period III (1.087%). The style is (theoretically) supposed to balance the price movements of the equity market by going long in undervalued securities and short in overvalued securities. Hence, it seems that hedge fund managers are better able to detect the intrinsic value of a security during economic boom periods. The *short selling* strategy in contrast exhibits extremely low (in Period III even negative) results as compared to the other styles. The pattern where *long/short equity* yields high returns whereas *short selling* earns low returns is in line with Sadek's (2010) findings. He states that *directional* strategies in general are more risky than other styles due to their high exposure to overall market fluctuations. Our dataset shows the same results. *Directional* styles yield the most extreme results. According to Fry (2008) the *distressed securities* strategy is supposed to have lower returns during bull periods. These findings cannot be observed in our dataset. *Distressed securities* yield one of the highest returns during the third period (1.244%) and exhibit an average return of 0.888% during the first period. One can argue that it seems more plausible to invest in distressed companies during bull markets since the probability of a successful restructuring is much higher during favourable market climates. The *relative value/arbitrage* strategies are all performing as expected with returns close to the average return of the hedge fund universe.

The *standard deviation* varies significantly between the two bull periods. The average risk is about twice as high in the first period (0.024) as compared to the third period (0.013). One should take into consideration that the third period is the longest and the observations might hence have a smoothing effect on the hedge fund variance. By examining the S&P 500 chart *(Figure 3.1)* one can conclude that the first period is characterized with more extreme swings than the third period. The fact that hedge funds (on average) are unable to outperform the S&P 500 during the two observed bull periods could be explained by their rather low standard deviations. The theory underlying the CAPM is applicable for boom periods in our empirical data (Markowitz, 1952). The less risk an investor is willing to take, the lower will be the expected returns. Looking at the descriptive statistics tables *(Figure 7.1* and *7.3)* investing in the S&P 500 is riskier (variance Period I: 0.049, Period III: 0.043) than investing in the average hedge fund. Nevertheless, in line with theory, the higher risk exposure also yields a higher return.

When examining *normality* during bull periods, one can observe high variations in return distributions during the first and the third period. During the first period the distribution of the hedge fund universe exhibits a low level of skewness and a high level of excess kurtosis, jointly causing an extremely high Jarque-Bera value. The observations during the first period are non-normally distributed. The only strategy exhibiting a normally distributed pattern is the *CTA global*. This strategy focuses on commodities, which by nature are more stable under market fluctuations than other derivatives and traditional investments. This reasoning might explain the normally distributed residuals. Overall, the skewness of the hedge fund universe is lower in period III then in period I.

Bearish Market Environments: Period II & IV

The second period is categorized by the burst of the dotcom bubble, which led to a deep depression of the global economy. The fourth period includes the crash of the US real estate bubble causing a worldwide recession, as well as the beginning of the after-crisis recovery until January 2011. Not surprisingly, due to the magnitude of the most recent financial crisis, the average monthly return is more than twice as high during the second period (0.636%), as compared to the fourth period (0.264%). For more detailed information see *Figure 7.2* and *7.4*. In both bear periods, the average hedge fund outperformed the equity market proxy by far (Period II: -1.967%, Period IV: -0.477%). Our empirical data supports the findings of Malkiel and Saha (2005) who conclude that hedge funds are good diversifiers in bearish market conditions. One interesting observation worth mentioning is that the S&P 500 performed worse in the period after the burst of the *dotcom bubble* than during the *subprime crisis*. The opposite is true for average hedge fund returns. One reason why the fourth period might demonstrate a higher average return for the S&P 500 than the second period is that period four covers a part of the recovery phase of the most recent crisis.

The best performing hedge fund strategy during the bear periods is *CTA global*. This finding is in accordance with Lowenstein (2000) who describes “a flight to quality” during market downturns. When the economic environment is very volatile investors tend to shift their investments to e.g. precious metals, such as gold or other commodities. As stated earlier, the *directional strategies* tend to have a volatile nature. This phenomenon can be observed during the two bear periods, where the *long/short equity* strategy exhibits a return well below the average (Period II: -0.259%, Period IV: 0.170%). This could be viewed as additional evidence that it might be more difficult to detect the under/overvalued securities during bear periods. *Short selling* performed differently well during the burst periods. In the aftermath of the burst of the dotcom bubble the strategy outperformed all the other strategies by exhibiting a remarkably high average return (2.582%). According to Dass et al. (2008) fund managers benefited most from following a contrarian strategy during the dotcom hype, which would explain the extraordinary high return during the second period. However, the fourth period does not follow the same pattern. This could be due to the imposed restriction on short selling after the crash of Lehman Brothers as well as due the negative publicity hedge funds were exposed to after the Northern Rock demise (Clifton & Snape, 2008). The low returns of the *short selling* strategy could also be due to the fact that our fourth period covers the subprime crisis, as well as a part of the economic recovery. Since *directional strategies* are generally known for being affected by fluctuations in the market environments, a period that is characterized by both a heavy crash and recovery might provide unreliable results for strategies such as *short selling*.

The *standard deviation* for the hedge fund universe appears to be higher during the fourth period (0.025) as compared to the second (0.017), a fact we consider as an additional support for the theory that the recent crisis was the most severe during the past decades. The *distribution* within the two bearish periods exhibits major differences. The fourth period demonstrates a high level of *non-normality* on average, mainly due to the high levels of excess kurtosis within the *relative value/arbitrage* strategies. Those strategies intend to find mispricing between related securities. The *leptokurtic* distributions might be caused by unpredictable market conditions during the recent financial crisis.

Multicollinearity

In order to rule out a possible problem of multicollinearity, we examine the correlation between our variables. Independent variables are said to suffer from a systematic dependency if their correlation exceeds 80%. *Figure 4.2* and *4.3* show that neither our independent, nor instrumental variables are highly correlated. We can therefore safely rule out a problem of multicollinearity.

	MKT	SMB	HML	MOM	MT	PUT
MKT	1					
SMB	0.25	1				
HML	-0.23	-0.36	1			
MOM	-0.30	0.10	-0.16	1		
MT	-0.35	-0.12	0.04	0.00	1	
PUT	0.62	0.18	0.05	-0.26	-0.49	1

Figure 4.2: Correlation – Independent Variables

Problem of multicollinearity if correlation >0.8

	DEFAULT	TED	TERM	GOLD	VIX	IND PROD
DEFAULT	1					
TED	0.55	1				
TERM	0.42	-0.08	1			
GOLD	0.08	0.04	0.06	1		
VIX	0.59	0.53	0.25	0.01	1	
IND PROD	-0.46	-0.35	-0.04	0.11	-0.24	1

Figure 4.3: Correlation – Instrumental Variables

The correlation determines the number of principal components needed in order to obtain a high explanatory level of the information in the variance/covariance matrix

4.2 CAPM

In a first step we are interested in investigating whether abnormal returns can be obtained by running an OLS regression using the traditional CAPM. As shown in part 2.3.1 the CAPM is estimated with the following econometric model:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_t \quad (2)$$

Heteroscedasticity & Autocorrelation

A crucial step before closer analysing Jensen's alpha, the market beta or the goodness of fit is to test for *autocorrelation* and *heteroscedasticity*. The Durbin-Watson test statistic is used to test for autocorrelation. A rule of thumb for serial correlation is a test statistic below 1 or above 3. Since only one of our hedge fund indices, *distressed securities* shows some signs of positive autocorrelation (0.973) in Period I, we can safely neglect a problem of autocorrelation. In addition, we are interested whether our error terms follow a certain pattern, hence are heteroscedastic. To test for heteroscedasticity, we employ the White test, which rejects homoscedasticity if the p-value is below 5%. In the first time period observed, we detect a few hedge fund indices reporting a p-value below 5%, in the other time-periods hardly any fund shows signs of heteroscedasticity. In order to overcome the problems of heteroscedasticity, we reran all regressions displaying problems with heteroscedasticity by using White's "heteroscedastic-consistent covariance matrix estimator." *Figure 7.5* (see appendix) shows the detailed CAPM regression outputs for the four different time-periods including the test statistics for the White and Durbin-Watson test.

Regression Results & Discussion

Figure 4.4 shows that during the first three periods a substantial amount of hedge fund indices was able to yield abnormal returns. During the first period, six funds have significant positive abnormal returns. In period II eight funds are able to yield positive alphas (of which two are only significant at 10%). In period three, all but three hedge funds show abnormal returns, whereas in period four only two funds have positive alphas at 5% and 10% significance. It is interesting to realize that no individual fund is able to yield significant alphas throughout all subperiods.

	Period I (Feb 97 - Aug 00)			Period II (Sep 00 - Feb 03)			Period III (Mar 03 - Oct 07)			Period IV (Nov 07 - Jan 11)		
	Intercept	Beta	Adj. R2	Intercept	Beta	Adj. R2	Intercept	Beta	Adj. R2	Intercept	Beta	Adj. R2
Convertible Arbitrage	0.006***	0.065*	0.053	0.007***	0.041	0.010	0.000	0.144***	0.118	0.005	0.383***	0.479
CTA Global	0.001	-0.017	-0.023	0.004	-0.282***	0.234	-0.005	0.551***	0.312	0.005	-0.011	-0.026
Distressed Securities	0.001	0.272***	0.440	0.006**	0.090**	0.102	0.007***	0.267***	0.418	0.004	0.329***	0.634
Emerging Markets	-0.007	0.737***	0.507	0.008**	0.389***	0.562	0.009***	0.470***	0.346	0.000	0.540***	0.704
Equity Market Neutral	0.005***	0.095***	0.426	0.003***	0.006	-0.025	0.002***	0.089***	0.197	0.000	0.099***	0.217
Event Driven	0.003	0.310***	0.549	0.004*	0.171***	0.447	0.005***	0.329***	0.558	0.003	0.311***	0.698
Fixed Income Arbitrage	0.000	-0.010	-0.023	0.004***	0.002	-0.035	0.002***	0.060**	0.087	0.003	0.242***	0.477
Funds Of Funds	0.004	0.336***	0.527	0.001	0.127***	0.487	0.002*	0.266***	0.387	-0.002	0.304***	0.552
Global Macro	0.002	0.278***	0.372	0.005*	0.058	0.035	0.002	0.285***	0.308	0.003*	0.137***	0.351
Long/Short Equity	0.007***	0.382***	0.640	0.000	0.283***	0.804	0.003**	0.462***	0.641	0.001	0.365***	0.766
Merger Arbitrage	0.006***	0.161***	0.399	0.001	0.074**	0.165	0.002***	0.197***	0.404	0.003**	0.126***	0.572
Relative Value	0.005***	0.109***	0.296	0.005***	0.155***	0.594	0.003***	0.201***	0.480	0.003	0.264***	0.684
Short Selling	0.012*	-1.219***	0.642	0.004	-0.990***	0.863	0.003*	-0.973***	0.812	-0.002	-0.630***	0.868

Note: ***, **, * significant at 1%, 5%, 10% respectively

Figure 4.4: Summarized CAPM Regression Output

$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_t$

Only the *relative value* strategies, *equity market neutral* and *relative value,* are able to yield significant positive alphas (at 1% significance) throughout the first three periods. Interestingly, but not surprisingly, we only observe one significant alpha (0.2%) for *funds of hedge funds.* This is probably due to the double fee structure (indirectly paying numerous fund managers). The realized alphas in periods I to III range from 0.2% to 0.9% and differ across styles over time. Only time period IV shows a different pattern with only two significant alphas (both 0.3%). *Short selling* yields the highest abnormal return of 1.2% per month in period I.

With the original idea of a hedge fund in mind, one would expect the betas to be (close to) zero, since a hedge fund by definition should perform equally well in market upswings and downturns. In reality however, it is obvious that a beta of zero is very unlikely, if not impossible to observe. Throughout all subperiods, almost all strategies have significant betas. The factor loadings vary substantially from -1.219 for *short selling* in period I to 0.737 for *emerging markets* (also period I). The *equity market neutral* strategy has the lowest observed beta coefficients in line with theory aiming for a beta neutral approach, the betas range from 0.089 – 0.099. The factor loadings for *fixed income arbitrage* are also expected to be close to zero. However, we can only observe one low significant beta (0.060) in period III.

When comparing different strategies over time and looking for a pattern in factor loadings, some findings are worth mentioning. *Event driven* strategies, such as *event* *driven*, *distressed securities* and *merger arbitrage* are able to keep their individual exposures in the bullish periods. The same holds for *global macro*. Interestingly, the factor loadings for the strategies *event driven* and *equity market neutral* are persistent in time periods I, II and IV. *Short selling* is the only style with statistically significant negative factor loadings throughout the entire time period. The coefficients are diminishing over time (period I: -1.219, period IV: -0.630). The negative loadings are in line with theory since this strategy is highly negatively correlated with the overall (equity) market (see part 4.1). In contrast with the persistent pattern of *short selling*, *fixed income arbitrage* is the only style following a random pattern over time.

Keeping in mind that the CAPM is a static model with only one risk parameter, the R^2 and adjusted R^2 values differ substantially across styles and over time. The adjusted R^2 values range from -0.026 (*CTA global*) to 0.868 (*short selling*). Overall, we can conclude that the CAPM is unable to capture the variability in returns of the different hedge fund indices equally well. The adjusted R^2 values for *convertible arbitrage* for instance are around 0.08 (period I to III). *Event driven*, *funds of funds* and *long/short equity* in contrast are the only styles yielding similar goodness of fit results throughout all periods (around 0.55, 0.50 and 0.70 respectively). The CAPM seems to be applicable for *short selling*, providing adjusted R^2 values above 0.8 for periods II to IV. In general, it seems that the highest goodness of fit can be achieved for strategies closely linked to the equity market (e.g. *short selling* and *long/short equity).*

Research has shown the inadequacy of static single factor models such as the CAPM in explaining hedge fund returns. Hedge funds follow dynamic strategies and are exposed to multiple risk sources for instance default risk, volatility risk or liquidity risk (Edhec, 2011). Investors should therefore be rewarded with multiple risk premiums.

Keeping the above reasoning in mind and now looking again at our alphas should give rise to a critical evaluation of the observed abnormal returns. An intercept of for instance 0.8% (per month) could very well mean that liquidity, default, volatility or any other risk source, not accounted for in the CAPM could have a major impact on our regression results. After accounting for these factors, the alphas could very well be positive, zero, or even negative.

Overall, in line with Ackermann et al. (1999), we argue that (most) hedge funds are good diversifiers due to their low beta values and should hence be included in an investor's portfolio. Nevertheless, backed by our analysis and academic literature, we conclude that beta alone is not sufficient for explaining the variations of our dependent variable. Hence, the presented results should be interpreted cautiously.

4.3 FAMA-FRENCH THREE-FACTOR MODEL

We are now interested in investigating whether abnormal returns can be obtained by running the Fama-French Three-Factor model. This model builds upon the CAPM by including two additional risk factors. The Fama-French model has historically been able to outperform the capital asset pricing model. As shown in part 2.3.2 the model is estimated with the following econometric model:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t \qquad (3)$$

Heteroscedasticity & Autocorrelation

By examining *Figure 7.6* and *7.7* (see appendix), one can conclude that some of the regressions suffer from heteroscedasticity. During the first and last period this problem is most severe. We adjust for heteroscedasticity by employing the heteroscedastic-consistent covariance matrix estimator. Looking at the Durban-Watson statistics, none, but *distressed securities* exhibits problems with serial correlation.

Regression Results & Discussion

A first look at the below presented regression outputs *(Figure 4.5* and *4.6)* shows a large number of significant positive alphas for the bullish periods (I and III) and a small(er) number for the bearish periods. It should be mentioned that the detected significant abnormal returns are those strategies that already had significant alphas under the CAPM. The observed returns however, vary between the two different models. For the vast majority of alphas under the Three-Factor Model, the realized abnormal returns decrease, some remain the same and only a very few alphas slightly increase. This finding is in line with prior reasoning (CAPM part), since adding additional risk factors should increase the amount of variance explained, which in turn should reduce the level of abnormal returns.

The strategies exhibiting abnormal returns vary between time periods, only *relative value* succeeds in persistently yielding significantly positive intercepts throughout the entire scope of our investigation. This particular style belongs to the family *relative value/arbitrage* where the returns are least affected by changing market conditions. This assumption is further supported by the findings that three out of four strategies that provide significant abnormal returns during the second period are members of the *relative value/arbitrage family*. Like in the CAPM regression, *short selling* is the only strategy with a monthly abnormal return above one percent (period I). *CTA global* in contrast generates a significant negative intercept of -0.65% in period III

	Period I (Feb 97 - Aug 00)					Period II (Sep 00 - Feb 03)				
	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Adj. R2	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Adj. R2
Convertible Arbitrage	0.006***	0.114***	0.120***	0.149**	0.202	0.007***	0.015	0.068	-0.023	0.005
CTA Global	0.001	-0.036	-0.050	-0.058	-0.066	0.004	-0.373***	0.101	-0.135	0.232
Distressed Securities	0.002	0.346***	0.251***	0.255***	0.701	0.004*	0.045	0.168**	-0.021	0.259
Emerging Markets	-0.006	0.815***	0.347***	0.301	0.571	0.005	0.327***	0.336***	0.014	0.720
Equity Market Neutral	0.006***	0.107***	0.060***	0.050*	0.534	0.002***	0.020	0.036**	0.041**	0.208
Event Driven	0.003	0.374***	0.226***	0.224***	0.750	0.001	0.184***	0.175***	0.093**	0.653
Fixed Income Arbitrage	0.000	0.004	0.079	0.061	-0.027	0.003***	-0.014	0.051*	-0.011	0.028
Funds Of Funds	0.005***	0.324***	0.228***	0.070	0.790	0.000	0.098***	0.124***	-0.007	0.669
Global Macro	0.003	0.287***	0.138**	0.075	0.430	0.003	0.045	0.134**	0.028	0.122
Long/Short Equity	0.008***	0.333***	0.187***	-0.021	0.888	-0.002	0.296***	0.139***	0.08***	0.893
Merger Arbitrage	0.006***	0.212***	0.118***	0.152***	0.538	-0.001	0.122***	0.070*	0.120***	0.411
Relative Value	0.005***	0.143***	0.096***	0.109**	0.439	0.003***	0.166***	0.125***	0.070**	0.767
Short Selling	0.011*	-0.977***	-0.293**	0.364*	0.790	0.004	-0.825***	-0.216**	0.231**	0.906
Note: *, **, * significant at 1%, 5%, 10% respectively**										

Figure 4.5: Summarized Fama-French Regression Output – Period I & II

$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t$

	Period III (Mar 03 - Oct 07)					Period IV (Nov 07 - Jan 11)				
	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Adj. R2	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Adj. R2
Convertible Arbitrage	0.000	0.127**	0.051	0.106	0.123	0.005	0.484***	-0.012	-0.377*	0.558
CTA Global	-0.006*	0.569***	-0.012	0.184	0.302	0.007*	0.031	-0.251	0.004	-0.006
Distressed Securities	0.006***	0.223***	0.120**	0.220***	0.559	0.004	0.364***	-0.006	-0.130	0.636
Emerging Markets	0.008***	0.466***	0.031	0.000	0.338	0.001	0.652***	-0.158	-0.325***	0.763
Equity Market Neutral	0.002**	0.076***	0.042	0.107***	0.314	0.000	0.113***	0.056	-0.092	0.221
Event Driven	0.004***	0.272***	0.138***	0.151***	0.642	0.003	0.363***	0.000	-0.199***	0.746
Fixed Income Arbitrage	0.002**	0.087***	-0.041	0.096**	0.203	0.004	0.294***	-0.059	-0.158	0.504
Funds Of Funds	0.002	0.236***	0.079	0.117*	0.413	-0.002	0.306***	-0.072	-0.228***	0.668
Global Macro	0.002	0.296***	-0.002	0.144	0.317	0.004**	0.190***	-0.126	-0.122*	0.445
Long/Short Equity	0.003**	0.385***	0.172***	0.114*	0.692	0.001	0.431***	-0.02	-0.236***	0.828
Merger Arbitrage	0.002**	0.165***	0.078*	0.075	0.439	0.003**	0.159***	0.006	-0.131***	0.690
Relative Value	0.003***	0.174***	0.068*	0.091**	0.530	0.003*	0.313***	-0.008	-0.181**	0.740
Short Selling	0.002	-0.816***	-0.308***	0.095	0.858	0.001	-0.589***	-0.389***	0.096	0.907
Note: *, **, * significant at 1%, 5%, 10% respectively**										

Figure 4.6: Summarized Fama-French Regression Output – Period III & IV

$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t$

We observe a large amount of significant market beta values. Almost all significant market betas under the CAPM are also significant under the Fama-French model. Market betas vary widely across strategies and over time. *Short selling* once again provides beta values that are almost perfectly negatively correlated with the overall market. *Relative value/arbitrage* strategies yield the lowest market betas.

Eleven out of thirteen SMB coefficients are significant in the first two periods. All but *short selling* have positive factor loadings in line with theory (Fama & French, 1993). The exposures to size risk and hence the portion of investment into small (low ME) companies varies substantially. Throughout the first two periods, *emerging markets* has the highest exposure to size risk (around 0.340). In periods III and IV, both the amount of significant betas and the level of exposure to size risk declines. Bird et al. (2010) among others provide similar findings showing declining SMB factor loadings during the time period 1994 and 2009. During the last period, SMB exhibits negative factor loadings with only one significant coefficient. The lack of significant factor loadings during the subprime crisis could stem from largely distorted financial markets.

According to theory, value stocks are riskier and should hence yield higher returns (Fama & French, 1993). Therefore, we would expect positive factor loadings for HML. Throughout all periods around 50% of the investigated strategies have significant coefficients. Interestingly though, their exposure and sign depend on the overall market condition. Throughout positive market climates, the significant factor loadings are all positive, whereas in bearish times, the factor loadings are negative. It also appears that significant betas do not only change over time, but also among strategies. The most plausible explanation for the changing pattern during bull and bear periods is that the market perceives value stocks to be more risky than growth stocks. The high BE/ME ratio of value stocks can be interpreted as a signal that the market judges the prospects of the firm(s) to be rather poor. The uncertain/negative future outlook increases risk, which is magnified under bearish market conditions. Hence, the negative factor loadings on HML can be interpreted as a shift towards growth stocks. Subperiod IV shows the largest exposure towards growth stocks, which is not too surprising given the magnitude of the recent financial crises.

Before investigating the conditional time-varying model, we will briefly analyse the goodness of fit of the Fama-French model. As expected, and in line with theory stating that the CAPM suffers from numerous anomalies, the adjusted R^2 values are (much) higher as compared to the static one factor model. We only observe lower adjusted R^2 values for a very few strategies, nevertheless, the differences is marginal. The highest R^2 can be obtained for the *directional* strategies *short selling* and *long/short equity* (around 85% and 80% respectively), as well as for the style *event driven* (around 70%). The Three-Factor model seems unfeasible for the styles *fixed income arbitrage* (adj. R^2 period I: -0.027, period II: 0.028) and *CTA global*.

Overall, we can conclude that the multifactor model employed in this section is better in explaining the variation in returns than is the CAPM. Nevertheless, there are numerous other risk factors influencing hedge fund returns and their alphas. The time-varying model presented in the next section will tackle this issue.

4.4 PRINCIPAL COMPONENT ANALYSIS

Before we are going to investigate the findings of our conditional model, we will have a closer look at our principal components. In order to reduce the number of instrumental variables used in the conditional model, we implement a principal component analysis. As described in part 2.3.4, the principal components aim to minimize the number of variables by only losing a minimum amount of information in the variance/covariance matrix. By measuring the amount of variance explained by the principal components, one can determine how many orthogonal principal components to include.

Our instrumental variables (DEFAULT, GOLD, TED, TERM, VIX & IND PROD) aim to explain the swings in the business cycle and proxy the current/future economic outlook over time. One of the down sides of a time varying conditional model is that the number of parameters and factor loadings increases exponentially with the number of instrumental variables. Five independent variables in combination with six instruments would generate a regression with 35 variables. Such a large multiple-regression would most probably suffer from high in-sample variance, which would generate highly insignificant coefficients, yet at the same time overly high R^2 values. A model with such specifications can only provide erroneous conclusions. Pedahazur (1997) suggests that a statistical test should approximately have 15 times as many observations as variables. To obtain viable econometric results we limited the numbers of instrumental variables to a maximum of two principal components. By examining the data provided in *Figure 4.7*, one can conclude that our two principal components are not able to explain the total variance of our instrumental variables.

	DEFAULT	**TED**	**TERM**	**GOLD**	**VIX**	**IND PROD**
PC 1	79.64%	55.41%	13.15%	0.17%	62.62%	35.49%
PC 2	2.67%	12.58%	59.82%	26.38%	0.31%	14.86%
Sum	82.30%	67.99%	72.97%	26.55%	62.92%	50.35%

Figure 4.7: Explained Variance – Principal Components

The reason for not reaching values above 85% can be explained by a combination of the initially modest correlations (see *Figure 4.3*) among instrumental variables as well as due to the fact that we only include two principal components. In general, principal component analysis is mostly employed when variables are highly correlated (above 0.8). To capture the variance that is not included in the first two principal components, one could add a third principal component. However, given the earlier explained problem of adding too many instrumental variables, we decided not to include a third PC in order not to generate a too large number of conditional variables.

The first principal component captures a very large fraction of the variance in the default spread and the variables that it is highest correlated with, namely the TED spread and the VIX. The default spread, the ted spread and the VIX all increase during market instabilities. When market risk is high and liquidity is low, the spread between the Baa and Aaa corporate bond yields is high. At the same time, a high Ted spread, which is an indicator of the current perceived credit risk in the economy, demonstrates a lack of confidence combined with greater risk aversion in the interbank market (Frenkel et al., 2005). The spread is supposed to increase during crisis periods. The VIX measures the volatility of the US equity market, hence the market's perception of risk. During periods of market instability, volatility and therefore the VIX are high.
As *Figure 4.7* shows, the second principal component has the highest explanatory power for the term spread. This is somewhat surprising according to both our data and Fama and French's (1989) findings. The authors argue that the term spread is expected

be highest prior to business cycle troughs. One would expect the correlation to be high with other counter-cyclical instrumental variables.
One can safely conclude that neither the first nor the second principal component can capture a large fraction of the variance of the gold returns, our proxy for inflation. It is likely that a third principal component would have been able to capture the lost variance within the variable.

Lastly, looking at the cyclical instrumental variable industrial productivity, we can observe that the first principal component captures most of the explained variance. Like for gold, a third principal component might have been able to capture additional variance.

4.5 CONDITIONAL TIME-VARYING PARAMETER MODEL

This part is devoted to the investigation of whether positive alphas can be observed under our conditional time-varying parameter model. This model adds two additional risk factors, market timing and the PUT index, as well as five instrumental variables. The instrumental variables, proxies for the business cycle and the current/future economic outlook are combined in two principal components. As shown in part 2.3.3 the model is estimated with the following econometric model:

$$
\begin{aligned}
&r_{it} - r_{ft} = \alpha_{i0} + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}PUT_t + \beta_{i5}MT_t + \\
&\beta_{i6}\left[PC1_{t-1}(r_{mt} - r_{ft})\right] + \beta_{i7}[PC1_{t-1}SMB_t] + \beta_{i8}[PC1_{t-1}HML_t] + \\
&\beta_{i9}[PC1_{t-1}PUT_t] + \beta_{i10}[PC1_{t-1}MT_t] + \beta_{i11}\left[PC2_{t-1}(r_{mt} - r_{ft})\right] + \\
&\beta_{i12}[PC2_{t-1}SMB_t] + \beta_{i13}[PC2_{t-1}HML_t] + \beta_{i14}[PC2_{t-1}PUT_t] + \\
&\beta_{i15}[PC2_{t-1}MT_t] + \varepsilon_t \qquad (8)
\end{aligned}
$$

Heteroscedasticity & Autocorrelation

The Durbin-Watson statistics in *Figure 7.8* (see appendix) clearly show that our model does not exhibit any signs of autocorrelation. Since the scope of measurement for the conditional model stretches over the entire time period, which includes two very distinct economic conditions, one would expect the variance of the error terms to be non-constant. The values of the White test in *Figure 7.8* show that indeed seven out of the

13 hedge fund strategies suffer from heteroscedasticity. To adjust for this problem, we use robust standard errors.

Regression Results & Discussion

Under the conditional time-varying model, we observe seven significant alphas (five at 5%). The majority of strategies with positive alphas also had significant abnormal returns for most periods under both the CAPM and Fama-French model. The abnormal returns vary between 0.3% and 0.6% per month. It seems that hedge funds are able to hedge their returns since they can generate positive abnormal returns during a time period that includes two major financial crises. The *event driven* family demonstrates both the most and highest abnormal returns. *Event driven* strategies are known for exploiting price movements, which are related to corporate events. Since the event driven strategies yield the largest amount of significant abnormal returns, as well as the largest total return (see *Figure 4.1*), one can conclude that it would be beneficial to invest in these types of hedge funds. Fund managers might possess superior knowledge or information unavailable to small investors. *Emerging markets* and *relative value* are two additional strategies that are able to yield relatively high abnormal returns. These strategies are also among the ones with the highest total returns between February 1997 and January 2011.

Style	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Beta (PUT)	Beta (MT)	Adj. R2
Convertible Arbitrage	0.001	0.054*	0.058	0.071**	0.183***	0.825**	0.596
CTA Global	-0.001	0.079	0.139*	0.054	-0.110	2.459***	0.063
Distressed Securities	0.006***	0.142***	0.108***	0.122***	0.158**	-0.544	0.677
Emerging Markets	0.005*	0.419***	0.072	0.159***	0.189*	-1.251*	0.609
Equity Market Neutral	0.003***	0.068***	0.021	0.040***	0.011	0.136	0.293
Event Driven	0.004***	0.205***	0.086***	0.120***	0.208***	-0.559	0.781
Fixed Income Arbitrage	0.002*	-0.011	0.039	0.036	0.102**	0.09	0.398
Funds Of Funds	0.001	0.177***	0.008	0.118***	0.146***	0.07	0.671
Global Macro	0.002	0.180***	0.057	0.089***	0.046	0.741*	0.314
Long/Short Equity	0.001	0.316***	-0.008	0.139***	0.168***	0.424	0.826
Merger Arbitrage	0.003***	0.110***	0.048***	0.057***	0.170***	-0.569***	0.673
Relative Value	0.003***	0.115***	0.045***	0.058***	0.156***	-0.074	0.750
Short Selling	0.002	-0.856***	-0.339***	0.211***	0.025	0.704	0.837

Note: ***, **, * significant at 1%, 5%, 10% respectively

Figure 4.8: Summarized Conditional Model Regression Output - Time-Varying Betas - Feb 97 - Jan 11

$$r_{it} - r_{ft} = \alpha_{i0} + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}PUT_t + \beta_{i5}MT_t + \beta'_p[z_{t-1}(r_{mt} - r_{ft})]$$
$$+\beta'_p[z_{t-1}SMB_t] + \beta'_p[z_{t-1}HML_t] + \beta'_p[z_{t-1}PUT_t] + \beta'_p[z_{t-1}MT_t] + \varepsilon_t$$

The good overall fit of the conditional time-varying model is proven through high adjusted R^2 values. The adjusted R^2 values vary between 6% and 84%. *CTA global* as in the previous models shows the lowest fit, *short selling* the best. Interestingly, these two strategies are the only ones that have a slightly lower fit under the conditional model than in the Fama-French and CAPM, on average. Besides those two, whose differences we neglect (overall low fit of CTA global and marginal difference for short selling), the conditional time-varying model proves to provide the highest R^2 values and hence the best overall fit.

RISK FACTORS

In the following we will closer analyse the five different risk factors.

MKT

The betas obtained by the conditional time-varying model are in eleven cases significant. The beta coefficients presented in *Figure 4.8* illustrate the average time-varying betas for each strategy. Except for *short selling*, all of the significant market loadings are positive. This suggests that most of the strategies have a positive sensitivity towards the movements of the market. Theoretically, the market beta values should be close to zero. After deducting fees, a hedge fund by definition should be able to generate positive returns irrespective of the overall state of the economy. When comparing the average market betas of the two static models with the time varying betas, one can conclude that all but one strategy *(CTA global)* exhibit lower factor loadings in the conditional model. The low goodness of fit and insignificant alpha of *CTA global* further exacerbates the interpretation of the results. *Short selling* is the only strategy with a negative factor loading, a result consistent with the previous tested models. Overall, it seems that the more variance the model is able to explain, the more will the market beta coefficients move towards zero.

By closer examining *Figure 7.9* (see appendix), which plots the market betas over time, one can conclude that the factor loadings are cyclical. The exposure to market risk increases during economic crises, whereas the beta values slowly decrease during bull periods. These findings indicate that hedge funds do hedge their investments. The time variation tends to increase with the absolute size of the factor loading. The more a fund is exposed to the market, the larger is the volatility in the factor loading. By further investigation the plotted betas, one can spot an overall pattern. The exposure to market risk seems to decline slightly over time. This could be interpreted as evidence for the existence of the overall ambition of hedge fund managers to decrease their exposure to market fluctuations, in order to generate positive returns throughout different business cycles. Our results are in line with Sadek (2010). We find that *directional strategies* exhibit the highest exposure to market risk and are hence overall riskier.

SMB

Fama and French (1993) find positive factor loadings for the SMB factor. We observe six significant factor loadings, all positive, but *short selling*. When looking at the SMB coefficients, we can directly observe the same pattern we investigated earlier. All *event driven strategies* have highly significant positive factor loadings, a finding we already observed throughout the first three periods under the Fama-French model. The coefficients for all *event driven* strategies are substantially lower than in the previous model. *Short selling* is the only strategy with a negative beta. At the same time, it has the highest factor loadings (-0.339). It seems that this particular strategy takes short positions in small-cap (low ME) stocks.

To further investigate the SMB factor loadings over time, one should have a look at *Figure 7.10*. The majority of factor loadings is very low and seems to change only marginally over time. Nevertheless, most strategies exhibit a slightly higher exposure to size risk during the real estate bubble. Starting around May 2007, the factor loadings for all but a very few strategies start decreasing and some even change their signs. Around August/September 2008, in line with the fall of Lehman Brothers, we observe the largest negative factor loadings. It seems that the financial crisis as compared to the period after the burst of the IT bubble had a much more severe impact on the SMB factor loadings. The beta coefficients following the crisis evolving in 2000 are stable, whereas the betas in the last crisis period vary substantially.

Two individual strategies are worth mentioning. *Distressed securities* has the most constant factor loadings of all strategies over time. The coefficient is around 0.1 and is not affected by either bull or bear markets. Short selling is counter-cyclical and exhibits significant negative factor loadings throughout the entire time period. The factor loadings show a stable pattern in period I and II, become less negative in Period III, and show their largest negative exposure in period IV.

HML

Eleven out of the thirteen HML betas are highly significant. In line with Fama and French's (1993) findings, all strategies demonstrate positive factor loadings varying between 0.040 and 0.211. We can therefore conclude that the portfolios of the vast majority of hedge fund strategies are exposed to *value risk. Short selling* faces the highest exposure to value risk with a factor loading of 0.211. One would expect a hedge fund following a short selling strategy to invest in overvalued securities. Our findings are in line with this reasoning. One can interpret the highly positive exposure to value risk as an indicator that the *short selling* portfolio is highly weighted towards taking short positions in *growth stocks* (often overvalued securities). A finding that is in line with theory.

Figure 7.11 (see appendix) provides an overview of the plotted time-varying betas. One can conclude that the exposure to value risk follows the business cycle. During boom periods coefficients tend to increase, whereas during crises sensitivities diminish. One can infer that hedge funds seem to follow the market cycles carefully, hedging their overall exposure to value risk. Hedge funds "ride the wave" in bubble periods and reduce their exposure in crisis periods. Friedman (1953) concludes that the appearance of mispriced assets is due to the raise of individual investors with little market knowledge. We interpret our empirical findings that hedge fund managers, with superior knowledge and information, take advantage of mispricing in the market by altering their exposure to value risk during different economic conditions. Furthermore, the overall stable value coefficients of the *merger arbitrage* strategy during different economic environments are worth mentioning. The strategy aims to gain abnormal returns from mispriced securities. The constant exposure to value risk might be explained by the strategy's focus to consistently capture the risk premium embedded in the high BE/ME companies.

PUT

Due to the high level of negative skewness, one would expect a positive exposure to the left tail risk, as measured by the *PUT* index. The index is highly negatively correlated with left tail events. This in turn means that a positive coefficient could be seen as a risk premium for extreme losses. Eight strategies exhibit a highly significant (< 5%) exposure to the left tail risk. The risk premium varies from ten to twenty percent of the increase in left tail events. *Fixed income arbitrage* demonstrates the highest level of negative skewness and at the same time the lowest significant risk premium. This relationship seems to be odd, since one would expect the largest adjustment for companies exposed to a high level of negative skewness. Nevertheless, one can conclude that the PUT index is a plausible adjustment for left tail events, since all strategies (except *equity market neutral*) with positive skewness are not significantly exposed to the *PUT Index*. One possible explanation for the high significance between hedge fund returns and their exposure to tail risks was proposed by Lo (2001). He conjectures that the specific fee structure of hedge funds encourages hedge fund managers to take on additional risk.

By examining *Figure 7.12*, one can conclude that the adjustments for left tail events tend to follow the market cycle over time. The risk premium increases during burst periods and decreases under stable periods. This seems logical, since one would expect the left tail events to become larger when markets are volatile. The strategy *funds of hedge funds* exhibits the most persistent coefficients over time, a plausible reason could be that this strategy invests in various different hedge fund strategies, all differently exposed to tail risk. By combining different strategies in one portfolio, it seems that managers of *funds of funds* are able to directly control their exposure to tail events.

MT

Given the inconclusive findings and opposing views on hedge fund managers' market timing ability, we decided to investigate whether such a skill exists. Whereas Fung et al. (2002) and Cerrahoglu et al. (2003) find evidence of a negative market timing ability, Chen and Liang (2007) find evidence of a positive market timing ability for a small number of hedge funds.

Unfortunately, as a brief look at *Figure 4.8* already reveals, we are not able to contribute any new findings on the market timing skill of hedge fund managers. Our results show that out of the thirteen investigated strategies, only three funds are able to provide significant coefficients at 5%. We find that fund manager's of two styles indeed possess a positive market timing skill (*convertible arbitrage* and *CTA global*), whereas *merger arbitrage* has a negative coefficient. Two additional styles yield significant loadings at 10%, *emerging markets* with a large negative coefficient (-1.251) arguing for negative market timing ability and *global macro* (0.741). Overall, the exposure of the significant strategies (at 10%) varies widely from -1.251 for *emerging markets* to 2.459 for *CTA global*.

To further investigate the market timing ability of hedge fund managers one should look at *Figure 7.13,* which plots the MT factor loadings over time. The coefficients of all strategies but *funds of funds* exhibit extremely large swings over time. Only the *funds of funds strategy,* which is only significant at 20 percent is able to provide remarkably stable factor loadings (around zero) over time. Of our significant strategies, *merger arbitrage* has the most stable coefficients over time, however exhibits a negative market timing ability throughout the vast majority of the investigated time period. Only around the collapse of Lehman Brothers and other large (financial) institutions does this strategy seem to have a positive market timing ability. Overall, *merger arbitrage* has a slightly lower negative exposure during crisis periods (even positive around September 2008) than during market upswings. Nevertheless, it seems that as long as the financial system is not totally distorted, as was the case after Lehman filed for Chapter 11, this strategy does have a negative market timing ability.

Convertible arbitrage and *CTA global* by contrast have a positive market timing skill and follow a very similar pattern. Both strategies are exposed to extremely high swings overall, with *CTA global* yielding the highest coefficients. One can observe a higher exposure during crisis periods. The lowest coefficients for both strategies can be observed around September 2008.Factor loadings increase sharply thereafter. Whereas *CTA global* consistently yields positive betas throughout the entire time period (except August/September 2008), *convertible arbitrage* fluctuates around zero, with changing signs, during both the IT bubble and the period June 2005 - June 2007.

Overall, we conclude that hedge fund managers, at large, lack the skill of a positive market timing ability. Only a very few strategies, in line with Chen and Liang (2007) are able to provide positive loadings whereas others, supporting Fung et al. (2002) and Cerrahoglu et al. (2003) have a negative market timing ability.

5. CONCLUSION

The last part summarizes the most important findings and will provide a direction for further research.

This thesis has examined whether different hedge fund strategies can yield abnormal returns during varying market conditions. The return data for the strategies are represented by unbiased indices, constructed by the Edhec-Risk Institute. The scope of our research covers two major market bubbles, the dotcom bubble and the US real estate bubble. We have applied three different models on our return data to test for abnormal returns and to investigate which risk factors affect hedge fund returns.

The results obtained from the CAPM clearly show a pattern between the market proxy and the excess returns of the different strategies. The number of significant abnormal returns varies widely over time. The market beta does not adjust for the multidimensional risk environment the hedge fund universe is exposed to. Furthermore, the static nature of the model fails to properly benchmark hedge fund returns due to their dynamic nature.

The Fama-French Three Factor model adds two additional risk factors (SMB and HML) in order to provide more reliable results in the quest for abnormal returns. The adjusted R^2 values observed in the Fama-French model are in general higher than under the CAPM. This suggests, that SMB and HML are able to capture additional information in the variance. Since the number of significant alphas under both the Fama-French model and CAPM vary over time, we argue that hedge fund managers' ability to generate abnormal returns differs in varying business cycles. Observed factor loadings for different risk factors vary over time and between strategies. The hedge fund universe in general has a significant and low exposure to market risk. The *short selling* strategy is the only type of hedge fund with a negative sensitivity to the market. This finding is line with theory since this particular strategy is counter-cyclical and meant to yield the highest returns in market downturns. The number of strategies exhibiting a significant exposure to size risk tends to diminish over time. Bird et al. (2010) find similar results. The signs of the factor loadings on value risk vary between different market conditions. Our findings are backed by Ferson and Harvey (1999) who state that the Fama and

French factors need to be adjusted for time variation in order to provide a reliable risk measure.

The conditional time-varying model presented in this thesis introduces two additional risk factors, the *Put Write Index* adjusting for the required risk premium for the exposure to left tail events, and *market timing* measuring the market timing ability of hedge fund managers. In addition to the new risk factors, we apply a conditional approach, adjusting independent variables for changes in the business cycle over time. The instrumental variables are represented by two principal components, which include variables directly linked to the business cycle and current/future economic conditions. Approximately half of the strategies exhibit positive abnormal returns under the time varying model. By examining the plotted time-varying betas for the different risk factors, it becomes obvious that their exposure varies widely over time.

In order to measure true abnormal returns in the hedge fund universe, one needs to adjust for the changes in risk premia received within the different phases of the business cycle. Concerning the risk factors, the number of significant factor loadings reveals a pattern where the value factor seems to be more important than the size factor. The high level of negative skewness within the hedge fund universe is proven to be a risk factor. One should hence incorporate this adjustment in order to obtain accurate (abnormal) returns. Whether hedge fund managers possess a superior market timing skill is inconclusive. The risk factor tends to explain very little of the volatility within the excess returns of the different hedge fund strategies.

Figure 5.1 provides a description of the significant abnormal returns between the different strategies. The conditional model, which has proven to be superior to the other models, obtains alphas that are slightly lower than average abnormal returns. The finding is in line with the expectation that the better the specification of the multidimensional risk environment the hedge fund universe is exposed to, the more of the return variability will be captured by the risk factors. Therefore, abnormal returns are expected to decrease with better model specifications.

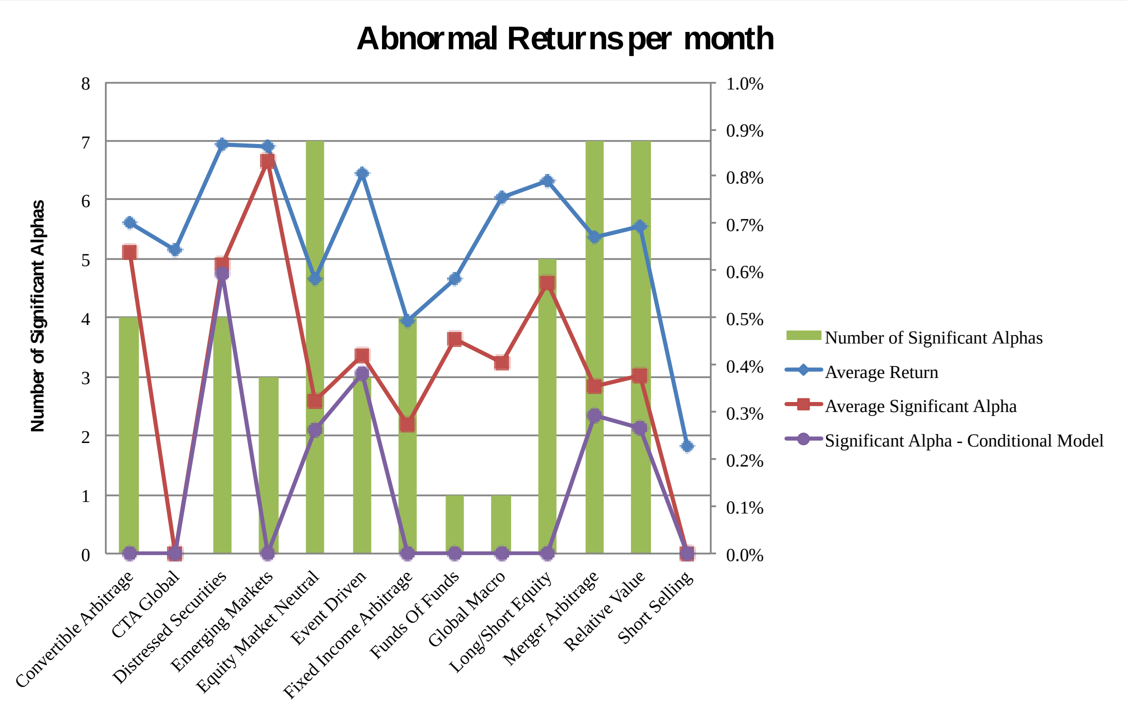

Figure 5.1: Abnormal returns per month

Plotted alpha of zero in graph means that no significant alpha was obtained

In line with Liang (1999) we demonstrate that abnormal returns are positive over the long term, at least for some strategies. These styles belong to the *event driven* family and the *relative value/arbitrage* group. All theses strategies are known for having a low exposure to market risk and their quest to detect mispricing in the market. One can therefore conclude that there must exist a risk premium rewarding market actors, which are exploiting the mispricing caused by less sophisticated investors.

According to our research, the *directional* strategies are supposed to be the riskiest strategies within the hedge fund universe. The static models demonstrate a pattern where *directional* strategies can provide a great abnormal return during market environments matching their risk exposure. *Short selling* for instance, is superior to all other strategies during burst periods. The long-term focus represented by the conditional time varying model provides no significant alphas for the directional strategies.

Most important findings summarized:

- The conditional model demonstrates the highest adjusted R^2 values.
- The hedge fund universe faces a multidimensional risk environment. Exposure to different risk factors varies with the business cycle.
- The static CAPM and Fama-French model lack the time variation needed to explain the complex and dynamic risk universe hedge funds are exposed to.
- The exposure to market risk is low but highly significant.
- The average hedge fund portfolio is weighted towards value stocks.
- The exposure to size risk tends to diminish over time.
- The hedge fund universe has a negatively skewed distribution for which investors require a risk premium.
- Hedge fund managers at large do not possess a positive market timing skill.
- *Directional strategies* are the most risky types of hedge funds. They are able to provide superior abnormal returns during market environments matching their risk exposure (e.g. *short selling* outperforms in crisis periods).
- Under the conditional model, which is adjusted for business cycle variations, *relative value/arbitrage* and *event driven strategies* are able to yield positive abnormal returns.
- Overall, about 50% of the investigated strategies yield positive abnormal returns in the conditional model. Strategies with the highest total return also yield the highest abnormal returns. Hence, at least some hedge fund managers are able to add value.

5.1 FURTHER STUDIES

In order to further investigate the existence of abnormal returns within the hedge fund universe, one would need to go into further depth analysing a multitude of potential risk factors. Factors that would be interesting to analyse are for instance the leverage effect, credit risk, etc. To obtain more detailed information on the volatility within hedge fund returns, one could choose to focus at one individual strategy. A thorough analysis of *directional strategies* during different business cycles for instance could provide additional scientific depth to the topic investigated. We believe that the ability/disability of hedge fund managers to time the market can be of substantial importance to the return of individual hedge funds. The lack of results in our empirical testing could stem from using (non-investable) indices. If a quantification of the market timing for individual fund managers were possible, the result could be a helpful guidance for future investments in hedge funds.

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7. APPENDIX

Style	Aver. Return	Std. Dev	Skewness	Kurtosis	J-B	Sharpe-Ratio	Cumul. Returns
Convertible Arbitrage	1.079%	0.012	-1.777	6.909	50.008	0.383	46.41%
CTA Global	0.504%	0.023	0.430	3.844	2.600	0.165	21.68%
Distressed Securities	0.888%	0.020	-2.110	11.357	157.039	0.305	38.18%
Emerging Markets	0.714%	0.051	-1.207	6.780	36.038	0.112	30.70%
Equity Market Neutral	1.082%	0.007	-0.213	3.425	0.650	0.457	46.51%
Event Driven	1.129%	0.021	-2.492	13.472	240.976	0.265	48.56%
Fixed Income Arbitrage	0.408%	0.016	-3.737	18.897	552.837	0.147	17.53%
Funds Of Funds	1.246%	0.023	-0.226	4.571	4.788	0.139	53.56%
Global Macro	1.012%	0.023	0.728	3.602	4.450	0.214	43.53%
Long/Short Equity	1.644%	0.024	-0.101	4.068	2.118	0.222	70.68%
Merger Arbitrage	1.210%	0.013	-3.514	19.374	568.825	0.334	52.01%
Relative Value	1.068%	0.010	-2.584	11.940	191.058	0.452	45.93%
Short Selling	0.017%	0.076	0.554	4.114	4.427	-0.001	0.71%
S&P 500	1.530%	0.049	-1.021	4.633	12.251	0.009	65.78%
Average all HFs	**0.923%**	**0.024**	**-1.250**	**8.643**	**139.678**	**0.246**	**39.69%**

Figure 7.1: Summary Statistics – Period I (Feb 1997 – Aug 2000)

The category Average of all Hedge Funds does not incorporate the market index (S&P 500)

Style	Aver. Return	Std. Dev	Skewness	Kurtosis	J-B	Sharpe-Ratio	Cumul. Returns
Convertible Arbitrage	0.888%	0.011	-0.008	3.277	0.096	0.582	26.64%
CTA Global	1.209%	0.031	-0.142	2.379	0.582	0.311	36.28%
Distressed Securities	0.666%	0.013	0.246	2.645	0.460	0.307	19.98%
Emerging Markets	0.313%	0.028	-0.090	2.140	0.965	0.021	9.40%
Equity Market Neutral	0.554%	0.004	0.537	3.410	1.650	0.783	16.61%
Event Driven	0.320%	0.014	-0.822	3.544	3.749	0.046	9.60%
Fixed Income Arbitrage	0.623%	0.005	-0.403	3.139	0.837	0.706	18.70%
Funds Of Funds	0.113%	0.010	-0.259	2.712	0.439	-0.150	3.38%
Global Macro	0.601%	0.012	1.158	5.448	14.193	0.282	18.02%
Long/Short Equity	-0.259%	0.017	-0.168	2.277	0.795	-0.296	-7.76%
Merger Arbitrage	0.218%	0.010	-1.296	4.500	11.205	-0.040	6.53%
Relative Value	0.445%	0.011	-0.134	3.872	1.040	0.169	13.36%
Short Selling	2.582%	0.059	0.076	2.761	0.100	0.391	77.46%
S&P 500	-1.967%	0.054	0.186	2.193	0.986	-0.374	-59.02%
Average all HFs	**0.636%**	**0.017**	**-0.100**	**3.239**	**2.778**	**0.239**	**19.09%**

Figure 7.2: Summary Statistics – Period II (Sep 2000 – Feb 2003)

The category Average of all Hedge Funds does not incorporate the market index (S&P 500)

Style	Aver. Return	Std. Dev	Skewness	Kurtosis	J-B	Sharpe-Ratio	Cumul. Returns
Convertible Arbitrage	0.413%	0.010	-0.911	4.119	10.671	0.164	23.14%
CTA Global	0.418%	0.025	-0.068	2.499	0.627	0.070	23.38%
Distressed Securities	1.244%	0.010	0.012	2.801	0.093	0.998	69.66%
Emerging Markets	1.689%	0.020	-0.758	3.266	5.523	0.718	94.61%
Equity Market Neutral	0.553%	0.005	-0.615	3.807	5.048	0.616	30.97%
Event Driven	1.104%	0.011	-0.434	3.003	1.757	0.774	61.83%
Fixed Income Arbitrage	0.545%	0.005	0.123	5.708	17.247	0.657	30.51%
Funds Of Funds	0.805%	0.011	-0.554	3.190	2.945	0.516	45.08%
Global Macro	0.815%	0.013	0.212	2.557	0.880	0.443	45.66%
Long/Short Equity	1.087%	0.015	-0.540	2.709	2.921	0.576	60.88%
Merger Arbitrage	0.725%	0.008	-0.199	3.446	0.835	0.590	40.60%
Relative Value	0.767%	0.007	-0.243	2.687	0.779	0.704	42.93%
Short Selling	-0.619%	0.028	0.079	2.880	0.091	-0.309	-34.65%
S&P 500	1.091%	0.023	0.161	3.106	0.269	0.322	61.08%
Average all HFs	**0.734%**	**0.013**	**-0.300**	**3.282**	**3.801**	**0.501**	**41.12%**

Figure 7.3: Summary Statistics – Period III (Mar 2003 – Oct 2007)

The category Average of all Hedge Funds does not incorporate the market index (S&P 500)

Style	Aver. Return	Std. Dev	Skewness	Kurtosis	J-B	Sharpe-Ratio	Cumul. Returns
Convertible Arbitrage	0.549%	0.035	-1.794	7.668	56.328	0.138	21.40%
CTA Global	0.597%	0.022	0.302	2.500	0.997	0.242	23.27%
Distressed Securities	0.441%	0.027	-0.891	4.017	6.834	0.143	17.20%
Emerging Markets	0.085%	0.042	-0.887	4.828	10.549	0.006	3.31%
Equity Market Neutral	0.069%	0.013	-2.633	12.208	182.838	0.006	2.70%
Event Driven	0.357%	0.024	-0.992	4.001	8.018	0.124	13.93%
Fixed Income Arbitrage	0.372%	0.022	-2.096	8.810	83.408	0.139	14.52%
Funds Of Funds	-0.177%	0.020	-1.271	4.786	15.679	-0.119	-6.92%
Global Macro	0.385%	0.015	-0.037	2.854	0.044	0.223	15.02%
Long/Short Equity	0.170%	0.027	-0.617	3.161	2.513	0.041	6.64%
Merger Arbitrage	0.327%	0.010	-1.367	4.415	15.398	0.257	12.77%
Relative Value	0.345%	0.020	-1.555	6.577	36.510	0.139	13.44%
Short Selling	-0.083%	0.045	0.357	2.816	0.883	-0.032	-3.25%
S&P 500	-0.477%	0.063	-0.667	3.057	2.897	-0.067	-18.62%
Average all HFs	**0.264%**	**0.025**	**-1.037**	**5.280**	**32.308**	**0.101**	**10.31%**

Figure 7.4: Summary Statistics – Period IV (Nov 2007 – Jan 2011)

The category Average of all Hedge Funds does not incorporate the market index (S&P 500)

		Period 1 (Feb 1997 - Aug 2000)						Period 2 (Sep 2000 - Feb 2003)						Period 3 (Mar 2003 - Oct 2007)						Period 4 (Nov 2007 - Jan 2011)					
		Intercept	Beta	DW	White	R2	Adj. R2	Intercept	Beta	DW	White	R2	Adj. R2	Intercept	Beta	DW	White	R2	Adj. R2	Intercept	Beta	DW	White	R2	Adj. R2
Convertible Arbitrage	Coefficient	0.006	0.065	1.029	0.000	0.076	0.053	0.007	0.041	1.426	0.856	0.045	0.010	0.000	0.144	1.217	0.486	0.134	0.118	0.005	0.383	1.225	0.001	0.492	0.479
	P-value	0.003	0.074					0.002	0.263					0.968	0.005					0.230	0.000				
CTA Global	Coefficient	0.001	-0.017	2.357	0.000	0.001	-0.023	0.004	-0.282	1.773	0.529	0.260	0.234	-0.005	0.551	1.588	0.606	0.325	0.312	0.005	-0.011	2.105	0.841	0.001	-0.026
	P-value	0.751	0.810					0.446	0.004					0.111	0.000					0.144	0.845				
Distressed Securities	Coefficient	0.001	0.272	0.973	0.000	0.454	0.440	0.006	0.090	1.302	0.917	0.133	0.102	0.007	0.267	1.522	0.513	0.429	0.418	0.004	0.329	1.578	0.299	0.644	0.634
	P-value	0.629	0.000					0.027	0.048					0.000	0.000					0.138	0.000				
Emerging Markets	Coefficient	-0.007	0.737	1.080	0.021	0.518	0.507	0.008	0.389	1.553	0.376	0.577	0.562	0.009	0.470	1.916	0.254	0.358	0.346	0.000	0.540	1.772	0.208	0.712	0.704
	P-value	0.245	0.000					0.033	0.000					0.001	0.000					0.897	0.000				
Equity Market Neutral	Coefficient	0.005	0.095	1.630	0.626	0.440	0.426	0.003	0.006	2.021	0.835	0.010	-0.025	0.002	0.089	1.891	0.995	0.212	0.197	0.000	0.099	2.166	0.310	0.237	0.217
	P-value	0.000	0.000					0.000	0.593					0.004	0.000					0.947	0.002				
Event Driven	Coefficient	0.003	0.310	1.304	0.000	0.560	0.549	0.004	0.171	1.771	0.061	0.466	0.447	0.005	0.329	1.504	0.520	0.566	0.558	0.003	0.311	1.763	0.438	0.706	0.698
	P-value	0.171	0.000					0.057	0.000					0.000	0.000					0.156	0.000				
Fixed Income Arbitrage	Coefficient	0.000	-0.010	1.128	0.349	0.001	-0.023	0.004	0.002	1.909	0.587	0.001	-0.035	0.002	0.060	1.838	0.202	0.104	0.087	0.003	0.242	1.508	0.000	0.490	0.477
	P-value	0.970	0.844					0.002	0.894					0.001	0.015					0.228	0.000				
Funds Of Funds	Coefficient	0.004	0.336	1.232	0.823	0.538	0.527	0.001	0.127	1.710	0.273	0.505	0.487	0.002	0.266	1.691	0.617	0.398	0.387	-0.002	0.304	1.900	0.200	0.564	0.552
	P-value	0.129	0.000					0.456	0.000					0.063	0.000					0.234	0.000				
Global Macro	Coefficient	0.002	0.278	1.952	0.306	0.387	0.372	0.005	0.058	1.358	0.431	0.068	0.035	0.002	0.285	1.818	0.301	0.321	0.308	0.003	0.137	2.098	0.445	0.368	0.351
	P-value	0.414	0.000					0.060	0.164					0.165	0.000					0.091	0.000				
Long/Short Equity	Coefficient	0.007	0.382	1.732	0.757	0.648	0.640	0.000	0.283	2.191	0.229	0.811	0.804	0.003	0.462	1.757	0.476	0.648	0.641	0.001	0.365	1.950	0.706	0.772	0.766
	P-value	0.003	0.000					0.810	0.000					0.036	0.000					0.556	0.000				
Merger Arbitrage	Coefficient	0.006	0.161	1.692	0.000	0.413	0.399	0.001	0.074	2.278	0.019	0.194	0.165	0.002	0.197	1.200	0.995	0.414	0.404	0.003	0.126	1.458	0.372	0.584	0.572
	P-value	0.000	0.000					0.528	0.015					0.010	0.000					0.021	0.000				
Relative Value	Coefficient	0.005	0.109	1.214	0.000	0.313	0.296	0.005	0.155	2.016	0.156	0.608	0.594	0.003	0.201	1.471	0.385	0.490	0.480	0.003	0.264	1.566	0.002	0.692	0.684
	P-value	0.000	0.000					0.001	0.000					0.001	0.000					0.124	0.000				
Short Selling	Coefficient	0.012	-1.219	1.651	0.657	0.651	0.642	0.004	-0.990	1.007	0.059	0.868	0.863	0.003	-0.973	1.551	0.808	0.816	0.812	-0.002	-0.630	1.982	0.688	0.872	0.868
	P-value	0.096	0.000					0.356	0.000					0.076	0.000					0.507	0.000				

Figure 7.5: Full CAPM Regression Output

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_t$$

H_0: Homoscedasticity is rejected when White Test < 5%

No autocorrelation if Durban Watson statistic between 1-3

		Period 1 (Feb 1997 - Aug 2000)								Period 2 (Sep 2000 - Feb 2003)							
		Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	DW	White	R2	Adj. R2	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	DW	White	R2	Adj. R2
Convertible Arbitrage	Coefficient	0.006	0.114	0.120	0.149	1.162	0.039	0.259	0.202	0.007	0.015	0.068	-0.023	1.355	0.745	0.108	0.005
	P-value	0.001	0.008	0.004	0.017					0.006	0.741	0.249	0.661				
CTA Global	Coefficient	0.001	-0.036	-0.050	-0.058	2.379	0.012	0.010	-0.066	0.004	-0.373	0.101	-0.135	1.840	0.328	0.312	0.232
	P-value	0.771	0.694	0.570	0.662					0.464	0.003	0.488	0.308				
Distressed Securities	Coefficient	0.002	0.346	0.251	0.255	0.970	0.100	0.722	0.701	0.004	0.045	0.168	-0.021	1.387	0.952	0.335	0.259
	P-value	0.369	0.000	0.000	0.000					0.088	0.376	0.013	0.718				
Emerging Markets	Coefficient	-0.006	0.815	0.347	0.301	1.223	0.267	0.601	0.571	0.005	0.327	0.336	0.014	1.604	0.366	0.749	0.720
	P-value	0.263	0.000	0.008	0.121					0.147	0.000	0.000	0.853				
Equity Market Neutral	Coefficient	0.006	0.107	0.060	0.050	1.649	0.500	0.568	0.534	0.002	0.020	0.036	0.041	1.792	0.170	0.290	0.208
	P-value	0.000	0.000	0.002	0.078					0.001	0.131	0.040	0.011				
Event Driven	Coefficient	0.003	0.374	0.226	0.224	1.190	0.000	0.768	0.750	0.001	0.184	0.175	0.093	1.586	0.799	0.689	0.653
	P-value	0.102	0.000	0.000	0.001					0.411	0.000	0.000	0.026				
Fixed Income Arbitrage	Coefficient	0.000	0.004	0.079	0.061	1.163	0.783	0.046	-0.027	0.003	-0.014	0.051	-0.011	1.829	0.339	0.129	0.028
	P-value	0.919	0.950	0.200	0.514					0.006	0.546	0.085	0.676				
Funds Of Funds	Coefficient	0.005	0.324	0.228	0.070	1.131	0.690	0.805	0.790	0.000	0.098	0.124	-0.007	1.627	0.801	0.704	0.669
	P-value	0.010	0.000	0.000	0.245					0.905	0.000	0.000	0.798				
Global Macro	Coefficient	0.003	0.287	0.138	0.075	2.123	0.566	0.471	0.430	0.003	0.045	0.134	0.028	1.249	0.158	0.213	0.122
	P-value	0.328	0.000	0.034	0.439					0.222	0.365	0.038	0.621				
Long/Short Equity	Coefficient	0.008	0.333	0.187	-0.021	1.754	0.088	0.896	0.888	-0.002	0.296	0.139	0.080	1.641	0.156	0.904	0.893
	P-value	0.000	0.000	0.000	0.648					0.160	0.000	0.000	0.008				
Merger Arbitrage	Coefficient	0.006	0.212	0.118	0.152	1.696	0.000	0.571	0.538	-0.001	0.122	0.070	0.120	2.429	0.057	0.472	0.411
	P-value	0.003	0.006	0.000	0.009					0.656	0.000	0.079	0.002				
Relative Value	Coefficient	0.005	0.143	0.096	0.109	1.406	0.006	0.479	0.439	0.003	0.166	0.125	0.070	2.403	0.178	0.791	0.767
	P-value	0.000	0.007	0.001	0.010					0.010	0.000	0.000	0.012				
Short Selling	Coefficient	0.011	-0.977	-0.293	0.364	1.281	0.699	0.805	0.790	0.004	-0.825	-0.216	0.231	1.231	0.072	0.916	0.906
	P-value	0.060	0.000	0.029	0.071					0.277	0.000	0.013	0.020				

Figure 7.6: Full Fama-French Three-Factor Model Regression Output – Period I & II

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t$$

H_0: Homoscedasticity is rejected when White Test < 5%

No autocorrelation if Durban Watson statistic between 1-3

		Period 3 (Mar 2003 - Oct 2007)								Period 4 (Nov 2007 - Jan 2011)							
		Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	DW	White	R2	Adj. R2	Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	DW	White	R2	Adj. R2
Convertible Arbitrage	Coefficient	0.000	0.127	0.051	0.106	1.180	0.220	0.170	0.123	0.005	0.484	-0.012	-0.377	1.363	0.000	0.593	0.558
	P-value	0.761	0.038	0.454	0.183					0.195	0.000	0.928	0.083				
CTA Global	Coefficient	-0.006	0.569	-0.012	0.184	1.548	0.661	0.340	0.302	0.007	0.031	-0.251	0.004	2.066	0.361	0.074	-0.006
	P-value	0.072	0.000	0.937	0.290					0.070	0.645	0.112	0.975				
Distressed Securities	Coefficient	0.006	0.223	0.120	0.220	1.947	0.784	0.583	0.559	0.004	0.364	-0.006	-0.130	1.511	0.840	0.665	0.636
	P-value	0.000	0.000	0.018	0.000					0.145	0.000	0.959	0.155				
Emerging Markets	Coefficient	0.008	0.466	0.031	0.156	1.845	0.326	0.374	0.338	0.001	0.652	-0.158	-0.325	1.876	0.422	0.782	0.763
	P-value	0.003	0.000	0.789	0.257					0.671	0.000	0.274	0.007				
Equity Market Neutral	Coefficient	0.002	0.076	0.042	0.107	1.737	0.432	0.351	0.314	0.000	0.113	0.056	-0.092	2.162	0.644	0.283	0.221
	P-value	0.016	0.005	0.158	0.003					0.920	0.003	0.495	0.162				
Event Driven	Coefficient	0.004	0.272	0.138	0.151	1.720	0.717	0.661	0.642	0.003	0.363	0.000	-0.199	1.680	0.300	0.766	0.746
	P-value	0.000	0.000	0.006	0.009					0.132	0.000	0.996	0.006				
Fixed Income Arbitrage	Coefficient	0.002	0.087	-0.041	0.096	1.937	0.025	0.246	0.203	0.004	0.294	-0.059	-0.158	1.505	0.000	0.543	0.504
	P-value	0.013	0.005	0.293	0.014					0.182	0.000	0.488	0.118				
Funds Of Funds	Coefficient	0.002	0.236	0.079	0.117	1.642	0.636	0.445	0.413	-0.002	0.306	-0.072	-0.228	1.923	0.567	0.694	0.668
	P-value	0.124	0.000	0.189	0.094					0.353	0.000	0.385	0.001				
Global Macro	Coefficient	0.002	0.296	-0.002	0.144	1.682	0.405	0.354	0.317	0.004	0.190	-0.126	-0.122	2.176	0.172	0.489	0.445
	P-value	0.359	0.000	0.982	0.111					0.032	0.000	0.109	0.053				
Long/Short Equity	Coefficient	0.003	0.385	0.172	0.114	1.757	0.442	0.709	0.692	0.001	0.431	-0.020	-0.236	2.100	0.458	0.842	0.828
	P-value	0.037	0.000	0.005	0.098					0.460	0.000	0.803	0.001				
Merger Arbitrage	Coefficient	0.002	0.165	0.078	0.075	1.183	0.674	0.470	0.439	0.003	0.159	0.006	-0.131	1.684	0.756	0.715	0.690
	P-value	0.017	0.000	0.070	0.129					0.010	0.000	0.888	0.000				
Relative Value	Coefficient	0.003	0.174	0.068	0.091	1.364	0.800	0.555	0.530	0.003	0.313	-0.008	-0.181	1.664	0.002	0.761	0.740
	P-value	0.002	0.000	0.066	0.035					0.099	0.000	0.906	0.030				
Short Selling	Coefficient	0.002	-0.816	-0.308	0.095	1.542	0.933	0.865	0.858	0.001	-0.589	-0.389	0.096	1.898	0.517	0.915	0.907
	P-value	0.237	0.000	0.000	0.277					0.800	0.000	0.000	0.204				

Figure 7.7: Full Fama-French Three-Factor Model Regression Output – Period III & IV

$r_{it} - r_{ft} = \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB + \beta_{i3}HML + \varepsilon_t$

H_0: Homoscedasticity is rejected when White Test < 5%

No autocorrelation if Durban Watson statistic between 1-3

Total Period (Feb 1997 - Jan 2011)

			Time varying betas					PC1					PC2					Descriptives			
		Intercept	Beta (MKT)	Beta (SMB)	Beta (HML)	Beta (PUT)	Beta (MT)	Beta (MKT*PC1)	Beta (SMB*PC1)	Beta (HML*PC1)	Beta (PUT*PC1)	Beta (MT*PC1)	Beta (MKT*PC2)	Beta (SMB*PC2)	Beta (HML*PC2)	Beta (PUT*PC2)	Beta (MT*PC2)	DW	White	R2	Adj. R2
Convertible Arbitrage	Coefficient	0.001	0.054	0.058	0.071	0.183	0.825	0.066	-0.120	-0.005	0.024	0.159	-0.046	0.020	-0.028	0.094	0.981	1.287	0.000	0.632	0.596
	P-value	0.562	0.057	0.101	0.013	0.003	0.045	0.022	0.000	0.866	0.252	0.079	0.284	0.519	0.348	0.080	0.003				
CTA Global	Coefficient	-0.001	0.079	0.139	0.054	-0.110	2.459	-0.090	0.057	-0.022	0.013	-0.325	-0.049	-0.042	-0.013	0.053	0.652	1.989	0.910	0.148	0.063
	P-value	0.738	0.193	0.055	0.338	0.326	0.001	0.016	0.187	0.665	0.736	0.103	0.342	0.462	0.822	0.532	0.199				
Distressed Securities	Coefficient	0.006	0.142	0.108	0.122	0.158	-0.544	-0.015	-0.004	-0.056	0.051	0.221	-0.045	-0.007	-0.046	0.106	0.615	1.549	0.000	0.000	0.677
	P-value	0.000	0.000	0.001	0.000	0.024	0.272	0.441	0.841	0.047	0.011	0.082	0.067	0.804	0.052	0.007	0.014				
Emerging Markets	Coefficient	0.005	0.419	0.072	0.159	0.189	-1.251	-0.005	-0.008	-0.092	0.025	0.560	-0.090	-0.040	-0.060	0.031	0.572	1.561	0.392	0.644	0.609
	P-value	0.056	0.000	0.299	0.004	0.082	0.089	0.885	0.845	0.067	0.491	0.004	0.071	0.464	0.285	0.705	0.242				
Equity Market Neutral	Coefficient	0.003	0.068	0.021	0.040	0.011	0.136	0.006	-0.022	0.005	0.019	-0.149	-0.021	0.021	0.002	0.027	-0.413	1.944	0.000	0.357	0.293
	P-value	0.003	0.000	0.299	0.010	0.727	0.694	0.693	0.219	0.856	0.443	0.195	0.368	0.261	0.872	0.384	0.099				
Event Driven	Coefficient	0.004	0.205	0.086	0.120	0.208	-0.559	0.000	-0.035	-0.048	0.008	0.223	-0.043	-0.033	-0.030	0.052	0.273	1.562	0.000	0.800	0.781
	P-value	0.002	0.000	0.001	0.000	0.000	0.198	0.989	0.075	0.035	0.678	0.036	0.100	0.151	0.141	0.133	0.205				
Fixed Income Arbitrage	Coefficient	0.002	-0.011	0.039	0.036	0.102	0.090	0.011	-0.018	-0.005	0.033	0.071	-0.009	0.007	-0.026	0.066	0.821	1.526	0.962	0.452	0.398
	P-value	0.098	0.701	0.237	0.160	0.046	0.794	0.512	0.347	0.824	0.050	0.432	0.688	0.772	0.320	0.087	0.000				
Funds Of Funds	Coefficient	0.001	0.177	0.008	0.118	0.146	0.070	-0.014	-0.012	-0.063	0.003	-0.016	-0.058	0.001	-0.026	0.008	0.021	1.617	0.002	0.701	0.671
	P-value	0.260	0.000	0.830	0.000	0.007	0.848	0.485	0.548	0.006	0.868	0.850	0.036	0.971	0.388	0.824	0.932				
Global Macro	Coefficient	0.002	0.180	0.057	0.089	0.046	0.741	-0.035	0.008	-0.027	-0.004	-0.029	-0.066	-0.036	-0.020	0.036	0.206	1.990	0.560	0.376	0.314
	P-value	0.198	0.000	0.157	0.005	0.458	0.081	0.089	0.728	0.357	0.836	0.791	0.022	0.249	0.546	0.445	0.463				
Long/Short Equity	Coefficient	0.001	0.316	-0.008	0.139	0.168	0.424	0.026	-0.049	-0.070	-0.020	-0.033	-0.041	-0.003	0.002	0.004	-0.243	1.732	0.001	0.842	0.826
	P-value	0.245	0.000	0.799	0.000	0.000	0.123	0.171	0.011	0.002	0.153	0.579	0.116	0.888	0.943	0.909	0.280				
Merger Arbitrage	Coefficient	0.003	0.110	0.048	0.057	0.170	-0.569	0.005	-0.031	-0.003	-0.043	0.122	-0.024	-0.052	-0.016	-0.019	0.039	1.522	0.092	0.702	0.673
	P-value	0.000	0.000	0.008	0.000	0.000	0.003	0.587	0.005	0.797	0.000	0.015	0.061	0.000	0.280	0.383	0.756				
Relative Value	Coefficient	0.003	0.115	0.045	0.058	0.156	-0.074	0.026	-0.048	-0.019	0.005	0.097	-0.016	0.001	-0.022	0.024	0.236	1.673	0.000	0.772	0.750
	P-value	0.001	0.000	0.007	0.000	0.000	0.639	0.150	0.009	0.328	0.661	0.020	0.523	0.953	0.222	0.401	0.209				
Short Selling	Coefficient	0.002	-0.856	-0.339	0.211	0.025	0.704	0.108	-0.040	-0.070	-0.037	-0.339	0.010	-0.002	0.037	0.083	-0.078	1.455	0.938	0.851	0.837
	P-value	0.366	0.000	0.001	0.000	0.805	0.305	0.002	0.072	0.396	0.271	0.060	0.829	0.463	0.977	0.279	0.863				

Figure 7.8: Full Conditional Model Regression Output – Feb 1997 – Jan 2011

$$r_{it} - r_{ft} = \alpha_{i0} + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}PUT_t + \beta_{i5}MT_t + \beta'_p[z_{t-1}(r_{mt} - r_{ft})] + \beta'_p[z_{t-1}SMB_t] + \beta'_p[z_{t-1}HML_t] + \beta'_p[z_{t-1}PUT_t] + \beta'_p[z_{t-1}MT_t] + \varepsilon_t$$

H_0: Homoscedasticity is rejected when White Test < 5%

No autocorrelation if Durban Watson statistic between 1-3

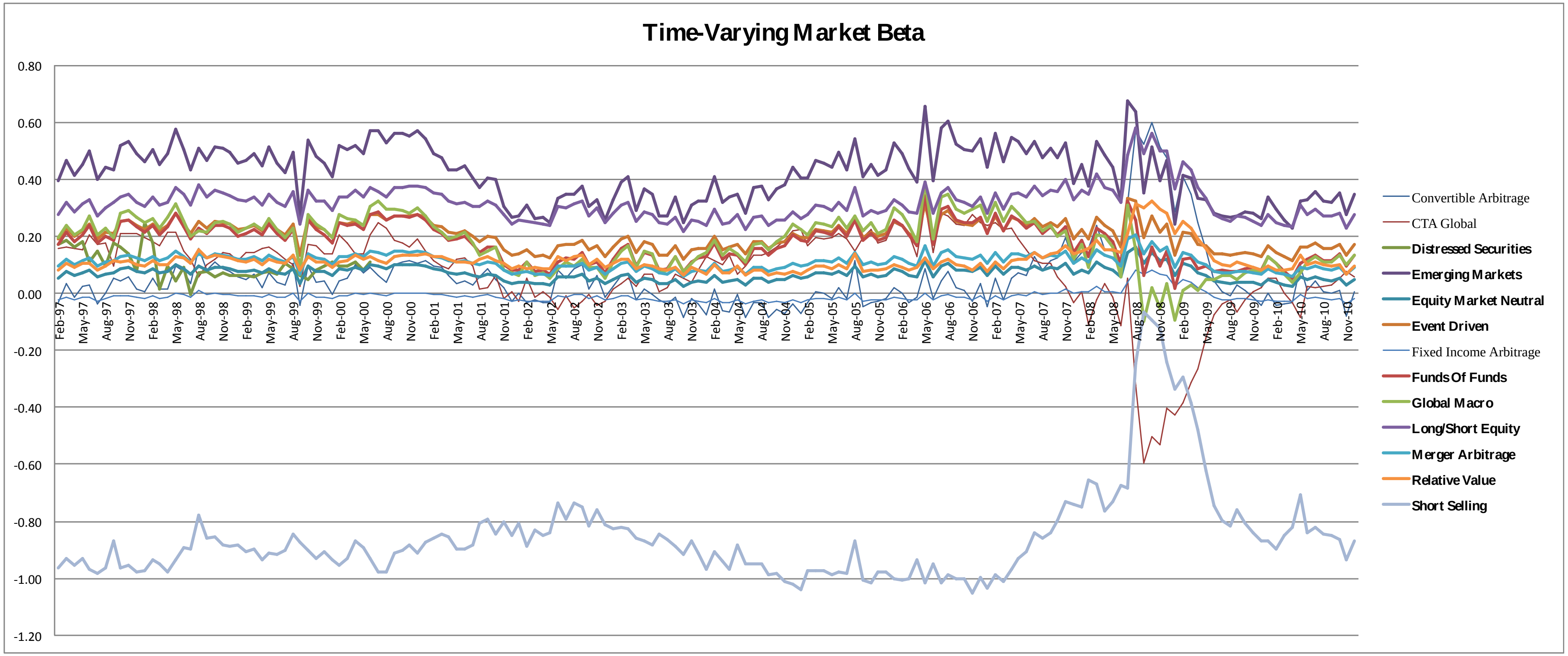

Figure 7.9: Plotted Time-Varying Market Beta

The bold strategies are significant at a 5% rejection level

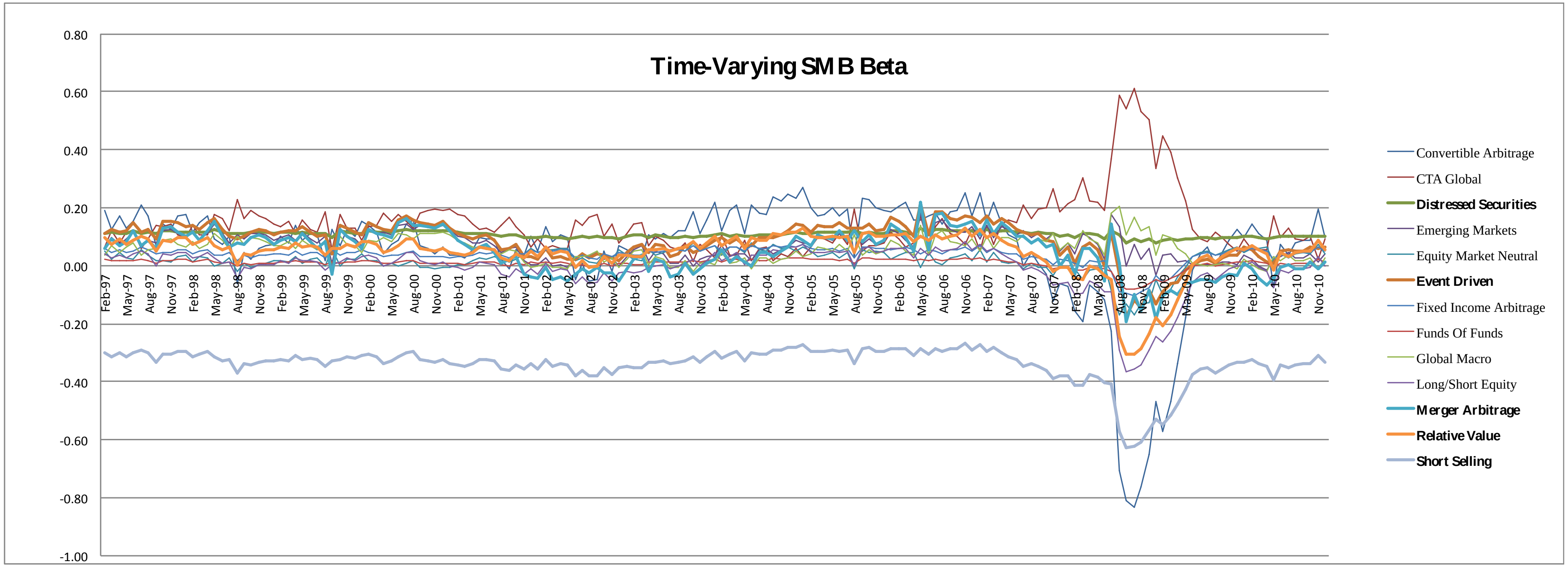

Figure 7.10: Plotted Time-Varying SMB Beta

The bold strategies are significant at a 5% rejection level

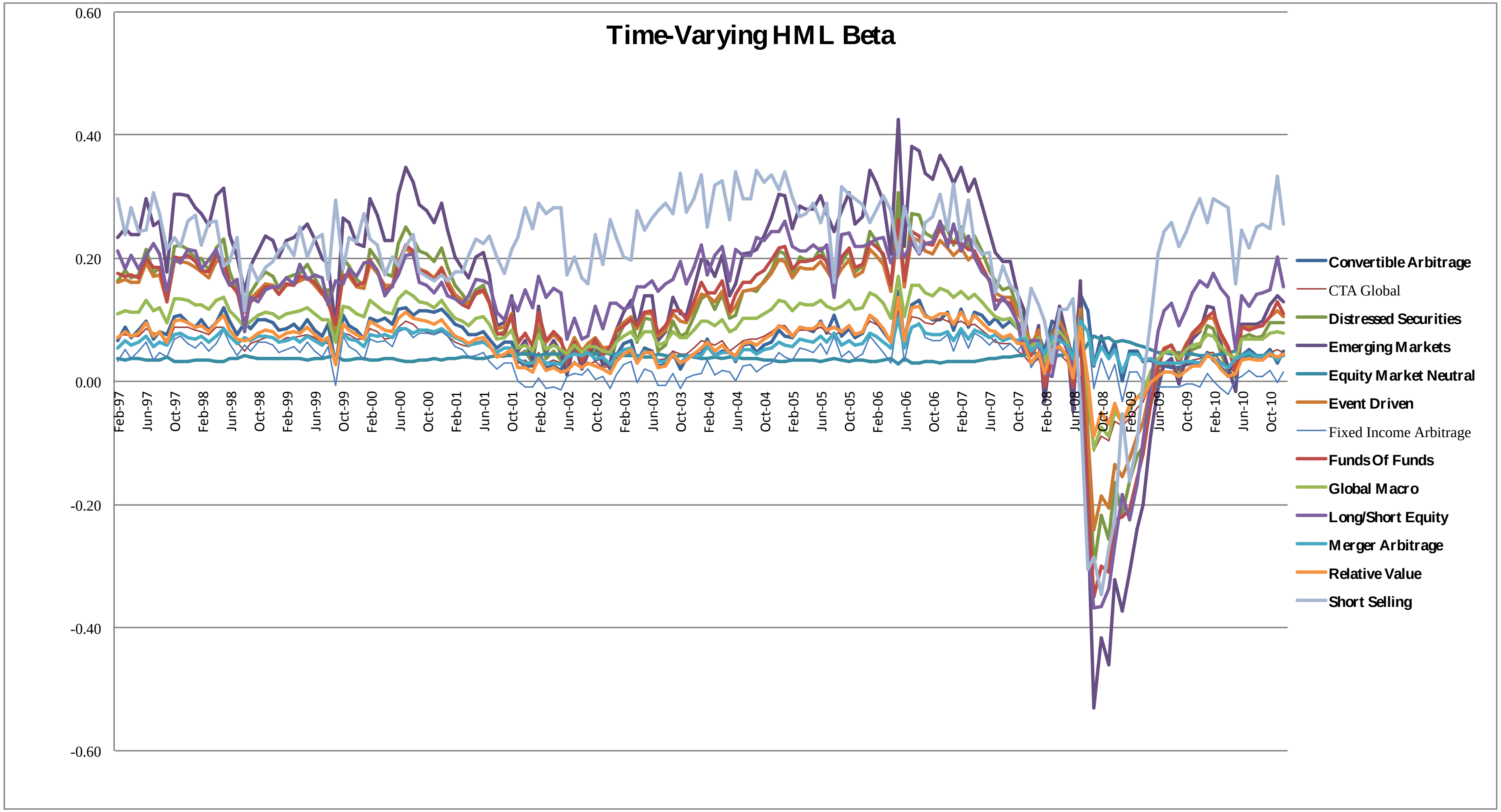

Figure 7.11: Plotted Time-Varying HML Beta

The bold strategies are significant at a 5% rejection level

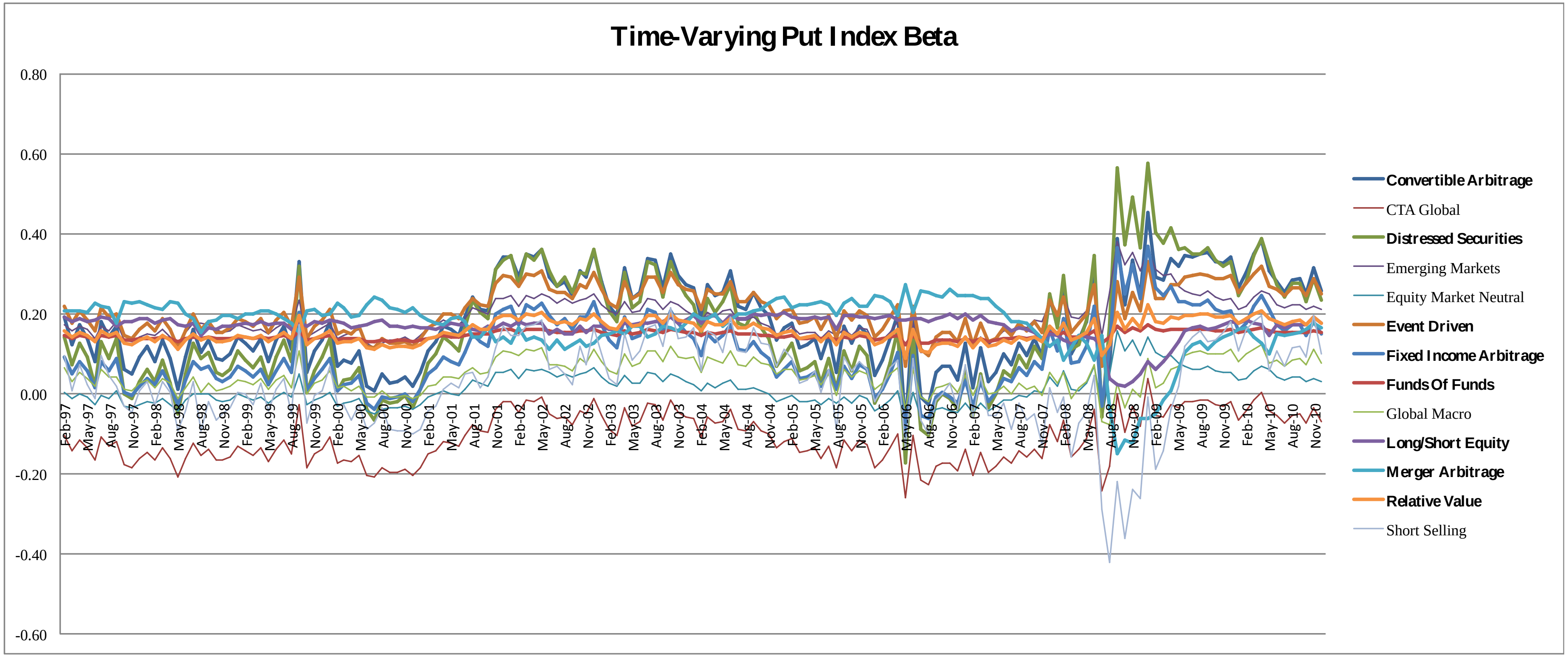

Figure 7.12: Plotted Time-Varying PUT Index Beta

The bold strategies are significant at a 5% rejection level

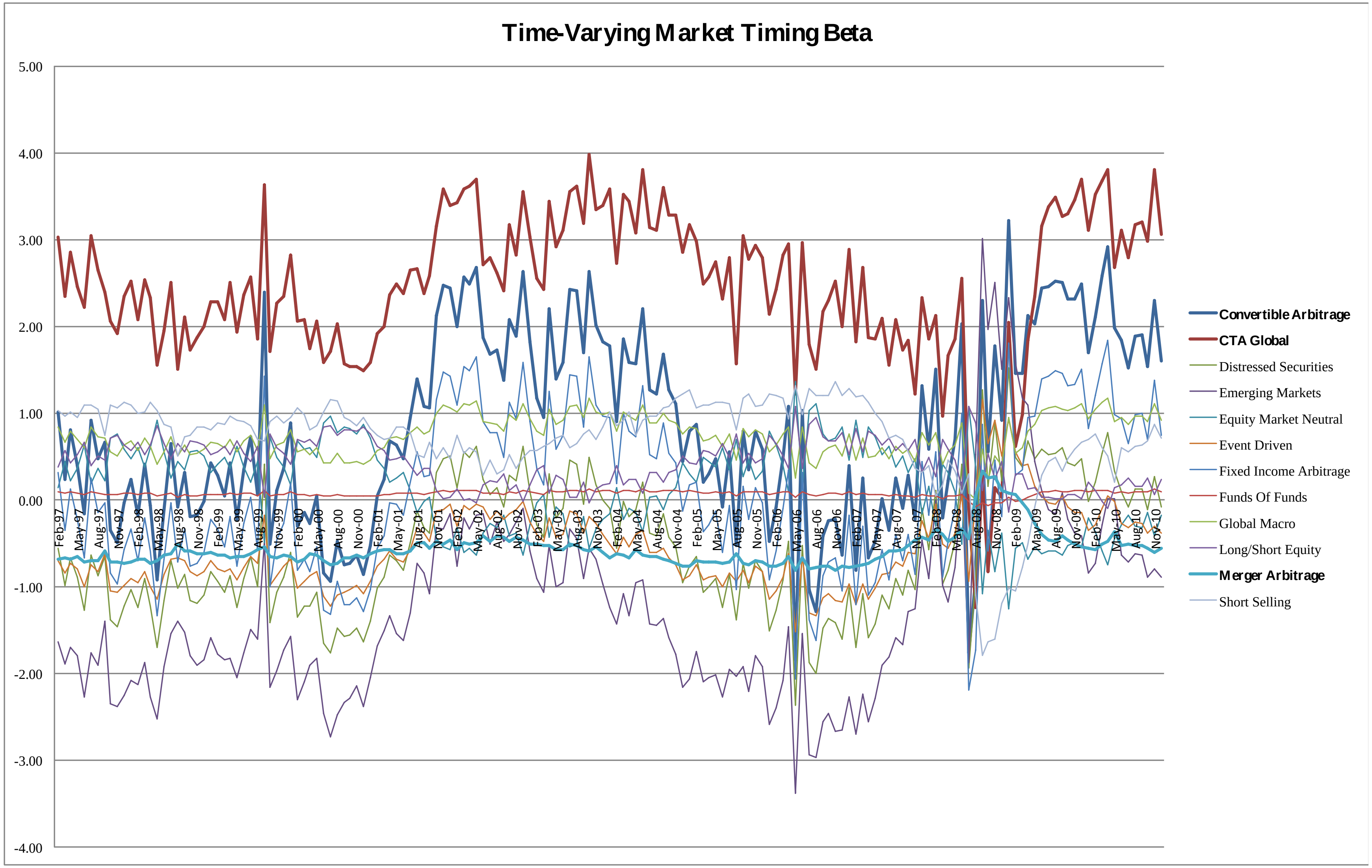

Figure 7.13: Plotted Time-Varying Market Timing Beta
The bold strategies are significant at a 5% rejection level