Convertible arbitrage: risk, return and performance

by

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I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Abstract

This study explores the risk and return characteristics of convertible arbitrage, a dynamic trading strategy employed by hedge funds. To circumvent biases in reported hedge fund data, a simulated convertible bond arbitrage portfolio is constructed. The returns from this portfolio are highly correlated with convertible arbitrage hedge fund indices and the portfolio serves as a benchmark of fund performance. Default and term structure risk factors are defined and estimated which are highly significant in explaining the returns of the hedge fund indices and the returns of the simulated portfolio, and when specified with a convertible bond arbitrage risk factor in a linear factor model, these factors explain a large proportion of the risk in convertible arbitrage hedge fund indices. The residuals of the hedge fund indices estimated from this model are serially correlated, and a lag of the hedge fund index return is specified correcting for the serial correlation and the coefficient of this term is also interpretable as a measure of illiquidity risk. A linear multi-factor model, incorporating several lags of the risk factors is specified to estimate individual fund performance. Estimates of abnormal performance from this model provide evidence that convertible arbitrageurs generate abnormal returns between 2.4% and 4.2% per annum. The convertible arbitrage hedge fund indices and individual hedge fund returns used to evaluate performance generally exhibit negative skewness and excess kurtosis. Residual Augmented Least Squares (RALS), an estimation technique which explicitly incorporates higher moments is used to robustly estimate multi-factor models of convertible arbitrage hedge fund index returns. Functions of the hedge fund index residuals are specified as common skewness and kurtosis risk factors in a multi-factor analysis of individual fund performance. Results from this analysis provide evidence that failing to specify third and fourth moment risk factors will bias upward estimates of convertible arbitrage individual hedge fund performance by 0.60% per annum. Theoretical non-linearity in the relationship between convertible arbitrage hedge fund index returns and default and term structure risk factor is then modelled using Logistic Smooth Transition Autoregressive (LSTAR) models.

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Chapter 1: Introduction

1.1 Introduction

This thesis proposes to examine the risk and return characteristics of a relatively new investment strategy, convertible arbitrage. This strategy has emerged along with several other alternative investment strategies in response to growing demand for investment products caused by increasing pension obligations and the low returns of traditional assets. Lane, Clark and Peacock (2005) estimate that in the UK the combined pension fund deficit of the top 100 companies stands at £37bn.[1] Six UK companies had pension deficits equal to thirty percent of market capitalisation at their 2004 year ends. Facing deficits and low returns from stocks and bonds, pension fund managers are being forced to look at non-traditional investments. This has led to rapid growth in the alternative investment sector. Calamos (2003) using data from Tremont advisors estimates that in 1994, the total convertible arbitrage assets under management stood at $768m; and by 2002 this had grown to $25.6bn. The Barclay Group estimates that convertible arbitrage assets under management had grown to $64.9bn by the end of 2004.[2] The convertible issuance market has also grown rapidly. This growth has coincided with a huge increase in issuance in the convertible bond market. Tremont (2004) estimates that global convertible bond issuance in 2004 was $113bn, almost three times the $44.1bn reported by BIS (2003) for 2002.

[1] Watson Wyatt, the actuarial firm, publish a Pension Deficit Index for the FTSE350. As at September 2005 this index stands at £-70.8bn from a low of £-108bn in March 2003.
[2] http://www.barclaygrp.com/indices/ghs/mum/HF_Money_Under_Management.html

The returns from convertible arbitrage relative to risk, as measured by standard deviation, have been impressive over the last twelve years with the strategy generating average annual returns of 10% with an average annualised standard deviation of 5%.[3] However mean variance analysis is only appropriate for performance evaluation if the series' distribution is normal. Brooks and Kat (2001) and Kat and Lu (2002) highlight that convertible arbitrage hedge fund returns (along with several other hedge fund strategy returns) are first order autocorrelated, negatively skewed and leptokurtic. Any analysis of convertible arbitrage conducted while ignoring these factors will understate the risks in the strategy and thereby overstate performance.

Studies to date which include analysis of convertible arbitrage have generally been limited to techniques developed for estimating performance of mutual funds[4], which share few statistical characteristics with hedge funds. These studies have also failed to fully identify risk characteristics with the result of overstating performance. Several studies focusing on other hedge fund trading strategies have added to the understanding of their performance and risks. Fung and Hsieh (2001) focus exclusively on trend following hedge funds, creating portfolios of look back straddles that intuitively and statistically share the characteristics of these funds. In isolation these portfolios provide evidence of the risks faced by the investor in trend following funds and also serve as useful benchmarks of fund performance. Adding to understanding of the risks faced by the investor in merger arbitrage funds, Mitchell and Pulvino (2001) simulate a merger arbitrage portfolio creating a return time series which has similar statistical attributes to

[3] As measured by the CSFB Tremont Convertible Arbitrage Index.
[4] Exceptions to this include Kat and Miffre (2005) and Kazemmi and Schneeweis (2003), both employing unconditional models of performance evaluation which allow for time variation in risk factor weightings.

individual merger arbitrage hedge funds. Both Mitchell and Pulino's (2001) portfolio and the returns of these funds display increased market risk during market downturns and lower market risk in upturns. Adjusting for this non-linearity reduces estimates of abnormal return.

The aim of this study is to add to the academic and practitioner understanding of convertible arbitrage return, risk and fund performance. Initially this involves simulating a convertible arbitrage portfolio. This simulated portfolio is useful in two ways. It provides preliminary evidence of the risks which affect convertible arbitrage and also serves as a benchmark/convertible bond arbitrage risk factor for assessing convertible arbitrage fund performance. As this convertible bond arbitrage risk factor is non-normally distributed it also helps account for the non-normality in the returns of convertible arbitrage hedge funds. The second strand of this study is a linear multi-factor analysis of the returns of the convertible arbitrage hedge fund indices and individual hedge funds. The initial multi-factor analysis of hedge fund indices provides evidence on the risk factors faced by the convertible arbitrageur. By defining a set of asset classes that match an investment strategies' aims and returns, individual fund's exposures to variations in the returns of the asset classes can be identified. This multi-factor analysis then serves as a model for assessing the performance of individual hedge funds as the effectiveness of the manager's activities can be compared with that of a passive investment in the asset mixes. Following on from the linear multi-factor analysis is the third strand of the study, a non-linear analysis of convertible arbitrage returns. This non-linear analysis allows for variation in risk exposures, a highly probable characteristic in a dynamic trading strategy such as convertible arbitrage. By being long a convertible bond and short an underlying stock, funds are hedged against equity market risk but are left exposed to a degree of downside default and term structure risk. Effectively, the convertible arbitrageur is short a fixed income put option. This non-linear analysis improves the understanding of the relationship between convertible arbitrage returns and risk factors. The final empirical study involves the re-estimation of convertible arbitrage index performance using an estimation technique explicitly incorporating the skewness and kurtosis found in convertible arbitrage hedge fund returns. Third and fourth moment functions are then employed as proxy risk factors, for skewness and kurtosis, in a multi-factor examination of individual hedge fund returns.

1.2 Definition of hedge funds

Hedge funds are private investment vehicles where the manager has a significant personal stake in the fund and enjoys a high level of flexibility to employ a broad spectrum of dynamic trading strategies involving use of derivatives, short selling and leverage in order to enhance returns and better manage risk. It is this dynamic use of derivatives and short selling that differentiates hedge funds from traditional investment vehicles such as mutual funds and index trackers.

Despite the perceived innovation, hedge funds are not an investment product of the 1990s. The person widely accepted as having started the first hedge fund is Alfred Winslow Jones (see Fung and Hsieh (1999), Argawal and Naik (2000a) Ineichen (2000) and Hutchinson (2003)). Coldwell and Kirkpatrick (1995) provide a concise profile of Jones and the earliest hedge fund model. Jones started his private partnership fund on the 1st of January 1949 and employed a leveraged long/short strategy in order to increase returns relative to a well managed long only fund by hedging a degree of market exposure. His fund also employed an incentive structure and when he converted his fund to a limited partnership in 1952 this became the model for the modern hedge fund. In 1954 Jones converted his limited partnership into a multi-manager hedge fund bringing in independent portfolio managers to manage the fund.

In April 1966, an article appeared in Fortune magazine[5] describing Jones' investment style, incentive fee structure and relatively strong returns. This article attracted significant attention, capital and new funds to the hedge fund industry. To illustrate the effect of the Fortune article Coldwell and Kirkpatrick (1995) estimate that at the beginning of 1966 there were *"a handful"* (p. 6) of hedge funds in operation and cite the SEC finding 140 hedge funds in operation by the year ended 1968. However, during and after the downturns of 1969-70 and 1973-74 (from December 1968 to December 1974 the Dow Jones Industrial Average dropped thirty five percent), many funds experienced difficulty due to their net long bias and there was a net outflow of money from hedge funds. Coldwell and Kirkpatrick (1995) estimate that for the twenty eight largest hedge funds assets under management fell by seventy percent.

In the mid- to late 1980s, with the emergence of managers such as George Soros and Julian Robertson, generating returns of at least 40 percent per annum, the industry began to return to prominence. Robertson's Tiger Fund was reported in Institutional Investor magazine in May 1986 as generating returns of 43% per annum while Soros' Quantum funds received attention for their role in pushing sterling out of the Exchange Rate Mechanism in 1992. Despite the high profile collapse of Long Term Capital

[5] Jones was an associate editor of Fortune in the 1940s.

Management (LTCM) in 1998, hedge funds are gradually becoming mainstream investments with regulators allowing fund of hedge fund products with minimum investments of €12,500.[6] The Barclay Group estimates at the end of 2004 there was a total of $1.042bn allocated to the hedge fund industry.[7]

1.3 Hedge fund trading styles

Hedge funds use a variety of different styles to generate high absolute returns independent of market conditions. These strategies aim to generate positive absolute returns rather than the mutual fund aim of outperforming relative to an equity or bond benchmark. Hedge funds can be classified into three main trading styles, according to their historic correlation with equity markets.[8] Figure 1.1 sets out the three main hedge fund style classifications – arbitrage, event driven and directional – and further subdivides them into nine distinct trading strategies. On the left side of Figure 1.1 are the strategies with the lowest historic correlation with financial markets, while those strategies on the right have the highest historic correlation with financial markets. Long/short equity is the largest strategy with an allocation of thirty percent of assets under management. Fixed income is the second largest sector with eleven percent of assets under management. The remaining strategies represent between five and eight percent of assets under management.

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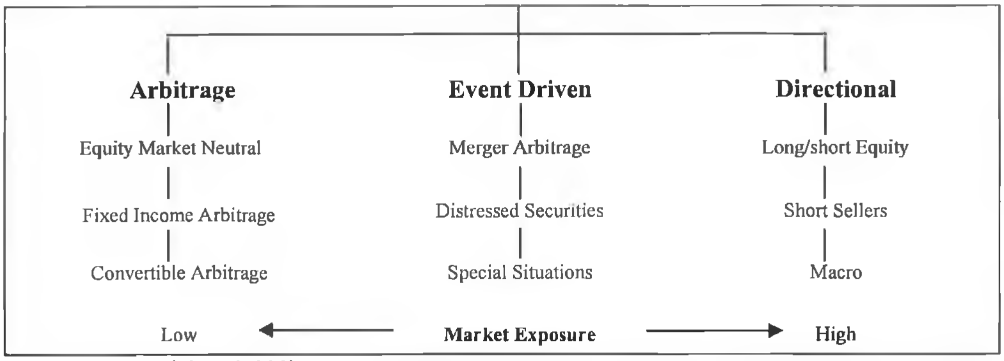
[6] In Ireland fund of hedge funds can be sold to investors with a minimum investment of €12,500. This limit is set at $25,000 in the United States.

[7] http://www.barclaygrp.com/indices/ghs/mum/HF_Money_Under_Management.html

[8] This method of classification is proposed by Ineichen (2000).

Figure 1.1
Hedge fund trading styles and strategies

This figure sets out the three main hedge fund style classifications: Arbitrage, Event Driven and Directional, and further subdivides them into nine distinct trading strategies. On the left side of Figure 1 are the strategies with the lowest historic correlation with financial markets, while those strategies on the right have the highest historic correlation with financial markets.



Source: Ineichen (2000)

The textbook definition of arbitrage is, *"the purchase and immediate sale of equivalent assets in order to earn a sure profit from difference in their prices"* (Bodie and Merton (1998) p. 160). However, in well-functioning capital markets, the opportunity for a risk-free profit does not normally arise. According to Taleb (1996), a trader definition of arbitrage is *"a form of trading that takes a bet on the differential between instruments, generally with the belief that the returns will be attractive relative to the risk incurred"* (Taleb (1996) p. 88). Within the broad arbitrage trading style, there are three main hedge fund trading strategies: equity market neutral, fixed income arbitrage and convertible arbitrage.

Equity market neutral funds take matched long and short positions of equal monetary value within a sector/country. Funds are heavily diversified with lots of long/short positions in many different stocks. The advantage of this strategy is that unlike a long only portfolio, a market neutral portfolio is not heavily exposed to market movements and, unlike a less diversified portfolio, the fund is not overly exposed to stock specific news. Trading decisions are taken based upon in-depth statistical analysis of historical data, identifying and exploiting equity relationships and inefficiencies. To illustrate with a simple example: if a fund observed that, historically, on 90 percent of the trading days following a rise in AIB's share price, Bank of Ireland rose 1 percent and AIB was unchanged; then, following a rise in AIB's share price, the fund would go long Bank of Ireland short AIB for one day hoping to capture the expected relationship/inefficiency.

The fixed income arbitrageur takes positions in a range of fixed income securities such as government bonds, investment grade corporate bonds, government agency securities, swap contracts and futures and options on fixed income securities, in order to exploit the relative values of the different instruments. The fund is constructed so that it is hedged against absolute changes in interest rates but may be exposed to term structure or default risk. As the margins on fixed income arbitrage are relatively small, a larger degree of leverage is usually employed relative to equity strategies.[9] Nonetheless, the largest hedge fund failure to date was Long Term Capital Management, a fixed income arbitrage fund whose positions were designed to be hedged against changes in interest rates.[10]

Fundamentally convertible arbitrage entails purchasing a convertible bond and selling short the underlying stock creating a delta neutral hedged long volatility position. This is considered the core strategy underlying convertible arbitrage. The position is set up so that the arbitrageur can benefit from income and equity volatility. The arbitrageur

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[9] As fixed income markets tend to be less volatile than equity markets more leverage does not necessarily mean more risk.

[10] See Lowenstein (2001) for details of LTCM's strategies and a review of the funds collapse.

purchases a long convertible and sells short the underlying stock at the current delta. The hedge neutralizes equity risk but is exposed to interest rate and volatility risk. Income is captured from the convertible coupon and the interest on the short position in the underlying stock. This income is reduced by the cost of borrowing the underlying stock and any dividends payable to the lender of the underlying stock. The non-income return comes from the long volatility exposure. The hedge is regularly rebalanced as the stock price and/or convertible price move. Rebalancing will result in adding to or subtracting from the short stock position. Transaction costs and the arbitrageur's attitude to risk will affect how quickly the hedge is rebalanced and this can have a large effect on returns. In order for the volatility exposure to generate positive returns the actual volatility over the life of the position must be greater than the implied volatility of the convertible bond at the initial set up of the hedge. If the actual volatility is equal to the implied volatility you would expect little return to be earned from the long volatility exposure. If the actual volatility over the life of the position is less than the implied volatility at setup then you would expect the position to have negative non-income returns. Convertible arbitrageurs employ a myriad of other strategies. These include the delta neutral hedge, bull gamma hedge, bear gamma hedge, reverse hedge, call option hedges and convergence hedges. However, Calamos (2003) describes the delta neutral hedge as the bread and butter hedge of convertible arbitrage.

Event driven is the second broad style of hedge fund. Generally, event-driven funds focus on generating returns from identifying securities that can benefit from the occurrence of extraordinary transactions. Examples of extraordinary transactions would be mergers, acquisitions and carveouts. More specifically event driven funds tend to specialise in one of three areas: merger arbitrage, distressed securities and special situations.

Merger arbitrage involves taking long and short positions in companies that are engaged in corporate mergers or acquisitions. These corporate deals can be divided into two main types, cash and share. With all share mergers, funds generally buy shares of the company being acquired and sell short the shares of the acquiring company in a proportion that reflects the proposed merger agreement. Whereas with cash mergers, the fund will buy the shares of the company being acquired below the agreed merger price and profit from the narrowing of the spread between the two when the deal is completed.

Distressed securities funds generally accumulate securities of financially troubled companies. These securities often trade at substantial discounts to par value. Hedge funds accumulate them with the belief that they can be sold at a profit in the secondary market or with the expectation that the company may be recapitalised, restructured or liquidated.

Special situations funds seek returns from a variety of corporate events. Examples of special situations strategies are capital structure arbitrage and the arbitrage of equity index constituent changes. With capital structure arbitrage, funds exploit the mispricing of different parts of the capital structure of a company. Arbitraging of equity index constituent changes takes place when an equity index that is heavily tracked (for example the FTSE 100) removes a company and replaces it with another.[11] By

[11] Companies are removed from indices for a variety of reasons such as mergers and acquisitions and poor stock price performance.

anticipating that the removed company will have to be sold by index trackers and the replacing company has to be purchased, the funds can generate returns.

The third broad style is the directional style. This category of hedge funds tends to have a higher expected return, standard deviation of returns and correlation with equity, fixed income and foreign exchange markets than the two other styles. This category can be further subdivided into three strategies: long/short equity, short sellers and macro funds.

Alfred Jones' fund, the original hedge fund, was a long/short equity fund, and it remains the most popular strategy, with 30 percent of total hedge fund assets. The long/short equity manager uses short positions for two reasons: to attempt to profit from a drop in prices or to hedge the portfolio from market risk. Returns are generated by the stock selection skill of the manager. These funds tend to specialise by region or sector and had excellent relative performance throughout the 1990s. However, their aggregate performance was poor from 2001 to 2003, as, in a repeat of the early 1970's managers had developed a long bias leaving them more exposed to a bear market.

Short sellers specialise in seeking profit from a decline in stocks, while earning interest on the proceeds from the short sale of stock. Obviously, the performance of these funds was poor during the 1990s due to the strong negative correlation with equity markets. These funds were the best performers in 2001 and 2002.

The strategies described so far in this section are clearly definable. In contrast, macro funds enjoy remarkable flexibility regarding investment and trading strategy. They take long and short positions in currencies, bonds, equities and commodities. Through their size (an estimated 15 percent of hedge fund assets under management) and the degree of leverage used, they are believed to have a considerable influence on world markets. Trading decisions are based upon the fund managers' macro economic views. The triggering of the 1992 break up of the Exchange Rate Mechanism in Europe was partly attributed to the activities of macro funds, which viewed the partially fixed exchange rates in Europe as being unsustainable considering the economics of the different countries.

1.4 Strategy returns

The mean returns, standard deviation, skewness and kurtosis of returns of the different hedge fund strategies over the period 31 December 1993 to 30 June 2003 are set out in Table 1.1. The data that was used to calculate these statistics is for aggregate hedge fund indices net of all fees and was sourced from HedgeIndex, a joint venture between Credit Suisse First Boston and Tremont Advisors, providing asset weighted indices of hedge fund performance. Equity and bond index data for the same period was downloaded from DataStream. The ISEQ, FTSE 100 and S&P 500 are broad based equity indices in Ireland, the United Kingdom and the United States respectively. US and Euro Bond Indices are MSCI aggregate value weighted indices of corporate and government bonds in the United States and the Eurozone.

The highest returning strategy index over the time period was global macro with an annualised mean monthly return of 13.5%. However, this strategy has the second highest standard deviation. Another strategy index with a high standard deviation is short sellers, which have performed consistently badly other than in 2001 and 2002, when they returned an average 6.3% per annum. Convertible arbitrage exhibits a high mean return of 10.1% per month combined with a standard deviation of 4.8% per month. Special situations, distressed securities and fixed income arbitrage have the highest kurtosis indicating more observations at the extreme tails of the distribution. These three strategies along with convertible arbitrage exhibit the largest negative skewness, indicating that the majority of extreme observations occurred on loss-making days. Excess kurtosis and negative skewness are both undesirable characteristics in an investments historical distribution as they indicate that there is an increased probability of large losses relative to a normally distributed investment. A closer look at the data shows that fixed income arbitrage, distressed securities and special situations worst monthly returns were -7.2%, -13.3% and -12.7%. All three of these observations occurred in a period of extreme market stress around the collapse of Long Term Capital Management from August to October 1998. Equity market neutral, short sellers and macro all have the smallest absolute levels of skewness and kurtosis. Convertible arbitrage also exhibits excess kurtosis.

Looking at equity indices, the ISEQ, FTSE 100 and S&P 500, while generally having insignificant skewness and kurtosis characteristics, generated lower returns for a higher standard deviation than the majority of hedge fund strategies, with the exception of short sellers. Bond indices demonstrate low standard deviation, reasonably high returns with insignificant skewness and kurtosis.

Table 1.1
Hedge fund, equity and bond returns 1993–2003

The returns, standard deviation, skewness and kurtosis of returns of the different strategies over the period 31 December 1993 to 30 June 2003 are set out below. The data that was used to calculate these statistics is net of all fees and was sourced from HedgeIndex, a joint venture between Credit Suisse First Boston and Tremont Advisors, providing asset-weighted indices of hedge fund performance. Equity and bond index data for the same period was downloaded from DataStream. The ISEQ, FTSE 100 and S&P 500 are broad-based equity indices in Ireland, the United Kingdom and the United States respectively. Ireland and Euro Bond Indices are MSCI aggregate value weighted indices of corporate and government bonds in Ireland and the Eurozone.

	MEAN %	STD DEV %	SKEWNESS	KURTOSIS	MEAN/STD DEV
Arbitrage					
Equity Mkt Ntrl	10.3	3.1	0.15	0.11	3.32
Fixed Inc Arb	6.7	4.1	-3.41	17.71	1.63
Convertible Arbitrage	10.1	4.8	-1.67	4.39	2.10
Event Driven					
Merger Arbitrage	8.0	4.6	-1.42	6.50	1.74
Distressed	12.3	7.3	-3.00	18.16	1.68
Special Situations	9.6	6.6	-2.92	18.59	1.45
Directional					
Long/Short Equity	11.1	11.1	-0.00	3.24	1.00
Short Sellers	-1.5	17.9	0.66	1.15	-0.08
Macro	13.5	12.3	-0.24	1.99	1.10
Equity Indices					
ISEQ	8.6	18.6	-0.79	1.05	0.46
FTSE 100	1.7	15.0	-0.66	0.35	0.11
S&P 500	7.8	16.2	-0.70	0.52	0.48
Bond Indices					
US Bond Index	7.6	4.5	-0.19	-0.11	1.69
Europe Bond Index	7.0	3.6	-0.23	-0.32	1.94

Source: Hutchinson (2003)

1.5 The structure of the thesis

This thesis is structured in the following manner. Chapter 2 reviews the convertible arbitrage and related hedge fund literature. This review highlights some of the issues which need to be addressed in an analysis of hedge fund risk and return, particularly convertible arbitrage. Chapter 3 is the first empirical chapter presenting details of the construction of a simulated convertible bond arbitrage portfolio and analysis of that portfolio. This simulated portfolio provides initial evidence of convertible arbitrage risk factors and serves as a risk factor in later analysis. Chapter 4, the second empirical chapter, presents details of a multi-factor analysis of hedge fund risk factors and performance evaluation. This multi-factor modelling focuses initially on the hedge fund indices, with the aim of identifying a common convertible arbitrage risk factor model, which is then utilised for estimating individual fund performance in Chapter 5. Chapter 6 reviews non-linear time series techniques and Chapter 7, the fourth empirical chapter, utilizes Smooth Transition Autoregressive (STAR) models to analyse the varying nature of convertible arbitrage risks. STAR models are utilised as they allow for a smooth adjustment in risk factor weightings, a feature likely to be found in financial markets where many traders act independently and at different intervals. A relatively new estimation technique which explicitly allows for the excess skewness and kurtosis found in many financial time series, Residual Augmented Least Squares (RALS) developed by Im and Schmidt (1999) is reviewed in Chapter 8. Given the negative skewness and excess kurtosis prevalent in convertible arbitrage hedge fund returns this estimation technique seems particularly appropriate and empirical results from RALS estimation of convertible bond arbitrage risk factors and performance is presented in Chapter 9. This chapter also provides details of common risk factors, mimicking skewness and kurtosis, which are specified in an analysis of individual convertible arbitrage hedge fund risk and return. Chapter 10 provides a conclusion and some avenues for future research.

1.6 The research objectives

The empirical analysis in this thesis addresses two key issues: identification and estimation of convertible arbitrage hedge fund risks; and given these risks, the evaluation of convertible arbitrage hedge fund performance. This section briefly introduces the research agenda underlying each of the empirical chapters.

1.6.1 Construction and evaluation of a simulated convertible arbitrage portfolio (Chapter 3)

The first objective of this thesis is to construct a historical simulated convertible arbitrage portfolio time series. Construction of this portfolio serves several purposes. It allows for the historical estimation of convertible arbitrage risk using higher frequency daily data (hedge funds only report monthly data). This simulated portfolio is free of survivor bias, self selection bias and instant history bias, unlike hedge fund data. As this is a passive portfolio the excess returns of this series also serve as a useful benchmark/risk factor for the evaluation of hedge fund performance in later chapters. The specific objectives of Chapter 3 are:

i. To create dynamically hedged positions in United States listed convertible bonds by combining long positions in convertible bonds with short positions in the underlying equity over the sample period January 1990 to December 2002.

ii. To combine these hedged positions into two portfolios, an equally weighted portfolio and a portfolio weighted by market capitalization of the issuer's equity.

iii. To compare the monthly returns from this portfolio with the monthly returns of two convertible arbitrage hedge fund indices and the monthly returns of market factors, ensuring that the simulated convertible arbitrage portfolios share risk and return characteristics with convertible arbitrageurs.

iv. To evaluate the relationship between the excess returns on the simulated convertible arbitrage portfolio and the excess returns on a broad based equity index.

v. To explore any non-linearity in the relationship between the excess returns on the simulated portfolio and the excess returns on a broad based equity index. If there is non-linearity in the relationship between the portfolio and the equity index then any linear analysis of returns will provide an inaccurate estimate of performance.

1.6.2 Identification and estimation of convertible arbitrage benchmark risk factors (Chapter 4)

The second objective of this thesis is to evaluate the risk factors which drive the returns of convertible arbitrage benchmark indices. At this stage of the thesis, skewness and kurtosis will be ignored as these two risk characteristics will be explored in detail later. Exploring the convertible arbitrage risk factors, initially of both convertible arbitrage hedge fund indices and the convertible arbitrage simulated portfolio in a linear multi-factor framework, provides evidence on the risks faced by convertible arbitrage investors and also guides toward a common factor model for assessing initial estimates of individual convertible arbitrage hedge fund performance. In the assessment of convertible arbitrage risk factors particular attention is paid to the serial correlation found in convertible arbitrage hedge fund indices and individual funds. Serial correlation is infrequently observed in monthly financial time series and its prevalence in convertible arbitrage hedge fund time series needs to be addressed. Getmansky, Lo and Makarov (2004) comprehensively examine this feature of hedge fund returns and drawing on their work a common risk factor mimicking illiquidity in the securities held by convertible arbitrage hedge funds is specified. The specific objectives of Chapters 4 are:

i. To review the asset pricing literature and empirically evaluate the performance of a variety of linear factor models when assessing convertible arbitrage risks.
ii. To conduct a univariate analysis of convertible arbitrage hedge fund indices.
iii. To specify and empirically test the proxy illiquidity factor in a factor model of convertible arbitrage hedge fund index return.
iv. Utilising the simulated convertible arbitrage hedge fund portfolio constructed in Chapter 3, specify and empirically test a convertible arbitrage risk factor.
v. Define and estimate a parsimonious linear multi-factor convertible arbitrage risk model.

1.6.3 Identification and estimation of individual convertible arbitrage hedge fund risk and return (Chapter 5)

The third objective of the thesis is to employ the factor model specification from the hedge fund benchmark indices to assess the risk and return of individual convertible arbitrage hedge funds. Analysing the returns of individual hedge funds using multi-factor risk models yields evidence on individual convertible arbitrage hedge fund's risk exposure and historical performance relative to other funds and a passive investment in the asset mixes. Moments higher than two are ignored in this model. The specific objectives of Chapters 5 are:

i. To empirically estimate the risk and performance of individual hedge funds utilizing the most efficient linear factor model from empirical tests on the convertible arbitrage hedge fund indices.

ii. To empirically estimate the risk and performance of individual hedge funds utilizing a non-synchronous trading type factor model incorporating lags of the dependent variables allowing for illiquidity in the securities held by hedge funds.

1.6.4 Identification and estimation of non-linearity in the relationship between convertible arbitrage index returns and risk factors (Chapter 7)

The fourth objective of this thesis is to examine any non-linearity in the relationship between convertible arbitrage returns and risk factors. If there is non-linearity in the relationship then this may contribute to serial correlation in hedge fund returns.[12] Convertible arbitrage is a dynamic hedge fund strategy where arbitrageurs adjust positions according to evolving market conditions and opportunities. The nature of the strategy is also affected by being long a hybrid bond/equity instrument. When convertible bonds fall in value they act more like bonds. *Ex ante* there is some expectation of a non-linear or time varying relationship between convertible arbitrage hedge fund returns and risk factors. When the underlying convertible bond market has fallen in value it is expected that the returns will be more exposed to fixed income risk factors as the long convertible bond positions will act more as bonds. Preliminary tests of this non-linearity involve ranking and subdividing the sample of convertible arbitrage returns and risk factors. Linear estimation of the relationships in the different sub-samples can then be examined. This then suggests a functional specification of the relationship and a non-linear model is specified and estimated. The specific objectives of Chapter 7 are:

[12] As outlined in Getmansky, Lo and Makarov (2004) time varying expected returns can induce serial correlation in realised returns without violating market efficiency.

i. To propose and discuss a hypothesis to explain the expected non-linearity.
ii. To rank and subdivide the sample by market factor and convertible arbitrage excess return, then estimate the linear model for each sub-sample. This provides preliminary evidence of any non-linearity in the relationship between convertible arbitrage returns and risk factors.
iii. Formally test linearity against the smooth transition family of models.
iv. Test the logistic form of the model against the exponential form.
v. Estimate using non-linear least squares the Logistic Smooth Transition Autoregressive (LSTAR) factor model of convertible arbitrage index returns.

1.6.5 Robust estimation of convertible arbitrage risk factors and evaluation of third and fourth moment risk factors (Chapter 9)

The final objective of this thesis is to robustly estimate convertible arbitrage risk factors using a relatively new estimation technique known as Residual Augmented Least Squares (RALS), developed by Im and Schmidt (1999). This technique allows for the excess skewness and kurtosis found in many time series, particularly hedge fund returns. The linear factor model of hedge fund index returns, from Chapter 4, is estimated using RALS. Utilising this estimation technique improves the efficiency of the linear convertible arbitrage risk factor model. Third and fourth moment functions of the HFRI convertible arbitrage index residuals are then employed as proxy factors, for skewness and kurtosis, in a multi-factor examination of individual hedge fund returns. The specific objectives of Chapter 9 are:

i. To robustly estimate a linear convertible arbitrage factor model.

ii. To demonstrate that RALS estimation improves efficiency over Ordinary Least Squares (OLS).

iii. To propose and estimate common factors in individual convertible arbitrage hedge fund returns mimicking negative skewness and excess kurtosis.

iv. To evaluate the risk and return characteristics of individual convertible arbitrage hedge fund returns by OLS estimation of a linear factor model incorporating these skewness and kurtosis common factors.

v. To evaluate the risk and return characteristics of individual convertible arbitrage hedge funds by OLS estimation of a model with lags of the explanatory variables incorporating the common factors mimicking skewness and kurtosis risk.

1.7 Innovation of this study

This study makes several original contributions to the academic literature on convertible arbitrage, hedge funds and dynamic trading strategies. These contributions will add to the debate and understanding of alternative investing. This is the first study to construct a simulated convertible arbitrage portfolio by combining convertible bonds with rebalancing delta neutral hedges in the underlying stocks in a manner consistent with arbitrageurs. This simulated portfolio adds to the understanding of convertible arbitrage risks and serves as a useful benchmark of hedge fund performance.[13]

The specification of default and term structure risk factors which are highly significant in explaining convertible arbitrage returns also adds to the literature on hedge fund

[13] A leading fund of hedge funds contacted the author looking for advice on the construction of a similar benchmark to aid their evaluation of potential investments.

performance. The empirical results indicate that these factors are highly significant in the returns of convertible arbitrage hedge fund benchmark indices and individual convertible arbitrage returns. The excess return on the simulated convertible arbitrage portfolio is also specified as a risk factor, mimicking the returns from a passive dynamic hedged convertible bond arbitrage portfolio. This factor is highly significant both in the returns of hedge fund indices and individual funds.

Another innovation of the study is the specification of STAR hedge fund risk factor models to model the theoretical relationship between convertible arbitrage returns and default and term structure risk factors. By being long a convertible bond and short an underlying stock, funds are hedged against equity market risk but are left exposed to a degree of downside default and term structure risk. When the convertible bond is above a certain threshold it acts more like equity than bond. However, when the convertible bond falls in value it acts more like bond than equity. Smooth transition models are particularly suited to modelling hedge fund returns as they allow a smooth transition rather than a sharp jump between different risk regimes. In arbitrage markets where positions are often kept open for medium horizons but adjusted in the shorter term in reaction to relative movements in the pricing of related securities a model which allows for a smooth transition seems appropriate.

This thesis is also the first study to estimate a hedge fund risk factor model using RALS and the first to specify convertible arbitrage skewness and kurtosis risk factors derived from hedge fund data. RALS explicitly allows for the negative skewness and excess kurtosis inherent in hedge fund returns and third and fourth moment functions of the convertible arbitrage index residuals are employed as proxy risk factors, for skewness and kurtosis, in a multi-factor examination of individual hedge fund returns. These skewness and kurtosis risk factors are highly significant in explaining the returns of convertible arbitrage hedge funds and evidence is presented that failing to specify higher moment risk factors biases upward estimates of performance.

1.8 Conclusion

The stated aim of this thesis is to examine the risk and return characteristics of convertible arbitrage. Although, as mentioned in the introduction, there have been several attempts at examining convertible arbitrage in more broad based hedge fund evaluation studies, this study adds to the literature by specifing appropriate convertible arbitrage risk factors, explicitly allowing for the autocorrelation in convertible arbitrage hedge fund returns, allowing for the negative skewness and excess kurtosis in convertible arbitrage hedge fund returns, and finally allowing for non-linearity in the relationship between convertible arbitrage and its risk factors. Chapter 3, Chapter 4 and Chapter 5 of this study provide evidence of appropriate convertible arbitrage risk factors and convertible arbitrage performance. Chapter 9 provides evidence of the importance of skewness and kurtosis common risk factors in assessing convertible arbitrage performance, and Chapter 7 provides evidence of non-linearity in the relationship between convertible arbitrage returns and risk factors.

The empirical evidence presented in these chapters adds to the existing debate and understanding in the hedge fund literature and provides useful guidelines for practitioners in the alternative investment universe on the specification and estimation of models for assessing convertible arbitrage risk, return and performance.

Chapter 2: Convertible arbitrage and related hedge fund literature: A review

2.1 Introduction

This chapter reviews the academic literature on the risk and return characteristics of dynamic trading strategies paying particular attention to convertible arbitrage. The aim of this chapter is primarily to review and analyze the existing convertible arbitrage and related literature. This review of literature highlights key issues and research questions, providing guidance on the overall research design of this thesis.

To date no study has focused exclusively on convertible arbitrage although several have incorporated an analysis of convertible arbitrage in broader analyses of trading strategies. These studies have made significant contributions to the understanding of how hedge funds operate and the risks inherent in hedge fund trading strategies. Research issues which have been raised and investigated include the statistical properties of hedge fund returns and biases in the data used in studies of hedge fund performance. Several studies have contributed to the understanding of hedge fund performance by specifying factor models as performance analysis tools. These performance evaluation studies can be broadly divided into linear normal factor models rooted in the mutual fund literature; linear non-normal models where the factors are specified to capture the statistical properties of hedge funds; and non–normal models where the functional model is specified to incorporate these properties. There is also related research focusing on underpricing of convertible bonds. This literature provides evidence of opportunities for arbitrage in the convertible bond market and adds to the understanding, by giving details of under pricing, of how the convertible arbitrage market functions.[14]

Several studies (e.g. Brooks and Kat (2001) and Kat and Lu (2002)) have focused on the statistical properties of hedge funds highlighting the skewness, kurtosis and first order autocorrelation in hedge fund returns. Despite these findings many of the performance evaluation studies use linear normal models to assess hedge fund performance. However, several studies have taken innovative approaches to dealing with the non-normality in hedge fund returns. Fung and Hsieh (2001) create portfolios of derivatives that intuitively and statistically share the characteristics of trend following funds. Mitchell and Pulvino (2001) create a merger arbitrage portfolio which has high explanatory power and similar statistical attributes to individual merger arbitrage hedge funds. More recently Kat and Miffre (2005) and Kazemi and Schneeweis (2003), recognizing the dynamic features of hedge fund returns have employed unconditional models which allow for time variation in risk factor weightings.

The remainder of the chapter is organized as follows. Section 2.2 provides a brief review of convertible arbitrage. Section 2.3 provides a review of the relevant hedge fund literature and Section 2.4 provides a conclusion.

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[14] Though the focus of this thesis is on arbitrageurs' performance, results should contribute to understanding of why convertible bonds appear undervalued when evaluated using standard asset pricing models.

2.2 Convertible arbitrage

Convertible bonds were first issued in the United States in the nineteenth century. A simple convertible bond is a relatively straightforward security. It is simply a regular corporate bond, paying a fixed coupon, with security, maturing at a certain date with an additional feature allowing it to be converted into a fixed number of the issuer's common stock. According to Calamos (2003) this convertible clause was first added to fixed income investments to increase the attractiveness of investing in rail roads in what was then the emerging economy of the United States. Calamos (2003) discusses how investors from Great Britain were interested in investing in United States rail roads but did not want to make an entirely equity based investment due to the risks involved. However, if the rail roads were a success investors were keen to avoid being in the position of not enjoying this success, due to just being a lender. Combining an equity component and a fixed income component into one security met investors' demands.

Convertible bonds have grown in complexity and are now issued with features such as put options, call protection, ratchet clauses, step up coupons and floating coupons. Perhaps due to this complexity relatively few investors incorporate convertibles into a long only portfolio. Barkley (2001) estimates that hedge funds account for seventy percent of the demand for new convertible issues and McGee (2003) estimates that hedge funds account for eighty percent of convertible transactions.

While the overall market for convertible bonds has been growing to an estimated $351.9 billion by the end of December 2003 (BIS, 2004) hedge fund investments have grown to over $1 trillion. Initially investors were interested in large global/macro hedge funds and the majority of the funds went into these strategies. Fung and Hsieh (2000a) estimate that in 1997 twenty seven large hedge funds accounted for at least one third of the assets managed by the industry. However, since the bursting of the dotcom bubble, perhaps due to a reduction in appetite for risk, investors have been increasingly interested in lower volatility non-directional arbitrage strategies. According to Tremont Advisors, convertible arbitrage total market value grew from just $768m in 1994 to $25.6bn in 2002 and the Barclay Group estimate the market value as $64.9bn by the end of 2004, a growth rate of 56% on average per annum.

The literature on securities arbitrage dates back more than seventy years. Weinstein (1931) has been credited as being the first to document securities arbitrage. He provides a discussion of how, shortly after the advent of rights, warrants and convertibles in the 1860's arbitrage was born. Although the hedges described by Weinstein lack mathematical precision they appear to have been reasonably successful. Thorp and Kassouf's (1967) seminal work, valuing convertible bonds by dividing them into fixed income and equity option components, was the first to provide a mathematical approach to appraising the relative under or over valuation of convertible securities. The strategies described by Thorp and Kassouf (1967) provide the foundation for the modern day convertible arbitrageur.

Several studies have documented inefficiencies in the pricing of the convertible bond market. Ammann, Kind and Wilde (2004) find evidence, over an eighteen month period, that twenty one French convertible bonds were underpriced by at least three percent relative to their theoretical values. This result is consistent with King (1986) who found on average that a sample of one hundred and three United States listed convertible bonds were undervalued by almost four percent. There is also evidence that convertible bonds are underpriced at issue. Kang and Lee (1996) identified an abnormal return of one percent from buying convertibles at the issue price and selling at the closing price on the first day of trading. Kang and Lee (1996) conclude that this may be due to the difficulty in estimating the value of the option component in unseasoned issues of convertible debt. However, it has also been suggested that in certain market conditions investment banks speak to hedge funds managers when pricing new issues of convertible debt to gauge hedge fund demand (Khan, 2002). This suggests that new issues may be priced attractively to ensure their success in a market dominated by non-traditional investors.

2.3 Hedge fund literature

The majority of the academic literature focusing on dynamic trading strategies can be characterised as hedge fund literature. This characterisation is due to the utilization of return data reported by hedge funds, to data providers[15], being used to evaluate the risk and return characteristics of the different dynamic trading strategies. This literature has made several contributions to the understanding of these dynamic trading strategies. This section will highlight and discuss the issues examined in these studies relevant to an analysis of convertible arbitrage.

[15] There are many vendors of hedge fund data including Tremont TASS, HFR, MAR, The Hennesse Group Eurekahedge and The Barclay Group.

2.3.1 Biases in hedge fund data

The difficulty with the use of hedge fund benchmark returns[16] to define the characteristics of a strategy and measure the performance of individual funds is that hedge fund data contains three main biases; instant history bias, selection bias and survivorship bias as discussed in detail by Fung and Hsieh (2000b).[17] An instant history bias occurs if hedge fund database vendors back fill a hedge fund's performance when they add it to a database. A selection bias occurs if the hedge funds in an observable portfolio are not representative of that particular class of hedge funds. Some funds may be classified as convertible arbitrage but may generally operate a long only strategy. If the vendor does not have a classification to fit the strategy they will include them in the closest fit. Survivorship bias occurs if funds drop out of a database due to poor performance. The resulting database is therefore biased upwards as poor performing funds are excluded. Liang (2000) examines the survivorship bias in hedge fund returns by comparing two large databases (HFR and TASS) finding survivorship bias of 2% per year. Liang (2000) provides empirical evidence that poor performance is the primary reason for funds disappearance from a database. Moreover, Liang (2000) finds significant differences in fund returns, inception dates, Net Asset Values (NAVs), incentive fees, management fees and investment styles for the funds which report to both data vendors. Liang's (2000) findings raise questions over the reliability of the hedge fund data provided by these vendors.[18]

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[16] These biases occur when using hedge fund indices' returns or average hedge fund returns (from a database) as a benchmark.

[17] Other studies including Ackermann, McEnally and Ravenscroft (1999) also discuss some of these biases.

[18] Mismatching between the reported returns in one database and percentage changes in NAVs reported by the other vendor partially explains some of the differences in the databases.

2.3.2 Statistical properties of hedge funds

In the development of a model of performance evaluation it is logical to begin with an initial examination of the statistical properties of the series. Several studies have examined the statistical properties of hedge funds and have highlighted several important features of hedge fund returns.

2.3.2.1 Skewness and kurtosis

Skewness and kurtosis are both important factors in the return distribution of an investment. Skewness characterises the degree of asymmetry of a distribution around its mean. Positive skewness indicates a distribution with an asymmetric tail extending towards more positive values. Negative skewness indicates a distribution with an asymmetric tail extending towards more negative values. Obviously, from the investors' perspective, positive skewed returns are superior to no skewness or negative skewness. Positive kurtosis indicates a relatively peaked distribution with more occurrences in the middle and at the extreme tails of the distribution. Negative kurtosis indicates a relatively flat distribution, with fewer occurrences in the middle and at the extreme tails of the distribution. Investors would view an investment with returns showing high positive kurtosis as unfavourable, indicating more frequent extreme observations. Brooks and Kat (2001) analyse the statistical properties of hedge fund index returns providing evidence that the return distribution of the indices are non-normal displaying negative skewness and positive excess kurtosis.[19] Brooks and Kat (2001) highlight the importance of the skewness and kurtosis when performance measures such as mean variance analysis are used which ignore moments higher than two. They also note the low correlations between the strategy indices of different data providers. The authors conclude that mean variance analysis is unsuitable for hedge funds as it overstates their benefits. Kat and Lu (2002) take a similar approach to Brooks and Kat (2001) examining the statistical properties of individual hedge fund returns, again finding evidence of negative skewness and excess kurtosis. Surprisingly, the authors find that the correlation between individual funds is low, irrespective of whether they are operating the same or different strategies. Intuitively, hedge funds operating the same strategy would be expected to have a higher correlation than hedge funds operating different strategies.[20] Combining individual funds into portfolios leads to return series with lower skewness relative to individual funds.

2.3.2.2 Serial correlation

Serial correlation is uncommon in monthly financial time series as it appears to violate the Efficient Markets Hypothesis; that price changes cannot be forecast if they fully incorporate the expectations of market participants. If monthly price changes are first order autocorrelated then it is possible to partially forecast month $t+1$ price change at time t. In the case of positive first order autocorrelation in hedge fund returns this would suggest that, given information at time t, an investor could invest in a hedge fund

[19] Convertible arbitrage hedge fund indices display all of these characteristics.
[20] This finding highlights one of the difficulties in evaluating hedge funds - the heterogeneity of funds even within the same strategy.

anticipating an increase in the funds value at time *t+1* and then withdraw their funds.[21, 22] Brooks and Kat (2001) document positive first order serial autocorrelation in the returns of hedge fund indices. Brooks and Kat (2001) then demonstrate that the unsmoothed standard deviation of a series which displays first order serial autocorrelation is understated, upward biasing mean variance analysis estimates of performance. Kat and Lu (2002) document positive first order autocorrelation in the returns of individual hedge funds. In these two studies a hypothesis is proposed to explain the serial correlation in hedge fund returns. Both studies hypothesise that the serial correlation may be caused by illiquidity in the securities held by hedge funds or alternatively some unknown institutional factor.

While not explicitly focusing on the statistical properties of hedge funds, Asness, Krail and Liew (2001) highlight indirectly a possible cause of the serial correlation in hedge fund returns. They demonstrate that lagged S&P500 returns are often significant explanatory variables for several hedge fund indices. The strategies where they observe this phenomenon are convertible arbitrage, event driven, equity market neutral fixed income arbitrage, emerging markets and long/short equity. Although, the coefficients of determination for these models suggest that the S&P500 may not be the best explanatory variable for several of these strategies, the relationship with previous months' returns is clear. Asness, Krail and Liew (2001) explain these results as being due to hedge funds holding either illiquid exchange traded securities or difficult to price over the counter securities, which can lead to non-synchronous price reactions. They derive their model

[21] In practice this would not be feasible as hedge funds have lockup periods preventing investors withdrawing funds for two to three months after requesting a withdrawal.

[22] Amenc, El Bied and Martellini (2003) examine the forecastability of hedge fund returns. Unsurprisingly given the strong serial correlation they find that a model incorporating previous month's hedge fund returns generates a good forecast.

from the non-synchronous trading literature proposed by Dimson (1979) and Scholes and Williams (1977).

Although previous studies such as Brooks and Kat (2001) and Kat and Lu (2002) identify serial correlation in hedge fund returns and propose testable hypotheses to explain its occurrence, Getmansky, Lo and Makarov (2004) contribute to the literature by investigating the source of serial correlation in hedge fund returns. They investigate four alternative hypotheses to explain the autocorrelation in hedge fund returns and test an econometric model related to one of them. These will be discussed in turn below. Irrespective of the cause, serial correlation results in a downward bias in estimated return variance and a consequent upward bias in performance when the fund is evaluated using mean variance analysis. For the purposes of developing their model Getmansky, Lo and Makarov (2004) consider the hypotheses competing, though they acknowledge that the serial correlation could be caused by a combination of factors. As autocorrelation is so unusual in monthly financial time series and introduces biases in performance evaluation, these four hypotheses deserve close attention.

The first hypothesis, which Getmansky, Lo and Makarov (2004) favour is that serial correlation is caused by the illiquidity of the securities held in the fund and/or deliberate smoothing of reported returns by hedge fund managers. In the case where the securities held by a fund are not actively traded, the returns of the fund will appear smoother that true returns, be serially correlated, resulting in a downward bias in estimated return variance and a consequent upward bias in performance when the fund is evaluated using mean variance analysis. The authors argue that in some cases hedge fund managers may take advantage of the difficulty in marking securities to market, gradually releasing profits and report smoothed returns. Serial correlation in financial time series is usually associated with studies of daily data in the non-synchronous trading literature but Getmansky, Lo and Makarov (2004) argue that hedge funds are a special case due to their holdings of illiquid securities.

The second hypothesis is that serial correlation is caused by market inefficiency. The validity of this hypothesis is more easily discounted by Getmansky, Lo and Makarov (2004) as it suggests that the hedge fund manager is not taking full advantage of the profit opportunities in the manager's strategy. If returns are positively correlated, following good performance the manager should increase his risk exposure, and following poor performance he should reduce his risk exposure. Given the sophisticated nature of hedge fund managers it seems highly improbable that fund managers would not be fully exploiting such obvious return generating opportunities.

The third hypothesis is also plausible. The authors consider that serial correlation could be the result of time varying expected returns due to changes in risk exposures. Getmansky, Lo and Makarov (2004) derive some estimates of the serial correlation which could be caused by time varying expected returns from a simple Markov switching model and conclude that to generate autocorrelations of the magnitude observed in hedge fund series would require implausible parameters.

Getmansky, Lo and Makarov (2004) conclude that:

> *"Given the implausibility of these parameter values, we conclude that time varying expected returns (at least of this form) are not the most likely explanation for serial autocorrelation in hedge fund returns."* (p. 538)

Getmansky, Lo and Makarov (2004) propose these as competing hypotheses, when clearly serial correlation could come from a combination of these hypotheses. Given the dynamic nature of hedge fund trading strategies time varying expected returns do seem likely to contribute in some part to serial correlation in hedge fund return. Getmansky, Lo and Makarov (2004) provide evidence that with a Markov-Switching functional specification this could be as much as 0.15 serial correlation.

The fourth possible source of serial correlation in hedge fund returns proposed by Getmansky, Lo and Makarov (2004) is time varying leverage, a special case of time varying expected returns. The authors propose a naïve data dependent mechanism through which a hedge fund determines its ideal leverage ratio based on the assumption that hedge fund leverage is a function of market prices and market volatility. For example in more volatile markets or when market prices move against a fund, leverage will be reduced. After Monte-Carlo analysis the authors conclude of their naïve leverage model:

> *"This suggests that time varying leverage, at least of the form described by the VaR constraint, cannot fully account for the magnitudes of serial correlation in hedge fund constraints."* (p. 542)

While the evidence presented suggests that time varying leverage could not fully explain the observed serial correlation, it seems plausible that time varying leverage may contribute in a small part to serial correlation in hedge fund returns. The results of Getmansky, Lo and Makarov's (2004) Monte-Carlo analysis indicate that this is likely to be a maximum 0.007 return-autocorrelation.

The final proposed source of autocorrelation regards incentives and high water marks. Fees are only charged if the cumulative returns of a hedge fund are above a high water mark (typically the return on a benchmark). When a fund's cumulative return moves from below to above a high water mark, the incentive fee is reinstated, and net of fee returns are reduced accordingly. This can induce serial correlation in net of fee returns due to the path dependence inherent in the high water mark. However, the serial correlation induced by this effect is actually negative leading to the conclusion that this is unlikely to explain the large positive serial correlation in hedge fund returns.

Having reviewed the alternative hypotheses, the authors come down firmly in favour of the illiquidity/smoothing hypothesis and propose a smoothed returns econometric model of serial correlation and illiquidity in hedge fund returns. This model assumes that all of the serial correlation found in hedge fund returns is due to illiquidity/smoothing, rather than being a combination of the four hypotheses. This assumption leads directly to estimation of illiquidity/smoothing parameters using a similar methodology to standard moving average time series models.

Previous studies focusing on the statistical properties of hedge funds have highlighted three important observations. Hedge fund returns tend to be negatively skewed, display excess kurtosis and are first order autocorrelated. Specification of a performance model without explicitly allowing for these features will lead to mis-estimation of risk and consequently performance.

2.3.3 Hedge fund performance evaluation models

The hedge fund performance evaluation literature can be divided into five main categories; performance indicator studies, linear normal factor model studies founded in the mutual fund literature, linear non-normal factor model studies which specify factors to capture the non-normality in hedge fund returns, non-normal studies whose functional specification captures the non-normality in hedge fund returns, and finally, studies of performance persistence.

2.3.3.1 Performance indicator studies

The Sharpe (1966) ratio (2.1) is a performance indicator widely used for the evaluation of investments calculated from the mean and standard deviation of a portfolios excess return. Modified versions of the ratio have been used in several studies of hedge funds as measures of performance.

$$S_p = \frac{R_p - r_f}{\sigma_p} \qquad (2.1)$$

Where S_p is the Sharpe ratio for portfolio p, R_p is the mean return of portfolio p, r_f is the return on the risk free asset and σ_p is the standard deviation of the portfolio return. Brown, Goetzmann and Ibbotson (1999) examine the performance of a sample of offshore hedge funds over the period 1989 through to 1995 using Sharpe ratios. The study uses annual data net of fees. Their sample does include surviving and dead funds and fund of funds. Given the acknowledged short sample period and annual data, few conclusions can be drawn on performance. Ackermann, McEnally and Ravenscraft

(1999) examine hedge fund performance using monthly data from 1988 to 1995. Ackermann, McEnally and Ravenscraft (1999) use the Sharpe ratio to assess hedge fund performance relative to equity indices and mutual funds ignoring higher moments. They find that the incentive fee is an important characteristic that drives hedge fund performance. Surprisingly, they also find that the returns of hedge funds have a larger variance than mutual funds. Anson (2002) demonstrates that the Sharpe ratio is unsuitable for the evaluation of a strategy with an asymmetric payoff, such as being short volatility. As the Sharpe ratio assumes a normal distribution of the asset's returns, it ignores moments higher than two, and overstates performance for hedge funds where the distribution exhibits negative skewness. Several studies have introduced modifications to the Sharpe ratio incorporating higher moments. Gregariou and Gueyie (2003) compared the relative rankings of fund of hedge funds using the Sharpe ratio and a similar ratio replacing the standard deviation in (2.1) with the modified Value-at-Risk, which takes into account the skewness and kurtosis of the return distribution. They present evidence that due to the non-normality in hedge fund returns the Sharpe ratio is ineffective for analysing the relative performance of fund of hedge funds. Madhavi (2004) introduces the Adjusted Sharpe Ratio where the distribution of a fund's return is adjusted to match the distribution of a normally distributed benchmark. The resulting estimated Sharpe ratio can then be compared directly with the benchmark Sharpe ratio. Madhavi (2004) provides evidence for hedge funds indices' performance that there is little statistically significant difference between the Adjusted Sharpe Ratios and the traditional Sharpe ratio.

A final issue related to the estimation of Sharpe ratios for hedge funds is autocorrelation. Brooks and Kat (2001) highlight that the positive first order autocorrelation, observed in hedge fund indices, will lead to underestimation of the indices' standard deviation with a corresponding overestimation of the Sharpe ratio. Brooks and Kat (2001) suggest unsmoothing the series to more efficiently estimate the standard deviation and Sharpe ratio. Also identifying the potential upward bias in estimated Sharpe ratios caused by first order serial correlation, Lo (2002) proposes an autocorrelation adjusted Sharpe ratio.

2.3.3.2 Linear normal factor model studies

Early studies of hedge funds implemented the estimation techniques developed for assessing mutual fund performance. These studies contribute to the literature by providing definitions and classifications of hedge funds and presenting evidence of the asset classes that hedge funds are exposed to. Brown, Goetzmann and Ibbotson (1999) estimate market model betas and alphas in addition to the estimated Sharpe ratios. Liang (1999) investigates hedge fund returns and risk from 1990 to June 1999 focusing in particular on the global financial crisis in 1998. Liang's (1999) analysis is limited to examining return and standard deviation (ignoring skewness and kurtosis), relative to the S&P500, a benchmark which could be judged inappropriate for the majority of hedge fund trading strategies. Liang (1999) does also consider survivorship bias and estimates that the average survivorship bias for hedge fund returns is 2.4%

In a more recent linear normal study Capocci and Hübner (2004) analyse the performance of a large sample of hedge funds utilising a Sharpe (1992) factor analysis methodology. The authors find that hedge funds generate significant abnormal returns over the sample period but several of their regression models have low explanatory power so perceived out-performance could possibly be due to misspecification of the factor models. Capocci and Hübner (2004) examine several hedge fund strategies using a Fama and French (1993) three factor model, a Carhart (1997) four factor model and a more general combined model. Evidence is presented that the excess market return, the Fama and French (1993) portfolios mimicking size and book to market, bond returns and default risk are all important in the returns of convertible arbitrage, but despite the inclusion of these factors convertible arbitrageurs appear to generate substantial risk adjusted returns. The explanatory power of Capocci and Hübner's (2004) models are relatively low when looking at convertible arbitrage hedge fund returns and this may lead to erroneous estimates of performance. Omitted variables could introduce bias in Capocci and Hübner's (2004) estimates of alphas. The authors do not include a rationale for specifying particular factors in their models and provide no expectation of factor coefficient sign or significance. The correlation between some of the factors such as the world government bond index, the US bond index and the emerging market bond index, are significant, which may bias results. The study does provides useful evidence when looking at the less dynamic trading strategies which are more correlated with traditional asset classes, but overall suffers from trying to specify a common factor model to capture the characteristics of a diverse range of trading strategies. This is highlighted by the range of coefficients of determination which vary from 22% to 94% across strategies. The evidence presented by Capocci and Hübner (2004) suggests that more success may be gleaned by focusing on fewer strategies with similar characteristics and paying more attention to the statistical properties of the funds. Like Capocci and Hübner's (2004) study, Fung and Hsieh (2002a) specify one factor model to capture the characteristics of a diverse range of trading strategies. Combined with a review of the linear factor model literature, Fung and Hsieh (2002a) construct linear normal asset based factor models of hedge fund returns. The authors look at several hedge fund strategy indices including convertible arbitrage. The results contribute to understanding of trading strategies that could *ex ante* be classified as being correlated with traditional market factors. In Fung and Hsieh's (2002a) factor model they specify three factors, small cap stocks, high yield bonds and emerging markets equities to model the returns of several hedge fund strategy indices. Looking specifically at the results for convertible arbitrage, although the explanatory power of the model is low with an adjusted R^2 of 18%, they find that high yield bonds are significant in explaining the returns of convertible arbitrage hedge fund index returns. In a similar study Fung and Hsieh (2004) repeat the linear factor model approach to analyzing hedge fund performance. However, they also test the stability of the risk factor coefficients using cumulative recursive residuals. For both the hedge fund indices and fund of funds they find variation in the risk factors weightings. This provides some evidence that a linear factor model may not fully capture the risk in hedge fund trading strategies.

2.3.3.3 Linear non-normal factor model studies

Several studies contribute to the understanding of hedge fund performance by developing factors for inclusion in a performance model which share the non-normal distributions of hedge fund returns. Fung and Hsieh (1997) extend Sharpe's (1992) asset class factor model for performance attribution and style analysis of mutual fund managers, to look at hedge funds. They focus on mutual funds, hedge funds and commodity trading advisors (CTAs). Fung and Hsieh (1997) find that mutual funds are highly correlated with traditional asset classes but hedge funds and CTAs generate returns that have low correlation with mutual funds and traditional asset classes. There is also a large diversity amongst the hedge funds and CTA pools and to deal with this diversity Fung and Hsieh (1997) use factor analysis to isolate five dominant investment styles in hedge fund and CTA returns. The authors then construct five benchmark factors from portfolios of hedge funds using only hedge funds that are correlated to that principal component. Funds are weighted within the factor portfolio to maximise the correlation with the principal component. These five statistically created portfolios are then used as explanatory variables in a factor model to explain hedge fund returns. The difficulty with this study is the use of statistical techniques to identify factors which then, by the nature of their construction, have good explanatory power for hedge funds.

Rather than using hedge fund benchmarks or traditional assets as factors, three studies by Fung and Hsieh (2001, 2002b) and Mitchell and Pulvino (2001) construct portfolios of securities/derivatives to serve as performance benchmarks. Fung and Hsieh (2001) focus exclusively on the trend following dynamic trading strategy. A trend follower attempts to capture market trends defined here as *"a series of asset prices that move persistently in one direction over a given time interval, where price changes exhibit positive autocorrelation."* (p. 315) The authors differentiate between market timers and trend followers, *"Generally market timers enter into a trade in anticipation of a price movement over a given time period, whereas trend followers trade only after they have observed certain price movements during a period."* (p. 317) This implies that market timers will generate greater returns than trend followers but trend followers will have fewer losses as they enter trades later when they are surer of a trend. The authors define the payoff to a trend follower as the difference between the maximum and minimum price in an asset over a time period. They acknowledge that this is not strictly correct as a trend follower may have multiple transactions in an asset within the time period but their definition is convenient as it matches the payoff from a lookback straddle: the difference between the maximum and minimum underlying asset price during a time period. Fung and Hsieh (2001) hypothesise that trend followers operate in stocks, bonds, currencies and commodities and construct portfolios of straddles mimicking the payoff from a lookback straddle which matches their definition of a trend following payoff. These portfolios have high explanatory power when looking at the returns of individual funds and serve as useful benchmarks of fund performance. Fung and Hsieh (2002b) follow a similar methodology to Fung and Hsieh (2001) providing evidence of convergence trading in several fixed income strategies. The authors look at a relatively small database of five fixed income hedge fund strategies. Three of the strategies, long convertible bonds, long high yield bonds and long mortgage backed securities would not normally be classified as dynamic trading strategies. The results for fixed income arbitrage, a form of convergence trading, are of most interest and the authors use short positions in lookback straddles to describe the returns from this strategy hypothesising that *"The convergence trading strategy is basically the opposite of the trend-following strategy."* (p. 11) This is not strictly correct as convergence trading is concerned with the relative returns on two different but similar assets whereas trend following is concerned with the absolute price movements of one asset.

Taking a similar approach to Fung and Hsieh (2001) and Fung and Hsieh (2002b) Mitchell and Pulvino (2001) examine the merger arbitrage trading strategy. Prior finding suggested that the returns from merger arbitrage are abnormally large relative to risk. Rather than constructing a portfolio of mimicking derivatives the authors construct a portfolio of merger arbitrage positions and then examine the returns from the portfolio. They focus on two types of merger arbitrage, cash merger arbitrage and stock merger arbitrage. Previous empirical research finds that cash merger arbitrage has the largest excess returns. The returns from cash merger arbitrage are equal to the agreed deal price minus stock purchase price plus any dividend accruing. The returns from stock merger arbitrage come from the long position in the target and the short position in the acquirer. The major risk for both types of merger arbitrage is deal failure which will result in the target's stock price collapsing. Mitchell and Pulvino look at an extensive sample of 9026 transactions between 1963 and 1998. The authors exclude deals for two reasons: overly complicated deal terms and a lack of accurate data. The advantage of Mitchell and Pulvino's approach to analysing a dynamic trading strategy is that the merger arbitrage strategy returns (represented by the portfolios returns) contain none of the biases described in Fung and Hsieh (2000b). The disadvantage of the approach is that in reality a merger arbitrageur would use relative valuations to analyse which deals to arbitrage. However their portfolio serves as a useful passive benchmark.

One alternate methodology which addresses the issue of non-normality in the returns of hedge funds in a linear framework is the inclusion of derivatives combined with the returns on traditional assets in an asset class factor model. Agarwal and Naik (2004) evaluate hedge fund performance using a Sharpe (1992) asset class factor model with derivative payoffs as factors. This adds to the explanatory power of the factor model and leads to improvements in the efficiency of performance evaluation. Aggarwal and Naik's (2004) study is focused on including options payoffs in an asset class factor model to allow for the non-normality inherent in a range of hedge fund returns. While being more focused on the non-linear behaviour of hedge fund returns rather than the identification of factors which affect the returns, the authors do provide evidence on factor loadings on a range of hedge fund strategies including convertible arbitrage.

Aggarwal and Naik (2004) document convertible arbitrage showing significant loadings on Fama and French (1993) size factor, a short position in an at the money S&P 500 put option and the return on emerging market equities.

2.3.3.4 Non-normal studies

In addition to the linear factor model literature there are also studies utilizing models whose functional specification, rather than factor specification, captures the non-normal characteristics of hedge funds. Rather than specifying factors with non-normal distributions these studies relax the assumption of a linear relationship between the risk factor and the hedge fund return. Kat and Miffre (2005) recognise that linear asset pricing models may fail to capture the dynamic asset allocation and non-normality in the returns of hedge funds, and this in turn will affect any estimate of performance. The authors employ a conditional model of hedge fund returns which allows the risk coefficients and alpha to vary. Kat and Miffre (2005) assume that there is a linear relationship between the risk coefficients and a set of information variables (including the lag of hedge fund returns). This type of performance evaluation for hedge funds is more efficient than other studies which employ models where the coefficients on the risk factors are fixed. Hedge funds by definition employ dynamic investment strategies. Managers adjust risk exposure in response to market conditions. Restricting a model to fixed coefficients fails to fully capture this dynamic adjustment in risk exposure and consequently biases estimates of performance. The risk factors which Kat and Miffre (2005) employ are an equity index, a bond index, a commodity index, a foreign exchange index and factor mimicking portfolios for size, book to market, skewness and kurtosis risk. Utilising a similar methodology to Kat and Miffre (2005), Kazemi and

Schneeweis (2003) have also attempted to explicitly address the dynamics in hedge fund trading strategies by employing conditional models of hedge fund performance. Kazemi and Schneeweis (2003) employ the stochastic discount factor (SDF) model which has previously been employed in the mutual fund literature.[23] The results are quite similar for the SDF model and the linear model and some evidence is provided of hedge fund out-performance although the study is constrained by applying one factor model to a variety of uncorrelated trading strategies.

In an innovative study evaluating hedge fund performance, which imposes zero restrictions on the distribution of the funds returns, Amin and Kat (2003b) evaluate hedge funds from a contingent claims perspective. They begin by assuming an initial investment at the beginning of each month in each hedge fund and in the S&P500 to create a cumulative distribution. A non-decreasing function of the S&P500 which yields an identical payoff to the hedge fund is then estimated. Finally, a dynamic S&P500 and cash trading strategy that generates the hedge fund payoff function is valued. The price of this function is then compared to the assumed initial investment in the hedge fund to benchmark the manager's performance. If the initial investment is less than the estimated price then the hedge fund manager has added value. If the initial investment is greater than the calculated price of the function then the hedge fund manager has acted inefficiently. Their findings indicate that the majority of hedge funds operate inefficiently but acknowledge that the size of the sample may lead to sampling errors. Amin and Kat (2003b) assume a constant risk free rate of interest and dividend yield for the sample period. The authors also initially assume zero transaction costs for the dynamic S&P500 and cash trading strategy, which will bias downward their estimates of

[23] See for example Chen and Knez (1996) and Farnsworth, Ferson, Jackson and Todd (2002).

hedge fund efficiency. When this assumption is relaxed the efficiency of funds increases.

2.3.3.5 Performance persistence studies

The issue of performance persistence in the returns of hedge funds has been explored in several studies. Agarwal and Naik (2000b) examine performance persistence in a multi-period framework using quarterly and annual data. The authors seek to identify whether performance persistence is short or long term and employ a multi-period framework to ensure the robustness of results. Agarwal and Naik (2000b) compare the appraisal ratio of a hedge fund from period to period. The appraisal ratio is defined as the return of the fund manager using a particular strategy, minus the average return on all the funds using the same strategy in that period, divided by the standard errors of the residuals from the regression of the fund return on the average return of all the funds following that strategy in that period. The denominator is included to reflect the relative volatility of the fund. To consider this a risk adjusted ratio assumes that the standard errors of the residuals capture all of the risk in the fund. Agarwal and Naik (2000b) find evidence of quarterly performance persistence but at longer horizons the performance persistence disappears. Agarwal and Naik's (2000b) finding for longer horizons is consistent with the findings of Brown, Goetzmann and Ibbotson (1999) and Capocci, Corhay and Hübner (2005) who find no evidence of performance persistence using annual data.

Rather than examining performance persistence in terms of a risk adjusted ratio Kat and Menexe (2003) use a two period framework to examine the persistence of hedge funds' mean return, standard deviation, skewness, kurtosis and correlation with stocks and bonds from one period to the next. They provide evidence that the persistence in mean, skewness and kurtosis are all low, but that standard deviation of returns and correlation with stocks is persistent across periods.

2.3.4 Convertible arbitrage hedge fund literature

Several of the studies discussed above provide some evidence on the risk, return and performance of convertible arbitrage hedge funds. Brooks and Kat (2001) and Kat and Lu (2002) provide evidence on the statistical properties of convertible arbitrage hedge funds. Brooks and Kat (2001) document significant negative estimates of skewness, ranging from -0.78 to -2.41, significant positive estimates of excess kurtosis, ranging from 2.28 to 8.73 and significant positive estimates of first order serial correlation[24], with coefficients ranging from 0.40 to 0.53, in four convertible arbitrage hedge fund indices. Kat and Ku (2002) document similar characteristics in the returns of individual convertible arbitrage hedge funds, with a mean estimate of skewness of -1.12, a mean estimate of excess kurtosis of 8.51 and an average first order serial correlation coefficient of 0.30.

Convertible arbitrage performance evaluation studies using linear normal models include Capocci and Hübner (2004) and Fung and Hsieh (2002). Capocci and Hübner (2004) include a sample of convertible arbitrage hedge funds in a broader multi-factor performance evaluation of hedge funds and present evidence of a significantly positive United States equity market coefficient of 0.05, significantly positive coefficients on

[24] Brooks and Kat (2001) also document significantly positive second order serial correlation in the CSFB Tremont Convertible Arbitrage Index.

SMB (0.05) and HML (0.04), Fama and French's (1992, 1993) size and book to market factors, a significantly negative coefficient (-0.02) on Carhart's (1997) momentum factor, a significantly positive coefficient of 0.05 on the MSCI World Equity Index (excluding the United States), a significantly negative coefficient on the Salomon World Government Bond Index (-0.11) and significantly positive coefficients on JP Morgan Emerging Bond (0.03) and Lehman BAA Corporate Bond index factors (0.16). Capocci and Hübner (2004) estimate that convertible arbitrage hedge funds generated significantly positive alpha of 0.42% per month over the sample period. Fung and Hsieh (2002) specify three factors, small cap stocks, high yield bonds and emerging markets equities to model the returns of several hedge fund strategy indices including convertible arbitrage. They estimate significant positive emerging market equity and significantly negative small cap stock coefficients for the convertible arbitrage hedge fund index. Fung and Hsieh (2002) estimate that the strategy index generated abnormal returns of 0.74% per month over the sample period. Agarwal and Naik's (2004) linear non-normal study provides useful evidence on convertible arbitrage risk and performance augmenting a linear factor model specification with the payoff from equity index options. Agarwal and Naik (2004) specify the lagged Russell 3000 index, the payoff of an at the money S&P500 put option, Fama and French's (1992, 1993) size factor, the Salomon Brothers Government and Corporate Bond index, Salomon Brothers World Bond index, the Lehman High Yield Bond index and the MSCI Emerging Markets index as risk factors to explain the returns of the HFRI and CSFB Tremont convertible arbitrage indices. They estimate the CSFB Tremont index and the HFRI index generated abnormal returns of 0.59% and 0.24% per month, respectively over the sample period.

In two studies which do not impose restrictions on the distribution of the hedge fund return series, Kazemi and Schneeweis (2003) and Kat and Miffre (2005) provide estimates of convertible arbitrage risk and performance. Kazemi and Schneeweis (2003) specify the returns of growth, value, small cap and large cap stocks, Lehman High Yield and Lehman Long Term Bond indices as risk factors. The two factors which are significant at a statistically acceptable level are the returns on the Small Cap portfolio and the Lehman High Yield with coefficients of 0.05 and 0.14 respectively. Kazemi and Schneeweis (2003) estimate that convertible arbitrage generates abnormal returns of 0.52% per month over the sample period. In their study incorporating higher moment risk factors, discussed in detail above, Kat and Miffre (2005) estimate that the average convertible arbitrage hedge fund generated abnormal returns ranging from 6.5% to 7.3% per annum over the sample period.

2.4 Conclusion

This chapter has reviewed hedge fund literature relevant to an analysis of convertible arbitrage. The chapter began with a brief introduction to convertible arbitrage and then progressed to review literature looking first at the statistical properties of hedge funds and then at hedge fund performance measurement. The two important statistical properties of hedge funds which will affect any evaluation of performance are, firstly, the non-normal distribution characterized by negative skewness and positive excess kurtosis and, secondly, the first order autocorrelation in their returns.

Evidence suggests that the autocorrelation in hedge fund returns is primarily driven by illiquidity in their security holdings combined with time varying expected return and time varying leverage. It is also possible that funds deliberately smooth returns though this will only be feasible if they hold illiquid securities so this smoothing is also a function of illiquidity. Illiquidity is a risk which must be borne by an investor in a hedge fund and needs to be addressed in any analysis of convertible arbitrage.

In terms of hedge fund performance literature, studies which have attempted to recreate the payoff from a hedge fund strategy, or utilize a performance measurement model which allows for the non-normal distribution of hedge fund returns, have made the most significant contributions to the understanding of hedge fund risk, return and performance.

Chapter 3: Convertible bond arbitrage portfolio simulation and analysis of daily returns

3.1 Introduction

Convertible bond arbitrageurs attempt to exploit inefficiencies in the pricing of convertible bonds by purchasing the undervalued security and hedging market and credit risks using the underlying share and credit derivatives. Existing literature indicates that this strategy generates positive abnormal risk adjusted returns. Due to limitations in hedge fund reporting, performance measurement to date has been limited to studies of monthly returns. The use of monthly returns ignores important short run dynamics in price behaviour. The innovation of this chapter is the replication of the core underlying strategy of a convertible bond arbitrageur producing daily convertible bond arbitrage returns. This contributes to the existing literature by providing evidence of convertible arbitrage performance and risks and serves as a useful benchmark of convertible arbitrage hedge fund performance.

This chapter follows Mitchell and Pulvino's (2001) study of merger arbitrage, in attempting to recreate an arbitrageur's portfolio. Rather than using combinations of derivatives which would be expected to intuitively share the characteristics of a trading strategy's returns, a convertible arbitrage portfolio is created by combining financial instruments in a manner akin to that ascribed to practitioners who operate that strategy. The core strategy is replicated by constructing an equally weighted and a market capitalisation weighted portfolio of 503 hedged convertible bonds from 1990 to 2002, producing two daily time series of convertible bond arbitrage returns. The portfolio is created by matching long positions in convertible bonds, with short positions in the issuer's equity to create a delta neutral hedged convertible bond position which captures income and volatility. Delta neutral hedged positions are then combined into two convertible bond arbitrage portfolios, one equally weighted, the other weighted by market capitalisation of the convertible issuers' equity. To confirm that the portfolios have the characteristics of a convertible bond arbitrageur the returns of the convertible bond arbitrage portfolio and the returns from two indices of convertible arbitrage hedge funds are compared in a variety of market conditions. The simulated portfolios and the hedge fund indices share similar characteristics and are highly correlated.

The relationship between convertible bond arbitrage and a traditional buy and hold equity portfolio is also examined, highlighting the non-linear relationship between daily convertible bond arbitrage returns and daily equity returns. In severe market downturns convertible arbitrage exhibits negative returns. Evidence is also found that in severe market upturns the daily returns from the equally weighted convertible bond arbitrage portfolio are negatively related to equities. In effect the returns to convertible bond arbitrage are akin to writing naked out of the money put and call options. Although this is not the first study to document the short put option like feature in convertible arbitrage returns (Agarwal and Naik (2004) also document this feature of convertible arbitrage using monthly hedge fund asset values), it is the first to document the negative correlation between daily convertible bond arbitrage and equity market returns in extreme up markets. This negative correlation is explained by the long volatility nature of convertible bond arbitrage. In extreme up markets implied volatility generally decreases having a negative effect on portfolio returns. This is an important finding for any investor considering adding a convertible bond arbitrage fund to an existing buy and hold long only equity portfolio.

The remainder of the chapter is organised as follows. In Section 3.2, a description of a typical convertible bond arbitrage position and a thorough description of how the simulated portfolio is constructed are provided. In Section 3.3, the returns of the convertible bond arbitrage portfolio are compared with the returns of two convertible arbitrage hedge fund indices and market factors. In Section 3.4, results are presented from examining the relationship between convertible bond arbitrage and a traditional buy and hold equity portfolio. Section 3.5 concludes the chapter and Section 3.6 discusses potential limitations in the analysis.

3.2 Description of a convertible bond arbitrage position and portfolio construction

Fundamentally convertible bond arbitrage entails purchasing a convertible bond and selling short the underlying stock creating a delta neutral hedge long volatility position. The arbitrageur may also hedge credit risk using credit derivatives, although these instruments are a relatively recent development. The short stock position partially hedges credit risk as generally if an issuer's credit quality declines this will also have a negative effect on the issuer's equity. This is considered the core strategy underlying convertible bond arbitrage. The position is set up so that the arbitrageur can benefit from income and equity volatility.

The strategy involves purchasing a long convertible and selling short the underlying stock at the current delta. The hedge neutralizes equity risk but is exposed to interest rate and volatility risk. Income is captured from the convertible coupon and the interest on the short position in the underlying stock. This income is reduced by the cost of borrowing the underlying stock and any dividends payable to the lender of the underlying stock. The non-income return comes from the long volatility exposure. The hedge is rebalanced as the stock price and/or convertible price move. Rebalancing will result in adding or subtracting from the short stock position. Transaction costs and the arbitrageur's attitude to risk will affect how quickly the hedge is rebalanced and this can have a large effect on returns.

In order for the volatility exposure to generate positive returns the actual volatility over the life of the position must be greater than the implied volatility of the convertible bond at the initial set up of the hedge. If the actual volatility is equal to the implied volatility one would expect little return to be earned from the long volatility exposure. If the actual volatility over the life of the position is less than the implied volatility at setup then one would expect the position to have negative non-income returns. It should be noted that the profitability of a long volatility strategy is dependent on the path followed by the stock price and how it is hedged.

Convertible bond arbitrageurs employ a myriad of other strategies. These include the delta neutral hedge, bull gamma hedge, bear gamma hedge, reverse hedge, call option hedges and convergence hedges.[25] However Calamos (2003) describes the delta neutral hedge as *"the bread and butter"* (p. 35) hedge of convertible bond arbitrage.

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[25] For a detailed description of the different strategies employed by convertible arbitrageurs see Calamos (2003).

Convertible securities are of various different types including traditional convertible bonds, mandatory convertibles and convertible preferred. This study focuses exclusively on the traditional convertible bond as this allows a universal hedging strategy across all instruments in the portfolio. It also focuses exclusively on convertible bonds listed in the United States between 1990 and 2002. Convertible securities are listed on most international markets, predominately in the United States, Europe and Japan but also in smaller Asian countries such as Taiwan, Hong Kong and Korea. According to Khan (2002) until recently Japan represented the largest market share of the global convertibles market. Due to the economic situation, there has been a marked decrease in the primary issuance of convertible securities and other debt securities there. With low coupon rates in Japan income returns are at a minimum and, other than volatility trades, there are few opportunities for convertible arbitrageurs. With the surge in issuance in the United States, due in part to the hostile equity issuance climate since the bursting of the dot com bubble, it can be assumed that a large proportion of recent convertible arbitrage activity is focused in the United States.

To enable the forecasting of volatility, issuers with equity listed for less than one year were excluded from the sample. Any non-standard convertible bonds and convertible bonds with missing or unreliable data were removed from the sample. The final sample consists of 503 convertible bonds, 380 of which were live at the end of 2002, with 123 dead. The terms of each convertible bond, daily closing prices and the closing prices and dividends of their underlying stocks were sourced from Monis and DataStream.

Perhaps the most important parameter for calculating the theoretical value of a convertible bond and the corresponding hedge ratio is the estimate of volatility. As convertible bonds are generally of reasonable long maturity it is important to allow for volatility's mean reverting nature and the GARCH(1,1) model is employed. For each convertible bond one estimate of future volatility σ_{n+k}^2 is forecast following Hull (2001). Equation (3.1) sets out how future volatility was estimated from the inclusion date, day *n* to the redemption date, day *k*, using five years of historical closing prices of the underlying stock up to and including day *n-1*, the day before the bond is included in the portfolio. For some equities in the sample five years of historic data was unavailable. In this situation volatility was forecast using available data, restricted to a minimum of one year. Only equities with a minimum of one year of historical data were included in the original sample.

$$E(\sigma_{n+k}^2) = V_L + (\alpha + \beta)^k (\sigma_n^2 - V_L) \tag{3.1}$$

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{3.2}$$

Subject to

$$\gamma + \alpha + \beta = 1 \tag{3.3}$$

where σ_n^2 is the estimate of volatility on day *n*, V_L is the long run variance rate, u_{n-1}^2 is the squared percentage change in the market variable between the end of day *n-2* and the end of day *n-1* and σ_{n-1}^2 is the estimate of volatility on day *n-1*. The parameters α and β are estimated to maximise the objective function (3.4).

$$\sum_{i=1}^{m} \left(-\ln(v_i) - \frac{u_i^2}{v_i} \right) \tag{3.4}$$

Where v_i is the estimate of the variance rate σ_i^2, for day *i* made on day *i-1*.

In order to initiate a delta neutral hedge for each convertible bond an estimate of the delta is needed for each convertible bond on the trading day it enters the portfolio. The delta estimate is then multiplied by the convertible bond's conversion ratio to calculate Δ_{it} the number of shares to be sold short in the underlying stock (the hedge ratio) to initiate the delta neutral hedge. On the following day the new hedge ratio, Δ_{it+1}, is calculated, and if $\Delta_{it+1} > \Delta_{it}$ then $\Delta_{it+1} - \Delta_{it}$ shares are sold, or if $\Delta_{it+1} < \Delta_{it}$, then $\Delta_{it} - \Delta_{it+1}$ shares are purchased maintaining the delta neutral hedge. As discussed earlier, due to transaction costs, an arbitrageur would not normally rebalance each hedge daily. However to avoid making *ad hoc* decisions on the timing of the hedge, the portfolio is rebalanced daily and transaction costs are excluded from the study.

Daily returns were calculated for each position on each trading day up to and including the day the position is closed out. A position is closed out on the day the convertible bond is delisted from the exchange. Convertible bonds may be delisted for several reasons. The company may be bankrupt, the convertible may have expired or the convertible may have been fully called by the issuer.

The returns for a position *i* on day *t* are calculated as follows.

$$R_{it} = \frac{P_{it}^{CB} - P_{it-1}^{CB} + C_{it} - \Delta_{it-1}(P_{it}^{U} - P_{it-1}^{U} + D_{it}) + r_{t-1}S_{i,t-1}}{P_{it-1}^{CB} + \Delta_{it-1}P_{it-1}^{U}} \tag{3.5}$$

Where R_{it} is the return on position *i* at time *t*, P_{it}^{CB} is the convertible bond closing price at time *t*, P_{it}^{U} is the underlying equity closing price at time *t*, C_{it} is the coupon payable at time t, D_{it} is the dividend payable at time t, Δ_{it-1} is the delta neutral hedge ratio for position i at time t-1 and $r_{t-1}S_{i,t-1}$ is the interest on the short proceeds from the sale of the shares. Daily returns are then compounded to produce a position value index for each hedged convertible bond over the entire sample period.

Table 3.1
Sample summary

This table presents a summary of the individual convertible bond hedges constructed in this paper. Position duration is measured as the number of trading days from the addition of the hedged convertible position to the portfolio to the day the position is closed out. Max position return is the maximum cumulated return of a position from the date of inclusion to the date the position is closed out. Min position return is the minimum cumulated return earned by a position from the date of inclusion to the date the position is closed out. Average position return is the average cumulated return of a position from the date of inclusion to the date the position is closed out. Number of positions closed out is the number of positions which have been closed during a year.

Year	Number of New Positions	Average Position Duration (Yrs)	Max Position Return %	Min Position Return %	Average Position Return %	Number of Positions Closed out
1990	66	11.6	460.7	(95.6)	70.1	
1991	9	9.8	127.5	7.9	51.6	
1992	11	10.1	154.9	(59.5)	20.5	1
1993	10	9.7	88.1	1.26	39.6	2
1994	27	8.3	178	(99.1)	51.4	2
1995	33	6.8	453	(85.5)	46.7	2
1996	10	6.9	194.4	2.9	52.5	14
1997	1	5.4	22.2	22.2	22.2	12
1998	1	5	1	1	1	11
1999	4	3.5	24.1	(69.6)	(7.7)	8
2000	15	2.3	80.7	(85.5)	(4.6)	4
2001	235	1.6	344.3	(96.9)	9.81	16
2002	81	0.27	58.7	(29.6)	0.9	431
Complete Sample	503					503

Table 3.1 presents a summary of the individual convertible bond arbitrage return series. 2001, 2002 and 1990 are the years when the majority of new positions were added. In

1990 sixty six new positions were added. Fifty five of these positions were convertible bonds which were listed prior to 1990, and eleven were new listings. The average position duration was 11.6 years, and the average position return was 70.1%, 4.7% per annum. The maximum return on an individual position was 460.7% and the minimum position return was -95.6%. In 2001 two hundred and thirty five new positions were added with average position duration of 1.6 years and average position return of 6% per annum. 1997, 1998 and 1999 are the years when the fewest new positions were added to the portfolio. In 1997 and 1998 one new position was added in each year, and in 1999 only four new positions were added. The worst returns were generated by positions added in 1999 and 2000, with average annual returns of -2.25% and -2% respectively. The closing out of positions is spread reasonably evenly over the sample period, with the exception of 2002 where the majority of positions are closed out when the portfolio is liquidated at 31st December 2002.

Next the asset values of the individual positions are combined into two convertible bond arbitrage portfolios. This is a similar methodology to that utilized in the CSFB Tremont Hedge Fund Index calculation described in CSFB Tremont (2002). The first portfolio is an equally weighted portfolio calculated assuming an equal initial investment in each hedged convertible bond position. In the second portfolio the individual positions are weighted by the market capitalization of the issuer's equity. This portfolio is then focused on the bigger issues. These bigger convertible bond issues should be more liquid and of a higher credit quality and intuitively one would expect fewer arbitrage opportunities.

The value of the two convertible bond arbitrage portfolios on a particular date is given by the formula.

$$V_t = \frac{\sum_{i=1}^{i=N_t} W_{it} PV_{it}}{F_t} \tag{3.6}$$

Where V_t is the portfolio value on day t, W_{it} is the weighting of position i on day t, PV_{it} is the value of position i on day t, F_t is the divisor on day t and N_t is the total number of positions on day t. For the equally weighted portfolio W_{it} is set equal to one for each live hedged position. For the market capitalization index the weighting for position j is calculated as follows.

$$W_{jt} = \frac{MC_{jt}}{\sum_{i=1}^{i=N_t} MC_{it}} \tag{3.7}$$

Where W_{jt} is the weighting for position j at time t, N_t is the total number of positions on day t and MC_{it} is the market capitalization of issuer i at time t. To avoid daily rebalancing of the market capitalization weighted portfolio, the market capitalizations on the individual positions are updated at the end of each calendar month. However, if a new position is added or an old position is removed during a calendar month then the portfolio is rebalanced.

On the inception date of both portfolios, the value of the divisor is set so that the portfolio value is equal to 100. Subsequently the portfolio divisor is adjusted to account for changes in the constituents or weightings of the constituent positions in the portfolio. Following a portfolio change the divisor is adjusted such that equation (3.8) is satisfied.

$$\frac{\sum_{i=1}^{i=N_t} W_{ib} PV_i}{F_b} = \frac{\sum_{i=1}^{i=N_t} W_{ia} PV_i}{F_a} \tag{3.8}$$

Where PV_i is the value of position i on the day of the adjustment, W_{ib} is the weighting of position i before the adjustment, W_{ib} is the weighting of position i after the adjustment, F_b is the divisor before the adjustment and F_a is the divisor after the adjustment.

Thus the post adjustment index factor F_a is then calculated as follows.

$$F_a = \frac{F_b x \sum_{i=1}^{i=N_t} W_{ib} PV_i}{\sum_{i=1}^{i=N_t} W_{ia} PV_i} \tag{3.9}$$

As the margins on the strategy are small relative to the nominal value of the positions convertible bond arbitrageurs usually employ leverage. Calamos (2003) and Ineichen (2000) estimate that for an individual convertible arbitrage hedge fund this leverage may vary from two to ten times equity. However, the level of leverage in a well run portfolio is not static and varies depending on the opportunity set and risk climate. Khan (2002) estimates that in mid 2002 convertible arbitrage hedge funds were at an average leverage level of 2.5 to 3.5 times, whereas Khan estimates that in late 2001 average leverage levels were approximately 5 to 7 times.

From a strategy analysis perspective it is therefore difficult to ascribe a set level of leverage to the portfolio. Changing the leverage applied to the portfolio has obvious effects on returns and risk as measured by standard deviation. It should also be noted when estimating the market model that as leverage increases, the estimate of alpha will also increase. Applying leverage of two times to the two portfolios produces portfolios with a similar average return to the HFRI Convertible Arbitrage Index and the CSFB Tremont Convertible Arbitrage Index.[26]

Table 3.2 presents annual return series for the equally weighted and market capitalization weighted convertible bond arbitrage portfolios, the CSFB Tremont Convertible Arbitrage Index, the HFRI Convertible Arbitrage Index, the Russell 3000 Index, the Merrill Lynch Convertible Securities Index and the risk-free rate. All annual returns are obtained by compounding monthly returns. Annual standard deviations are obtained by multiplying the standard deviation of monthly returns by $\sqrt{12}$. The CSFB Tremont Convertible Arbitrage Index is an index of convertible arbitrage hedge funds weighted by assets under management. The HFRI Convertible Arbitrage Index is an equally weighted index of convertible arbitrage hedge funds. The Russell 3000 Index is a broad based index of United States equities and the Merrill Lynch Convertible Securities Index is a broad based index of convertible securities. The risk free rate of interest is represented by the yield on a three month treasury bill.

[26] To test the effect of leverage market model regressions are performed using portfolios with leverage between zero and six times. Results of these regressions are reported in Table 3.6.

Table 3.2
Annual convertible bond arbitrage return series

This table presents the annual return series for the equally weighted and market capitalization weighted convertible bond arbitrage portfolios, the CSFB Tremont Convertible Arbitrage index, the HFRI Convertible Arbitrage Index, the Russell 3000 Index, the Merrill Lynch Convertible Securities Index and the risk-free rate. All annual returns are obtained by compounding monthly returns. Annual standard deviations are obtained by multiplying the standard deviation of monthly returns by $\sqrt{12}$.

Year	Equally Weighted (%)	Mkt Cap Weighted (%)	CSFB Tremont Index (%)	HFRI CA Index (%)	Russell 3000 (%)	Merrill Lynch CB Index (%)	Risk Free Rate (%)
1990	-15.83	0.63		2.14	-9.13	-14.43	7.75
1991	18.42	21.08		16.21	26.36	21.63	5.54
1992	16.09	8.82		15.14	6.38	14.70	3.51
1993	6.51	6.13		14.17	7.82	12.67	3.07
1994	4.17	2.72	-8.41	-3.80	-2.51	-12.33	4.37
1995	25.64	21.12	15.33	18.11	28.95	17.00	5.62
1996	10.36	8.21	16.44	13.59	17.55	8.63	5.15
1997	13.73	15.00	13.52	11.98	25.83	13.12	5.20
1998	3.57	11.80	-4.51	7.48	20.15	3.94	4.91
1999	6.27	6.46	14.88	13.47	17.75	33.17	4.78
2000	6.21	7.65	22.82	13.54	-8.90	-15.51	6.00
2001	8.80	4.88	13.61	12.55	-13.49	-7.13	3.48
2002	6.13	2.97	2.32	8.68	-25.89	-8.15	1.64
Mean	8.47 (9.43)	9.30 (9.20)	9.74	11.02 (10.62)	6.99 (6.61)	5.18 (3.64)	4.69 (4.57)
Standard Deviation	6.04 (4.48)	7.03 (5.91)	4.88	3.37 (3.56)	15.41 (16.37)	12.51 (13.52)	5.30 (4.56)
Skewness	-1.22	0.13	-1.69	-1.39	-0.73	-0.29	-0.11
Kurtosis	8.49	2.08	4.38	3.35	1.00	1.92	0.85

*To aid comparison with the CSFB Tremont Convertible Arbitrage Index figures in parenthesis are the average annual rate of return and annual standard deviation of returns from January 1994 to December 2002.

The two highest returning years for the convertible bond arbitrage portfolios, 1991 and 1995 correspond with the two highest returning years for the Russell 3000, the Merrill Lynch convertibles index and the HFRI hedge fund index. In 1991 the equally weighted index returned 18.4%, the market capitalization weighted index returned 21.1% and the

HFRI index returned 16.2%. Although obviously a good year for convertible arbitrage, the strategy was outperformed by a simple buy and hold equity (26.4%) or convertible bond (21.6%) strategy. 1995 produced strong returns with the equally weighted portfolio 25.6%, the market capitalization weighted portfolio 21.1%, the HFRI index 18.1% and the CSFB Tremont hedge fund index 15.3%. Again the strategy was outperformed by a simple buy and hold equity strategy (29%) but outperformed the general convertible securities market.

The worst returning years for the equally weighted convertible bond arbitrage portfolio, 1990, 1994[27] and 1998, correspond with two negative returning years (1990 and 1994) for the Russell 3000 and Merrill Lynch convertible securities index. The HFRI index had a below average return of 2.14% in 1990 and had its lowest return of -3.8% in 1994. The CSFB Tremont index does not date back to 1990 but in 1994 it had also had its lowest return of -8.4% and also had a negative return in 1998. The two lowest returning years for the market capitalization weighted portfolio were 1990 and 1994.

More recently in 2000, 2001 and 2002, after the bursting of the dotcom bubble, both of the convertible bond arbitrage portfolios (returning an average 7.1% for the equally weighted and 5.2% for the market capitalization weighted), the HFRI Convertible Arbitrage Index and the CSFB Tremont Convertible Arbitrage Hedge Fund Index have performed well. During this period the Russell 3000 and the Merrill Lynch Convertible Securities Index had an average annual return of -16.1% and -10.26%. This performance has demonstrated the obvious diversification benefits of the convertible

[27] Ineichen (2000) notes that 1994 was not a good year for convertible arbitrage characterised by rising US interest rates.

bond arbitrage strategy but it should be noted that the sample period has been characterized by rapidly falling interest rates and an increase in convertible issuance. In the current hostile equity issuance environment there has been an increase in issues of convertible bonds in the United States which provides more opportunities for the convertible bond arbitrageur. Intuitively, it would be expected that in such an environment convertible bond arbitrage returns would be positive.

Looking at the distribution of the monthly returns, of the two simulated portfolios only the equal weighted displays negative skewness (-1.22). The CSFB Tremont index and the HFRI index also display negative skewness. This is consistent with other studies (see Agarwal and Naik (2004) and Kat and Lu (2002)). The monthly returns from the equal weighted and the market capitalization weighted portfolios also display positive kurtosis. The estimate of the equally weighted portfolio's kurtosis appears to be high relative to the two hedge fund indices, although Kat and Lu (2002) find that the returns of the average individual hedge fund exhibit excess kurtosis relative to portfolios or indices of hedge funds.

3.3 Out of sample comparison

In order to validate the two convertible arbitrage portfolios this section of the paper more formally explores their correlation with two hedge fund indices and market factors over a variety of market conditions. While demonstrating the robustness of the two portfolios this also enables an observation of the behaviour of convertible bond arbitrage in different market conditions. As highlighted earlier, investors have become interested in lower volatility non-directional arbitrage strategies, because of the diversification benefits they bring to their portfolios in a low return equity environment. It is therefore important to see if this diversification benefit is constant or varies depending on market conditions.

Table 3.3
Correlation between monthly convertible bond arbitrage returns and market factors 1994 to 2002

This table presents correlation coefficients for monthly returns on the equally weighted (Equal Portfolio) and market capitalization weighted (MC Portfolio) convertible bond arbitrage portfolios, the CSFB Tremont Convertible Arbitrage Index, the HFRI Convertible Arbitrage Index, and market factor returns. The Russell 3000 is a broad based index of US equities. The Merrill Lynch Convertible Securities Index is an index of US convertible securities and the VIX is an equity volatility index calculated by the Chicago Board Option Exchange. It is calculated by taking a weighted average of the implied volatilities of 8 30-day call and put options to provide an estimate of equity market volatility.

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	CSFB Tremont Convertible	MC Portfolio	HFRI Convertible
Russell 3000	1.00						
ML Convertible Securities	0.73***	1.00					
VIX	-0.64***	-0.42***	1.00				
Equal Portfolio	0.50***	0.51***	-0.29***	1.00			
CSFB Tremont Convertible	0.17*	0.29***	0.04	0.33***	1.00		
MC Portfolio	0.58***	0.48***	-0.32***	0.68***	0.24**	1.00	
HFRI Convertible	0.37***	0.49***	-0.13	0.49***	0.80***	0.42***	1.00

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 3.3 presents the correlation coefficients between the monthly returns on the equally weighted convertible bond arbitrage portfolio (Equal Portfolio), the market capitalization weighted portfolio (MC Portfolio), the CSFB Tremont Convertible Arbitrage Index (CSFB Tremont Convertible), the HFRI Convertible Arbitrage Index (HFRI Convertible), the Russell 3000, the Merrill Lynch Convertible Securities Index

(ML Convertible Securities) and the VIX Index (VIX). The VIX index is an equity volatility index calculated by the Chicago Board Option Exchange. It is calculated by taking a weighted average of the implied volatilities of 8 30-day call and put options to provide an estimate of equity market volatility. As the CSFB Tremont data is unavailable prior to 1994 the correlation coefficients cover returns from January 1994 to December 2002.

The equal weighted portfolio, the market capitalization weighted portfolio, the CSFB Tremont index and the HFRI index are all positively correlated with the Merrill Lynch convertible index. They are also all significantly[28] positively correlated with equities. The equal weighted portfolio is positively correlated with the market capitalization weighted portfolio, the CSFB Tremont index and the HFRI index over the entire sample period. Unsurprisingly, the market capitalization weighted portfolio is also correlated with the CSFB Tremont index, although it is positively correlated with the HFRI index. Monthly returns on the VIX are negatively correlated with both the equal weighted portfolio and the market capitalization weighted portfolio indicating that they are both negatively correlated with implied volatility. Neither of the hedge fund indices has any significant correlation with the VIX. This is surprising as convertible bond arbitrage is a long volatility strategy.

[28] In discussions in the text statistical significance indicates t-stats are significant from zero at least at the 10% level unless reported.

Table 3.4
Correlation between monthly convertible bond arbitrage returns and market factors from 1990 to 2002

This table presents correlation coefficients for monthly returns on the equally weighted (Equal Portfolio) and market capitalization weighted (MC Portfolio) convertible bond arbitrage portfolios, the HFRI Convertible Arbitrage Index, and market factor returns. The Russell 3000 is a broad based index of US equities. The Merrill Lynch Convertible Securities Index is an index of US convertible securities and the VIX is an equity volatility index calculated by the Chicago Board Option Exchange. It is calculated by taking a weighted average of the implied volatilities of 8 30-day call and put options to provide an estimate of equity market volatility.

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	MC Portfolio	HFRI Convertible
Russell 3000	1.00					
ML Convertible Securities	0.76***	1.00				
VIX	-0.65***	-0.46***	1.00			
Equal Portfolio	0.52***	0.53***	-0.32**	1.00		
MC Portfolio	0.64***	0.54***	-0.35**	0.73***	1.00	
HFRI Convertible	0.36***	0.49***	-0.14*	0.49***	0.41***	1.00

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Correlation coefficients were also estimated for the entire sample period 1990 to 2002 for all variables excluding the CSFB Tremont data. These correlation coefficients are reported in Table 3.4. There is no change in the sign or significance of any of the coefficients other than the correlation between the HFRI index and the VIX, which are negatively correlated at the 10% level. Other than this they are almost identical in magnitude to the coefficients reported in Table 3.3.

Table 3.5
Correlation between monthly convertible bond arbitrage returns and market factors in different states of the economy 1994 to 2002

This table presents correlation coefficients for monthly returns on the equally weighted (Equal Portfolio) and market capitalization weighted (MC Portfolio) convertible bond arbitrage portfolios, the CSFB Tremont Convertible Arbitrage Index, the HFRI Convertible Arbitrage Index, and market factor returns in different states of the economy. The sample was ranked according to equity market returns and then divided into 4 equal sized groups with lowest returns in state 1, next lowest returns in state 2, highest returns in state 4 and next highest returns in state 3. Panels A to D represent correlation coefficients between simulated portfolio returns and market factors in each state, 1-4.

Panel A: State 1 returns

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	CSFB Tremont Convertible	MC Portfolio	HFRI Convertible
Russell 3000	1.00						
ML Convertible Securities	0.56***	1.00					
VIX	-0.55***	-0.40**	1.00				
Equal Portfolio	0.15	0.47**	-0.35*	1.00			
CSFB Tremont Convertible	0.57***	0.44**	-0.73***	0.59***	1.00		
MC Portfolio	0.29	0.54***	-0.39**	0.41**	0.15	1.00	
HFRI Convertible	0.40**	0.41**	-0.65***	0.62***	0.90***	0.23	1.00

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 3.5 (continued)

Panel B: State 2 returns

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	CSFB Tremont Convertible	MC Portfolio	HFRI Convertible
Russell 3000	1.00						
ML Convertible Securities	0.54***	1.00					
VIX	-0.42**	-0.05	1.00				
Equal Portfolio	0.08	0.06	-0.13	1.00			
CSFB Tremont Convertible	0.03	0.40**	0.32	0.06	1.00		
MC Portfolio	0.06	0.11	0.16	0.44**	0.14	1.00	
HFRI Convertible	-0.13	0.40**	0.45*	0.11	0.79***	0.16	1.00

Panel C: State 3 returns

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	CSFB Tremont Convertible	MC Portfolio	HFRI Convertible
Russell 3000	1.00						
ML Convertible Securities	0.44**	1.00					
VIX	-0.09	0.05	1.00				
Equal Portfolio	0.30	0.20	0.02	1.00			
CSFB Tremont Convertible	0.13	0.44**	0.26	0.26	1.00		
MC Portfolio	0.13	0.10	-0.24	0.67***	0.28	1.00	
HFRI Convertible	0.31	0.57***	0.13	0.36*	0.82***	0.36*	1.00

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 3.5 (continued)

Panel D: State 4 returns

	Russell 3000	ML Convertible Securities	VIX	Equal Portfolio	CSFB Tremont Convertible	MC Portfolio	HFRI Convertible
Russell 3000	1.00						
ML Convertible Securities	0.13	1.00					
VIX	-0.34*	0.07	1.00				
Equal Portfolio	-0.23	0.16	0.23	1.00			
CSFB Tremont Convertible	-0.12	0.10	0.51***	0.39**	1.00		
MC Portfolio	0.02	-0.05	0.37*	0.59***	0.32	1.00	
HFRI Convertible	-0.13	0.22	0.47**	0.44**	0.80***	0.48**	1.00

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Next, the sample of one hundred and eight monthly returns is ranked by equity market return and subdivided into four sub-samples of twenty seven months. State 1, which is presented in Panel A of Table 3.5, covers the correlations between convertible bond arbitrage returns and market factors in the twenty seven lowest equity market returns (ranging from -16.8% to -2.6%). The equal weighted portfolio and the two hedge fund indices are positively correlated with the Merrill Lynch convertible securities index in this sub-sample. The equal weighted portfolio is positively correlated with the two hedge fund indices and the three are all negatively correlated with the VIX. In this sub-sample the market capitalization portfolio is not correlated with any of the other hedge fund series and the equal weighted portfolio appears to share more characteristics than the market capitalization weighted portfolio with the hedge fund indices.

Panel B of Table 3.5 looks at the correlations between convertible bond arbitrage returns and market factors in the twenty seven next lowest equity market returns (ranging from -2.2% to 1.3%). None of the convertible arbitrage portfolios or indices has any correlation with equities in this sub-sample. Both the CSFB Tremont and HFRI indices are correlated with the Merrill Lynch convertible securities indices and the VIX index. The equal weighted portfolio is positively correlated with the market capitalization weighted portfolio and the two hedge fund indices are positively correlated.

Panel C of Table 3.5 looks at the correlations between convertible arbitrage returns and market factors in the twenty seven next lowest equity market returns (ranging from 1.4% to 3.9%). The two hedge fund indices are positively correlated with the Merrill Lynch convertible securities index and each other. The market capitalization weighted portfolio is also correlated with the HFRI index and the equal weighted portfolio.

The final sub-sample, looking at the correlations between convertible arbitrage returns and market factors in the twenty seven highest equity market returns (ranging from 4.0% to 7.6%) is presented in Panel D of Table 3.5. The equal weighted portfolio is positively correlated with the market capitalization weighted portfolio, the CSFB Tremont and the HFRI indices. Both the CSFB Tremont and HFRI indices and the market capitalization portfolio are positively correlated with the VIX in this sample period which is negatively related to equity market returns. This indicates that in periods of high equity market returns, the change in volatility is negative and hedge fund returns are affected.

Based on the evidence presented so far, the two hedge fund indices appear to share many of the characteristics of the convertible bond arbitrage portfolios. Over the entire sample period they are all positively correlated, and when the sample is subdivided they share similar characteristics. The hedge fund indices share more characteristics with the equal weighted portfolio than the market capitalization weighted portfolio particularly in market downturns. This provides weak evidence that convertible arbitrageurs do not weight positions in their portfolio according to the size of the issuer, perhaps due to greater arbitrage opportunities in the relatively smaller issues. It is also interesting to note that convertible arbitrage is positively correlated with the underlying convertible securities market in downturns and there is a weak negative relationship with equity market returns in market upturns.

3.4 Market model regressions

The analysis so far indicates that the relationship between convertible arbitrage and equity market returns is non-linear. As discussed previously this is not the first study to come to this conclusion. However, studies to date have been restricted to analyzing relatively low frequency monthly returns data. In this section of the paper the results of estimating, using the Ordinary Least Squares (OLS) estimation technique, the market model using the two portfolios of daily convertible arbitrage returns are reported. Estimating the market model using daily data allows this study to examine the short run dynamics in the relationship between a buy and hold equity portfolio (using the Russell 3000 as a proxy) and convertible bond arbitrage. This is particularly important for an investor considering combining a convertible bond arbitrage strategy with a traditional buy and hold equity portfolio. The model is initially estimated using the entire sample period and then subdivided according to ranked equity market returns. The appendix at the end of this chapter contains a review of the OLS estimation technique.

The following model is estimated using OLS.

$$R_{CB} - R_f = \alpha + \beta_{Mkt}(R_{Mkt} - R_f) + \varepsilon_t \tag{3.10}$$

Where R_{CB} is the daily return on the equally weighted convertible bond arbitrage portfolio, R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill.

Table 3.6 reports the results from estimating (3.10) on equally weighted portfolios of R_{CB} with various levels of leverage varying from 1 time to 6 times. It is very apparent that the α coefficient, often known as Jensen's alpha, and used to judge the level of out-performance is inappropriate when looking at strategies employing leverage. As the level of leverage increases so too does the magnitude and significance of the perceived out-performance. The β coefficient also increases in magnitude as the level of leverage increases, although its significance is constant. As discussed earlier, the remainder of the results are reported for a portfolio with two times leverage as this seems to match what is being used in practice.

Table 3.6
Regression of daily equally weighted convertible bond arbitrage returns under different leverage

This table presents results from the following regression of convertible bond arbitrage returns.

$$R_{CB} - R_f = \alpha + \beta_{Mkt}(R_{Mkt} - R_f) + \varepsilon_t$$

where R_{CB} is the daily return on the equally weighted convertible bond arbitrage portfolio, R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill. Panel A of the table presents results for no leverage. Panel B presents results for two times leverage. Panel C presents results for three times leverage. Panel D presents results for four times leverage. Panel E presents results for five times leverage. Panel F presents results for six times leverage. T-stats are in parenthesis.

Dependent Variable	α	β_{mkt}	Adj. R^2	Sample Size
Panel A: No leverage				
R_{CB} - R_f	0.0000	0.03	3.4%	3391
	(-0.69)	(10.90)***		
Panel B: 2 x leverage				
R_{CB} - R_f	0.0001	0.06	3.4%	3391
	(2.39)**	(10.92)***		
Panel C: 3 x leverage				
R_{CB} - R_f	0.0003	0.10	3.4%	3391
	(3.46)***	(10.92)***		
Panel D: 4 x leverage				
R_{CB} - R_f	0.0004	0.13	3.4%	3391
	(3.98)***	(10.92)***		
Panel E: 5 x leverage				
R_{CB} - R_f	0.0006	0.16	3.4%	3391
	(4.29)***	(10.93)***		
Panel F: 6 x leverage				
R_{CB} - R_f	0.0008	0.19	3.4%	3391
	(4.50)***	(10.93)***		

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 3.7 reports the results from modeling the returns from the equal weighted convertible arbitrage portfolio. In Table 3.7, R_{CB} is the daily return on the equal weighted convertible bond arbitrage portfolio R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill. Table 3.8 reports the results from modeling the returns from the market capitalization weighted convertible arbitrage portfolio. The variables in Table 3.8 are identical to Table 3.7 with the exception of R_{CB}, which is the daily market capitalization weighted convertible bond arbitrage portfolio return.

Both tables are organized as follows. Panel A covers the entire sample, Panel B reports the results when restricting the sample to those observations when the equity risk premium is within one standard deviation of the mean, Panel C reports the results when the sample is restricted to those observations at least one standard deviation less than the mean, Panel D reports the results when the sample is restricted to more than one standard deviation greater than the mean, Panel E restricts the sample to at least two standard deviations less than the mean and Panel F restricts the sample to more than two standard deviations greater than the mean.

Looking first at Table 3.7, Panel A it can be seen that over the entire sample period results from estimating the market model indicate that convertible bond arbitrage has a positive equity market beta of 0.06. Panel B of Table 3.7 shows the relationship between convertible bond arbitrage and equity market returns when the equity risk premium is less than one standard deviation from the mean. Assuming the equity risk premium is normally distributed, this represents approximately 68.3% of trading days or 174 days per year.[29] Again beta is approximately 0.07 and alpha is lower at 0.000128.

[29] Calculations here and elsewhere assume 255 trading days per year.

Table 3.7
Regression of daily equally weighted convertible bond arbitrage returns

This table presents results from the following regression of convertible bond arbitrage returns.

$$R_{CB} - R_f = \alpha + \beta_{Mkt}(R_{Mkt} - R_f) + \varepsilon_t$$

where R_{CB} is the daily return on the equally weighted convertible bond arbitrage portfolio, R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill. Panel A of the table presents results for the entire sample period. Panel B presents results after restricting the sample to those days with excess market returns within one standard deviation of their mean. Panel C presents results after restricting the sample to days with excess market returns at least one standard deviation less than the mean. Panel D presents results after restricting the sample to those days with excess market returns more than one standard deviation greater than the mean. Panel E presents results after restricting the sample to days with excess market returns at least two standard deviations less than the mean. Panel F presents results after restricting the sample to days with excess market returns more than two standard deviations greater than the mean. T-stats are in parenthesis.

Dependent Variable	α	β_{mkt}	Adj. R^2 (%)	Sample Size
Panel A: Entire Sample				
R_{CB} - R_f	0.000141	0.0635	3.4	3391
	(2.39)**	(10.92)***		
Panel B: Market Return - R_f (within 1 S.D. of the mean)				
R_{CB} - R_f	0.000128	0.0678	0.8	2605
	(1.91)*	(4.82)***		
Panel C: Market Return - R_f (1 S.D. less than the mean)				
R_{CB} - R_f	0.000749	0.0949	5.0	397
	(1.89)*	(4.67)***		
Panel D: Market Return - R_f (1 S.D. greater than the mean)				
R_{CB} - R_f	0.000799	0.0264	0.0	389
	(1.74)*	(1.07)		
Panel E: Market Return - R_f (2 S.D. less than the mean)				
R_{CB} - R_f	0.002069	0.1329	13.8	108
	(2.31)**	(4.26)***		
Panel F: Market Return - R_f (2 S.D. greater than the mean)				
R_{CB} - R_f	0.005663	-0.1235	2.5	85
	(2.73)***	(-1.77)*		

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Panel C of Table 3.7 reports the relationship when equity risk premium is at least one standard deviation less than the mean, about 40 trading days per annum. The beta coefficient increases to 0.095 and the adjusted R^2 also increases, indicating that the relationship between convertible arbitrage and equity returns is stronger on these days. Panel D reports the results of the regression when equity risk premium is more than one standard deviation greater than the mean, again about 40 trading days per annum. In this sub-sample there is little relationship between convertible bond arbitrage and equities.

Panel E of the table reports the results from the market model when the sample is restricted to those days when the equity risk premium is at least two standard deviations less than the mean. This is relatively infrequent, about 2.3% of trading days. Like in Panel C the regression's explanatory power has increased (adjusted R^2 of 13.8%) and the convertible arbitrage beta has increased to 0.13. Finally Panel F reports the results from the regression when the sample is restricted to those days when the equity risk premium is more than two standard deviations greater than the mean. Here evidence is found to support the observations in the previous section that convertible arbitrageurs appear to suffer in periods of extreme positive equity market performance. In these extremely positive days long volatility strategies such as convertible bond arbitrage typically suffer.

Table 3.8
Regression of daily market capitalization weighted convertible bond arbitrage returns

This table presents results from the following regression of convertible bond arbitrage returns.

$$R_{CB} - R_f = \alpha + \beta_{Mkt}(R_{Mkt} - R_f) + \varepsilon_t$$

Where R_{CB} is the daily return on the market capitalization weighted convertible bond arbitrage portfolio, R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill. Panel A of the table presents results for the entire sample period. Panel B presents results after restricting the sample to those days with excess market returns within one standard deviation of their mean. Panel C presents results after restricting the sample to days with excess market returns at least one standard deviation less than the mean. Panel D presents results after restricting the sample to those days with excess market returns more than one standard deviation greater than the mean. Panel E presents results after restricting the sample to days with excess market returns at least two standard deviations less than the mean. Panel F presents results after restricting the sample to days with excess market returns more than two standard deviations greater than the mean. T-stats are in parenthesis.

Dependent Variable	α	β_{mkt}	Adj. R^2	Sample Size
Panel A: Entire Sample				
$R_{CB} - R_f$	0.000161	0.1254	7.9	3391
	(2.17)**	(17.00)***		
Panel B: Market Return - R_f (within 1 S.D. of the mean)				
$R_{CB} - R_f$	0.000156	0.1065	1.4	2605
	(1.92)*	(6.23)***		
Panel C: Market Return - R_f (1 S.D. less than the mean)				
$R_{CB} - R_f$	0.001398	0.1910	8.9	397
	(2.37)**	(6.31)***		
Panel D: Market Return - R_f (1 S.D. greater than the mean)				
$R_{CB} - R_f$	0.00020	0.1233	3.0	389
	(0.32)	(3.62)***		
Panel E: Market Return - R_f (2 S.D. less than the mean)				
$R_{CB} - R_f$	0.00322	0.2415	16.7	108
	(2.20)**	(4.74)***		
Panel F: Market Return - R_f (2 S.D. greater than the mean)				
$R_{CB} - R_f$	0.00457	-0.0064	0.0	85
	(1.76)*	(-0.07)		

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 3.8 reports the results from the market capitalization weighted portfolio. The findings are similar to those reported for the equal weighted portfolio with one exception. In extreme positive equity market performance, although the equity market beta coefficient is negative, the market capitalization weighted portfolio has no significant relationship with equities. As this portfolio is weighted according to market capitalization of the issuer's equity, the explanation for this difference may be that the effect of falling volatility has more of an affect on the convertible bonds of smaller issuers. However, as discussed in Section 3.3, the equal weighted portfolio shares more characteristics with the two hedge fund indices and both these indices had a positive correlation with volatility in the top quartile of monthly equity returns.

Table 3.9
Regression of daily equally weighted convertible bond arbitrage returns at market extremes

This table presents results from the following regression of convertible bond arbitrage returns.

$$R_{CB} - R_f = \alpha + \beta_{Mkt}(R_{Mkt} - R_f) + \varepsilon_t$$

Where R_{CB} is the daily return on the equal weighted convertible bond arbitrage portfolio, R_{Mkt} is the daily return on the Russell 3000 stock index and R_f is the daily yield on a three month treasury bill. Panel A of the table presents results after restricting the sample to those days with excess market returns at least two and a half standard deviations less than their mean. Panel B presents results after restricting the sample to those days with excess market returns at least two and a half standard deviations greater than their mean.

Dependent Variable	α	β_{mkt}	Adj. R^2	Sample Size
Panel A: Market Return - R_f (2.5 S.D. less than the mean)				
$R_{CB} - R_f$	0.00185	0.1298	17.3	44
	(1.26)	(3.16)***		
Panel B: Market Return - R_f (2.5 S.D. greater than the mean)				
$R_{CB} - R_f$	0.0131	-0.3155	9.6	42
	(2.72)***	(-2.32)**		

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

To provide a closer examination of this effect Table 3.9 looks at the estimation of the market model using the equally weighted portfolio limiting the sample to those days when the equity risk premium is more than two and a half standard deviations from its mean. This represents a relatively infrequent seven trading days per year but from an investors perspective these may be the most important. Panel A looks at those days when the equity risk premium is at least two and a half standard deviations less than its mean. Like in Panel C and E of Table 3.7 the explanatory power of the regression is higher than for the entire sample (adjusted R^2 of 17.3%) and the convertible bond arbitrage beta has again increased, to 0.13. Panel B of Table 3.9 looks at those days when the equity risk premium is at least two and a half standard deviations greater than its mean and the results are striking. The explanatory power of the regression is high with an adjusted R^2 of 9.6%, and the beta is -0.32, providing further evidence of the negative relationship between convertible bond arbitrage and equity returns in extremely positive equity markets.

3.5 Conclusion

The analysis of the convertible bond arbitrage simulated portfolio provides useful evidence on the characteristics of this dynamic trading strategy. Long positions in convertible bonds are combined with short positions in the common stock of the issuer to create individual delta neutral hedged convertible bonds in a manner consistent with an arbitrageur capturing income. These individual positions are then dynamically hedged on a daily basis to capture volatility and maintain a delta neutral hedge. These positions are then combined into two convertible bond arbitrage portfolios and it is demonstrated that the monthly returns of the convertible bond arbitrage portfolio are positively correlated with two indices of convertible arbitrage hedge funds.

Across the entire sample period the two portfolios have estimated market betas of between 0.048 and 0.061. Assuming the market model is correctly specified the equal weighted portfolio appears to generate abnormal positive returns of 3% per annum. However, it is also demonstrated that the relationship between daily convertible bond arbitrage returns and a traditional buy and hold equity portfolio is non-linear. In normal market conditions, when the equity risk premium is within one standard deviation of its mean, the two portfolios have market betas of between 0.07 and 0.10. When the sample is limited to extreme negative equity market returns (at least two standard deviations below the mean) these betas increase to 0.13 and 0.24 for the equal weighted portfolio and the market capitalization weighted portfolio respectively. This indicates that on the average eight days per annum of extreme negative equity market returns, convertible arbitrage will exhibit a large increase in market risk.

Perhaps most interesting is the finding that in extreme positive equity markets an equal weighted convertible bond arbitrage portfolio will exhibit a negative relationship with a traditional buy and hold portfolio. This is due to the drop in implied volatility associated with such market conditions and is an important factor for any investor considering the addition of a convertible bond arbitrage portfolio or fund to a traditional long only equity portfolio.

3.6 Limitations of this analysis

There are several potential limitations within this analysis which need to be highlighted. Several of these will be addressed in later chapters.

3.6.1 Omitted variables

It is not totally clear why there should be a dependent relationship between convertible bond arbitrage returns and returns on an equity index. Convertible arbitrageurs take long positions in convertible bonds and hedge equity market risk with the underlying share. Returns come from the long volatility exposure, exposure to credit risk (unless hedged) and income. It could be argued that in this context equity market returns will not capture much of the risk in convertible arbitrage. This seems to be supported by the empirical evidence, but it is important to note that the majority of investment portfolios have large equity market exposure. If considering an investment in a convertible arbitrage fund it is likely that one of the key qualities investors are seeking is the supposed diversification benefit of the strategy. It is therefore appropriate in the first stage in an analysis of convertible bond arbitrage, or any other trading strategy, to begin with an empirical analysis of the relationship between the returns on that strategy and the returns on the equity market portfolio.

In the next chapter the analysis of convertible arbitrage will be broadened to include other market factors such as default risk, term structure risk, liquidity, the size and book to market factors of Fama and French (1992, 1993) and the momentum factor of Carhart (1997).

3.6.2 Specifying a linear model for non-linear data

In the review of OLS in the Appendix of this chapter, functional misspecification is discussed. Evidence has been provided in this chapter that the relationship between convertible arbitrage and equity market returns is non-linear. Given the observed non-linearity, OLS, by definition a linear technique is likely to result in biased estimators. OLS is nonetheless a useful starting point for evaluating the nature of the relationship between convertible arbitrage and risk factors, whether equity market returns or other factors explored in the following chapters. The issue of non-linearity and the correct functional specification will be dealt with in later chapters following a thorough analysis of convertible arbitrage in a linear framework

3.6.3 Beta estimation under thin trading

There is a large body of literature highlighting the biases in OLS beta estimation when using daily data. Fisher (1966) was the first to recognize the potential problems caused by non-trading which has been subsequently shown to bias beta estimates. Scholes and Williams (1977), Dimson (1979) and Fowler, Rorke and Jog (1989) amongst others show that betas of securities that trade less (more) frequently than the index used as the market proxy are downward (upward) biased. Given that convertible bonds are less liquid than equities it is likely that beta estimates are downward biased. Techniques for estimating betas so as to control for thin trading bias have been proposed by Scholes and Williams (1977) and Dimson (1979) amongst others. There is also a rich body of literature testing the adequacy of these robust beta estimates. Fowler and Rorke (1983) and Fowler, Rorke and Jog (1989) provide evidence that the Scholes and Williams (1977) approach and the Dimson (1979) approach do not adequately control for thin trading bias in beta estimation. McInish and Wood (1986) test the techniques of Scholes and Williams (1977), Dimson (1979), Fowler, Rorke and Jog (1989) and Cohen, Hwanaii, Maier, Schwartz and Whitcomb (1980) finding that all of the techniques reduce the bias to an extent but the maximum amount of the reduction is twenty nine percent. Even with the potential downward bias in beta estimation in this chapter it is clear that there is a non-linear relationship between equity market and convertible bond arbitrage returns.

Given the literature on biases in beta estimation perhaps the most efficient way to remove the bias is to analyze monthly rather than daily data. This may result in missing some of the short run dynamics in convertible bond arbitrage risk. However, this negative is outweighed by the removal of some of the biases in estimating the risk weighting coefficients. In the following empirical chapters this study will be limited to examining monthly returns.

3.6.4 Volatility

There is a rich body of literature evaluating the relative forecasting prowess of the various techniques. In the creation of the portfolio GARCH(1,1) was chosen to estimate the future volatility of the underlying stocks. It could be argued that E-GARCH would have provided superior forecasts of volatility. It could also be argued that rather than one estimate of volatility it would be more appropriate to plot a term structure of volatility and perhaps a volatility smile for each stock. In reality, convertible bonds pricing is subjective, and uses a mixture of implied volatility and historic volatility calculations. However, considering the number of observations and the number of estimations that this would involve, this is not practical and would introduce the biases of the investigator.

Given these considerations it was considered superior to choose one generally accepted method of estimating volatility over the life of the position, employing this estimate and given that the results appear to share the characteristics of convertible arbitrage fund returns, this appears to be a reasonably successful approach.

3.6.5 Transaction costs and the analysis of convertible bond undervaluation

These two problems relate to the rules for constructing the portfolio. It is acknowledged that the returns on the portfolio will be biased upwards as transaction costs have not been included. Returns are also biased downwards by not trading in and out of positions as they become fairly or under valued. In practice an arbitrageur will not buy a convertible bond unless he considers it to be undervalued. Likewise if an undervalued bond becomes fairly valued the arbitrageur will close the position.

Any attempt to control these biases will introduce further biases and, given the likelihood that these two biases will to an extent counterbalance one another, it was considered optimal to recognize them and allow them.

Chapter 3 Appendix: Ordinary Least Squares Estimation

Dougherty (1992) provides a useful overview of the OLS estimation technique which is used in the case where one can hypothesise that one variable y depends on another x. As this relationship is not exact a disturbance term is also included in the model.

$$y = \alpha + \beta x + u \tag{3.11}$$

Where y the dependent variable, has two components: (1) the non-random component $\alpha + \beta x$, x being described as the independent variable, and fixed quantities α and β as the parameters of the equation, and (2) the disturbance term u. The disturbance term u exists for several reasons.

1. Omission of explanatory variables: The relationship between y and x is likely to be an oversimplification of the true relationship. In reality there will be other factors affecting y and their influence will lead to errors in the estimation of (3.11). These other factors could be psychological factors which are difficult to measure, or factors which have a weak effect on y and so for reasons of parsimony are not worth including. There may also be other factors that one is unaware of. All these contribute to a pool, known as u the disturbance, or error, term.
2. Aggregation of variables: In many cases the relationship is an attempt to summarize in aggregate a number of micro relationships. An example would be linking the returns on a UK stock to a US stock index, whereas the relationship is likely to be rather more complex with US stock indices, perhaps, affecting UK stock indices and

indirectly affecting UK stocks. Since the individual relationships are likely to have different parameters, any attempt to relate UK individual stock returns to US stock indices can only be an approximation.

3. Model misspecification: The model may be misspecified in terms of its structure. As an example y may react to announcements of unexpected changes in x, so specifying a model where y depends on x will lead to an approximation of the true relationship and the error term will pick up the discrepancy.

4. Functional misspecification: The functional relationship between y and x may be misspecified mathematically. Perhaps the relationship between y and x is non-linear. The discrepancy between the true functional relationship and that modelled will appear in the disturbance term.

5. Measurement error: If the measurement of one or more of the variables in the relationship is subject to error, the observed values do not appear to conform to an exact relationship and the discrepancy again contributes to the disturbance term.

Given the simple regression model (3.11) the regression equation (3.12) is being fit through OLS.

$$\hat{y} = a + bx \qquad (3.12)$$

Given that y consists of a non-random component ($\alpha + \beta x$) and a random component u this implies that when b, the slope, is calculated by the usual formula:

$$b = \mathrm{Cov}(x, y) \,/\, \mathrm{Var}(x) \qquad (3.13)$$

b also has a random component. Cov(x, y) depends on the values of y, and the value of y depends on the values of u. b can therefore be decomposed into random and non-random components so it can be shown that

$$b = \text{Cov}(x, y) \,/\, \text{Var}(x) = \beta + \text{Cov}(x, u) \,/\, \text{Var}(x) \tag{3.14}$$

Thus the regression coefficient b obtained from any sample consists of the true value β, plus a random component depending on Cov(x, u), which is responsible for its variations around the central tendency. Similarly, it can easily be shown that a has a fixed component equal to the true value, α, plus a random component depending on the random factor u. These decompositions, given certain assumptions, enable analysis of the theoretical properties of a and b.

Therefore, the properties of the regression coefficients depend critically on the properties of the disturbance term and the disturbance term must satisfy four conditions, known as the Gauss-Markov conditions if ordinary least square analysis is to give the best possible results

Gauss-Markov Condition 1: $E(u_i) = 0$

The first condition is that the expected value of the disturbance term in any observation should be 0. Some observations will be positive and some negative, but it should have no systematic tendency in either direction. It can usually be assumed that the constant term will pick up any systematic tendency in y not accounted for by x.

Gauss-Markov Condition 2: $E(u_i^2) = \sigma_u^2$ for all i

The second condition is that the variance of the disturbance term should be constant for all observations. There should be no *a priori* reason for the disturbance term to be more erratic in some observations than in others. If $E(u_i^2) = \sigma_u^2$ for all i does not hold then the disturbance term is heteroscedastic. If the disturbance term in (3.11) does not satisfy $E(u_i^2) = \sigma_u^2$ for all i then the OLS estimates of α and β are inefficient. It is essential that the variances of α and β are as small as possible so that there is maximum precision. In principle, given a heteroscedastic disturbance term, other estimators could be found that have smaller variances and are still unbiased. The second reason heteroscedasticity is important is that the estimators of the standard errors of the regression coefficients will be incorrect. They are computed on an assumption that the distribution of the disturbance term is homoscedastic and if this is not the case they are invalid. This will, likely, lead to underestimates of the error terms and the t-statistics will be overestimated.

Gauss-Markov Condition 3: $E(u_i, u_j) = 0$ $(i \neq j)$

This condition states that there should be no systematic association between the value of the disturbance term in any two observations. For example, if the disturbance term is large and positive in one observation, there should be no expectation for its size or magnitude in the next observation. The disturbance terms should be absolutely independent of one another. When this condition is not satisfied the disturbance term is said to be subject to autocorrelation. The consequences of autocorrelation are that the regression coefficients remain unbiased, but become inefficient as their standard errors are incorrectly estimated, most likely biased downward with the resulting upward bias in the t-stats. Positive serial correlation in the disturbance term is more prevalent and is most often caused by the omission of explanatory variables (for example lags of y the dependent variable).

Gauss-Markov Condition 4: $E(x_i, u_i) = 0$

This condition states that the disturbance term should be distributed independently of the explanatory variables. The value of any observation of the explanatory variable should be regarded as exogenous, determined entirely by forces outside the scope of the regression equation. The stronger assumption of the Gauss-Markov Condition 4 is that x is non-stochastic.

In addition to the Gauss-Markov conditions, it is usually assumed that the disturbance term is normally distributed. If u is normally distributed, so will be the regression coefficients. The Central Limit Theorem states, in essence, that if a random variable is the compound result of the effects of a large number of other random variables, it will have an approximately normal distribution even if it's components do not, provided that none of them is dominant.

Unbiasedness of the regression coefficients

Given (3.14) b must be an unbiased estimator of β if $E(x_i, u_i) = 0$ holds:

$$E\{b\} = E\{\beta + \mathrm{Cov}(x, u) / \mathrm{Var}(x)\} = \beta + E\{\mathrm{Cov}(x, u) / \mathrm{Var}(x)\} \qquad (3.15)$$

since β is a constant. If the stronger assumption of the fourth Gauss-Markov condition is applied and it is assumed that x is non-random, Var(x) can also be assumed to be a constant and $E\{\text{Cov}(x, u)\} = 0$, so

$$E\{\text{b}\} = \beta \tag{3.16}$$

b is an unbiased estimator of β given Gauss-Markov condition 4 holds. Unless the random factor in the n observations cancels out exactly, which can only happen by coincidence, b will be different from β in any estimation of (3.11) but there will be no systematic tendency for it to be either higher or lower. This also holds for the regression coefficient a.

$$a = y' - bx' \tag{3.17}$$

Here y' and x' are the mean of the n observations of y and x. Hence

$$E\{a\} = E\{y'\} - x'E\{b\} \tag{3.18}$$

and since y is determined by (3.11)

$$E\{y_i\} = \alpha + \beta x_i + E\{u_i\} = \alpha + \beta x_i \tag{3.19}$$

because $E\{u_i\} = 0$ if the first Gauss-Markov condition holds. Hence

$$E\{y'\} = a + \beta x' \qquad (3.20)$$

and combining (3.16), (3.20) and (3.18) leads to (3.21).

$$E\{a\} = \alpha + \beta x' - \beta x' = \alpha \qquad (3.21)$$

Thus a is an unbiased estimator of α given that Gauss-Markov conditions 1 and 4 hold.

Chapter 4: A multi-factor analysis of the risks in convertible arbitrage indices

4.1 Introduction

Multi-factor asset class models have been specified extensively in the hedge fund and mutual fund literature to assess risk and performance of investment funds.[30] By defining a set of asset classes that match an investment strategy's aims and returns, individual fund's exposures to variations in the returns of the asset classes can be identified. Following the identification of exposures, the effectiveness of the manager's activities can be compared with that of a passive investment in the asset mixes. The focus of this chapter is the definition of a broad set of asset classes and identification of the exposures of convertible arbitrage benchmark indices to these asset classes.

The results provide evidence that default and term structure risk factors are highly significant factors in explaining the returns of convertible bond arbitrage hedge fund indices. A convertible bond arbitrage risk factor is also specified which is highly significant in explaining the returns of convertible arbitrage hedge fund indices. Results of previous studies analysing convertible arbitrage hedge fund performance are upward biased by failing to take into account the serial correlation in the returns of convertible arbitrageurs. When this serial correlation is corrected for, with the inclusion of a one period lag of the hedge fund index, which is interpretable as a proxy illiquidity risk factor, estimates of abnormal performance are lower. However, some evidence is still

[30] These models can be loosely classified as Sharpe (1992) asset class factor models following Sharpe's (1992) paper on asset allocation, management style and performance evaluation.

found supporting the convertible arbitrage indices generating abnormal returns though this is for a period when the hedge fund index was upward biased with the exclusion of dead funds. This chapter expands the existing literature on dynamic investment strategies by identifying and estimating risk factors that explain the convertible bond arbitrage index data generating process.

The analysis in this chapter indicates that the low explanatory power of the majority of the models used to look at convertible arbitrage in previous studies is accounted for by two key factors. First, the factor models used previously omit risk factors which are highly significant in explaining convertible arbitrage index returns. Second, generally these studies fail to address the autocorrelation inherent in convertible arbitrage hedge fund returns. As discussed by Getmansky, Lo and Makarov (2004) the majority of this autocorrelation is most likely caused by illiquidity in the securities held by convertible arbitrage hedge funds. The inclusion of a proxy illiquidity risk factor, mimicked by the one period lag of hedge fund index returns, greatly improves the explanatory power of all of the models employed in this study. Evidence presented here indicates that factors mimicking default and term structure risk account for much of the remaining unexplained return of convertible bond arbitrage indices.

A convertible bond arbitrage risk factor is also included which shares many of the risk characteristics of the convertible arbitrage hedge fund indices. This factor is simply the excess return on a primitive convertible arbitrage portfolio. To create this portfolio, long positions in convertible bonds are combined with delta neutral hedged short positions in the underlying stocks and hedges are rebalanced daily. This factor is highly significant in explaining convertible arbitrage returns in a parsimonious convertible arbitrage factor model. The convertible bond arbitrage risk factor also helps account for the non-linearity associated with convertible arbitrage indices that traditional risk factors are unable to capture.

The remainder of the chapter is organised as follows. Section 4.2 discusses the hedge fund data and the data used to create the convertible bond arbitrage portfolio. Section 4.3 reviews the relevant asset pricing literature and proposes multi-factor models of hedge fund risk and discusses the results of estimating these models. Section 4.4 provides evidence of the autocorrelation inherent in convertible arbitrage hedge fund returns. Section 4.5 provides details on the construction of the convertible bond arbitrage risk factor. Section 4.6 presents a parsimonious convertible arbitrage risk factor model and results from estimating this model. Section 4.7 concludes and Section 4.8 highlights some of the limitations in this chapter and suggests some avenues for further research.

4.2 Data

To examine the performance of convertible arbitrage hedge funds two indices of convertible arbitrage were employed: the CSFB Tremont Convertible Arbitrage Index and the HFRI Convertible Arbitrage Index.[31] The CSFB Tremont Convertible Arbitrage Index is an asset weighted index (rebalanced quarterly) of convertible arbitrage hedge funds beginning in 1994, whereas the HFRI Convertible Arbitrage Index is equally

[31] Although several data providers calculate indices of hedge fund performance CSFB Tremont and HFR are the two main market standard indices.

weighted with a start date of January 1990.[32] When looking at the returns to an index of hedge funds, the issue of survivor bias should be addressed.[33]

Survivor bias exists where managers with poor track records exit an index, while managers with good records remain. If survivor bias is large, then the historical returns of an index that studies only survivors will overestimate historical returns. Brown, Goetzmann and Ibbotson (1999) and Fung and Hsieh (1997) have estimated this bias to be in the range of 1.5 per cent to 3 per cent per annum for hedge fund indices. Although the CSFB Tremont indices control for survivor bias, according to Ackerman, McEnally and Ravenscraft (1999) HFR did not keep data on dead funds before January 1993. This will bias upwards the performance of the HFRI index pre 1993.

Table 4.1, Panel A presents summary statistics of the returns on the two convertible arbitrage indices in excess of the risk free rate of interest. Returns are logarithmic and the monthly yield on a 3 month treasury bill, sourced from the Federal Reserve website www.federalreserve.gov, is used as the risk free rate of interest. *CSFBRF* is the excess return on the CSFB Tremont Convertible Arbitrage Index and *HFRIRF* is the excess return on the HFRI Convertible Arbitrage Index. First note the significantly[34] positive mean monthly excess returns and the relatively low variances of the two indices. This suggests that the convertible arbitrage strategy produces high returns relative to risk. Second, the negative skewness and positive kurtosis indicates the distribution of the two

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[32] For details on the construction of the CSFB Tremont Convertible Arbitrage Index see www.hedgeindex.com. For details on the construction of the HFRI Convertible Arbitrage Index see www.hfr.com.
[33] For a discussion of the biases in hedge fund benchmark returns see Fung and Hsieh (2000b).
[34] In discussions in the text statistical significance indicates t-stats are significant from zero at least at the 10% level unless reported.

indices is non-normal and normally distributed factors may not adequately explain the risk in convertible arbitrage in a linear factor model.

Table 4.1
Summary statistics

RMRF is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is the factor mimicking portfolio for liquidity. *CSFBRF* is the excess return on the CSFB Tremont Convertible Arbitrage index, *HFRIRF* is the excess return on the HFRI Convertible Arbitrage index and *CBRF* is the excess return on the simulated convertible arbitrage portfolio. All of the variables are monthly from January 1990 to December 2002 except the CSFB Tremont Convertible Arbitrage Index which is from January 1994 to December 2002.

	Mean	T-Stat	Variance	Std Error	Skewness	Kurtosis	Jarque-Bera
			Panel A: Dependent Variables				
CSFBRF	0.440***	3.291	1.930	1.744	-1.76***	4.61***	151.16***
HFRIRF	0.538***	6.818	0.972	0.986	-1.42***	3.28***	122.46***
			Panel B: Explanatory Returns				
RMRF	0.486	1.345	20.391	4.516	-0.61***	0.57	11.66***
SMB	0.152	0.531	12.719	3.566	0.45**	1.72***	24.49***
HML	0.096	0.282	18.032	4.246	-0.64***	5.58***	212.90***
UMD	1.144***	2.805	25.926	5.092	-0.71***	5.46***	207.33***
DEF	0.540***	3.064	9.391	2.455	-0.37*	2.59***	47.2***
TERM	0.112	0.577	5.825	2.413	-0.36*	0.22	3.65
TO	0.089	0.354	9.845	1.118	-0.25	1.62	18.72***
			Panel C: Convertible Arbitrage Portfolio Return				
CBRF	0.325**	2.307	3.104	1.762	-1.36***	9.00***	573.96***

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Statistics are generated using RATS 5.0

To construct the convertible bond arbitrage factor, convertible bond terms and conditions were sourced from DataStream and Monis. Convertible bond prices, stock prices and stock dividends were taken from DataStream. Interest rate information was sourced from the US Federal Reserve. The sample includes all convertible bonds in issue in the United States between 1990 and 2002. As there is no comprehensive database containing this information the sample is limited to those convertible bonds with accurate information from DataStream and Monis. Any non-standard convertible bonds and convertible bonds with missing or unreliable data were removed from the sample. The final sample consists of 503 convertible bonds, 380 of which were alive at the end of 2002, with 123 dead convertible bonds.

4.3 Risk factor models

Six factor models are initially employed for the evaluation of hedge fund risk factors and performance measurement: the Capital Asset Pricing Model (CAPM) described in Sharpe (1964) and Lintner (1965), the Fama and French (1993) three factor stock model, the Fama and French (1993) three factor bond model, the Fama and French (1993) combined stock and bond model, the Carhart (1997) four factor model and Eckbo and Norli's (2005) liquidity factor model. This section briefly describes these models, providing an explanation of the expected relationship between convertible arbitrage excess returns and the individual factors.

The CAPM is a single index model which assumes that all of a stock's systematic risk can be captured by one market factor. The intercept of the equation, α, is commonly called Jensen's (1968) alpha and is usually interpreted as a measure of out- or under-performance. The equation to estimate is the following:

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \varepsilon_t \qquad (4.1)$$

Where $y_t = R_t - R_{ft}$, R_t is the return on the hedge fund index at time t, R_{ft} is the risk free rate at month t, $RMRF$ is the excess return on the market portfolio for month t and ε_t is the error term. α and β are the intercept and the slope of the regression, respectively. Although the CAPM is intended for the evaluation of securities it has been applied extensively in the mutual fund and hedge fund performance measurement literature.[35] It would be expected that as convertible arbitrageurs attempt to hedge equity market risk the relationship between convertible arbitrage returns and the market portfolio would be weak. However, as convertible arbitrageurs are exposed to credit risk which is typically strongly related to equity market returns, there should be a significantly positive β_{MKT} coefficient.

The Fama and French (1993) three factor stock model is estimated from an expected form of the CAPM model. This model extends the CAPM with the inclusion of two factors which take the size and market to book ratio of firms into account. It is estimated from the following equation:

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t \qquad (4.2)$$

Where SMB_t is the factor mimicking portfolio for size (small minus big) and HML_t is the factor mimicking portfolio for book to market ratio (high minus low). SMB and HML are constructed as in Fama and French (1992) by constructing six portfolios from sorts on market value of equity and the book to market ratio. In June of each year all NYSE stocks on CRSP are sorted by market value of equity. The median NYSE size is then

[35] See for example Carhart (1997) and Capocci and Hübner (2004).

used to split NYSE, Amex and NASDAQ stocks into small and big groups (these groups are not equal sized). NYSE, Amex and NASDAQ stocks are also divided into three groups based on book to market equity. Six portfolios are then constructed from the intersection of the size and book to market equity groups. The *SMB* factor represents the difference each month between the average of the returns in the three small stock portfolios and the three large stock portfolios. The *HML* factor represents the difference each month between two high book to market equity portfolios and the two low book to market equity portfolios. Fama and French (1993) employ this model to examine the risk factors in the returns of common stocks. Models incorporating the size and book to market factors have also been used in mutual fund[36] and hedge fund performance evaluation studies and the intercept from the model is often interpreted as a measure of performance. Capocci and Hübner (2004) specify the *HML* and *SMB* factors in their models of hedge fund performance. Agarwal and Naik (2004) specify the *SMB* factor in a model of convertible arbitrage performance and find it has a positive relation with convertible arbitrage returns. As the opportunities for arbitrage are greater in the smaller less liquid issues *ex ante* it would be expected that a positive relationship between convertible arbitrage returns and the size factor. There is no *ex ante* expectation of the relationship between the factor mimicking book to market equity and convertible arbitrage returns, though Capocci and Hübner (2004) report a positive *HML* coefficient for convertible arbitrage.

Fama and French (1993) also propose a three factor model for the evaluation of bond returns. They draw on the seminal work of Chen, Roll and Ross (1986) to extend the CAPM incorporating two additional factors taking the shifts in economic conditions that

[36] See for example Davies (2001) and Pástor and Stambaugh (2002).

change the likelihood of default and unexpected changes in interest rates into account. This model is estimated from the following equation

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \varepsilon_t \qquad (4.3)$$

Where DEF_t is the difference between the overall return on a market portfolio of long-term corporate bonds (here the return on the CGBI Index of high yield corporate bonds is used rather than the return on the composite portfolio from Ibbotson and Associates used by Fama and French (1993) due to its unavailability) minus the long term government bond return at month t (here the return on the Lehman Index of long term government bonds is used rather than the return on the monthly long term government bond from Ibbotson and Associates used by Fama and French (1993) due to its unavailability). $TERM_t$ is the factor proxy for unexpected changes in interest rates. It is constructed as the difference between monthly long term government bond return and the short term government bond return (here the return on the Lehman Index of short term government bonds is used rather than the one month treasury bill rate from the previous month used by Fama and French (1993)).

It is expected that convertible arbitrage returns will be positively related to both of these factors as the strategy generally has interest rate and credit risk exposure. The growth of the credit derivative market has provided the facility for arbitrageurs to hedge credit risk. The magnitude and significance of the DEF_t coefficient, (β_{DEF}) should indicate to what degree hedge funds have availed of this facility.

Fama and French (1993) also estimate a combined model when looking at the risk factors affecting stock and bond returns. As a convertible bond is a hybrid bond and equity instrument we also estimate this model using the following equation:

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \varepsilon_t \qquad (4.4)$$

As arbitrageurs attempt to hedge equity market risk it is expected that the bond market factors will be the most significant in explaining convertible arbitrage excess returns in this model.

Carhart's (1997) four factor model is an extension of Fama and French's (1993) stock model. It takes into account size, book to market and an additional factor for the momentum effect. This momentum effect can be described as the buying of assets that were past winners and the selling of assets that were past losers. This model is estimated using the following equation:

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_t \qquad (4.5)$$

where UMD_t is the factor mimicking portfolio for the momentum effect. *UMD* is constructed in a slightly different manner to Carhart's (1997) momentum factor.[37] Six portfolios are constructed by the intersection of two portfolios formed on market value of equity and three portfolios formed on prior twelve month's returns. *UMD* is the average return on the two high prior return portfolios and the two low prior return

[37] Carhart (1997) constructs his factor as the equally weighted average of firms with the highest thirty percent eleven-month returns lagged one period minus the equally weighted average of firms with the lowest thirty percent eleven month returns lagged by one period.

portfolios. This four factor model is specified extensively in the mutual fund literature[38] and the momentum factor is included in Capocci and Hübner's (2004) study of hedge fund performance and Agarwal and Naik's (2004) study. There is no *ex ante* expectation for the relationship between convertible arbitrage returns and the momentum factor. Capocci and Hübner (2004) report a negative coefficient for convertible arbitrage hedge funds.

The final model which is employed is Eckbo and Norli's (2005) extension of the Carhart model incorporating a liquidity factor. Several studies have found that stock expected returns are cross-sectionally related to stock liquidity measures.[39] Eckbo and Norli's (2005) model is estimated using the following equation:

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_{TO} TO_t + \varepsilon_t \quad (4.6)$$

Where *TO* is the return on a portfolio of low-liquidity stocks minus the return on a portfolio of high-liquidity stocks. *TO* is constructed by forming two portfolios ranked by market value of equity and three portfolios ranked by turnover. Six portfolios are formed by the intersection of these portfolios and *TO* is the equally weighted average return on the two low liquidity portfolios minus the equally weighted average return on the two high liquidity portfolios. Arbitrageurs generally operate in less liquid issues so a negative relationship between the liquidity factor and convertible arbitrage returns is expected.

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[38] See for example Bauer, Koedijk and Otten (2005) and Wermers (2000).

[39] See for example Brennan and Subrahmanyam (1996), Datar, Naik and Radclife (1998) and Brennan, Chordia and Subrahmanyam (1998).

Table 4.1, Panel B presents summary statistics of the explanatory factor returns.[40] The average risk premium for the risk factors is simply the average values of the explanatory variables. The average value of *RMRF* is 0.49% per month but is not statistically significant from zero. The average *SMB* return is 0.15% per month while the book to market factor produces an average return of less than 0.10% per month. *UMD* the momentum factor produces a large 1.14% average return but this factor also has the largest variance and standard error. The two bond market factors *DEF* and *TERM* have low standard errors but of the two only *DEF* exhibits an average return (0.54%) significantly different from zero. *TO* the liquidity risk factor has a low average return and high variance. Other than *SMB* and *TO* all of the explanatory variables' returns have significantly negative skewness and all have positive kurtosis other than *RMRF*, *TERM* and *TO*.

Table 4.2, Panel A presents a correlation matrix of the explanatory variables. The first thing that should be noted is the potential for multicollinearity. There is a high absolute correlation between *TO* and several factors, *RMRF*, *SMB* and *DEF*. *DEF* is also significantly positively correlated with *RMRF*, *SMB* and *UMD* the momentum factor is negatively correlated with *HML*.

Table 4.2, Panel B presents the correlations between the two dependent variables, *CSFBRF* and *HFRIRF* and the explanatory variables. Both of the variables are highly correlated as evident by a cross correlation of 0.80. Both are positively related to *DEF*

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[40] Data on *SMB*, *RMRF*, *HML* and *UMD* was provided by Kenneth French. Liquidity factor data was provided by Øyvind Norli.

the default risk factor and *SMB* the factor proxy for firm size. *HFRIRF* is positively correlated with *RMRF* and both are negatively related to *TO* the liquidity factor.

Table 4.2
Cross correlations January 1990 to December 2002

RMRF is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity. *CSFBRF* is the excess return on the CSFB Tremont Convertible Arbitrage index, *HFRIRF* is the excess return on the HFRI Convertible Arbitrage index and *CBRF* is the excess return on the simulated convertible arbitrage portfolio. All of the correlations cover the period January 1990 to December 2002 except for correlations with the CSFB Tremont Convertible Arbitrage Index which cover the period January 1994 to December 2002.

Panel A: Explanatory Variables

	RMRF	*SMB*	*HML*	*UMD*	*TERM*	*DEF*	*TO*
RMRF	1.00						
SMB	0.17	1.00					
HML	-0.34	-0.41	1.00				
UMD	-0.20	0.05	-0.62	1.00			
TERM	-0.06	-0.18	-0.03	0.27	1.00		
DEF	0.46	0.33	0.04	-0.39	-0.71	1.00	
TO	-0.68	-0.54	0.34	0.21	0.16	-0.52	1.00

Panel B: Dependent Variable and Explanatory Variables

	RMRF	*SMB*	*HML*	*UMD*	*TERM*	*DEF*	*TO*	*CSFBRF*	*HFRIRF*
CSFBRF	0.15	0.22	0.02	-0.05	0.04	0.23	-0.26	1.00	
HFRIRF	0.35	0.29	-0.10	-0.06	0.09	0.28	-0.42	0.80	1.00

Panel C: Convertible Arbitrage Portfolio, Dependent Variables and Explanatory Variables

	RMRF	*SMB*	*HML*	*UMD*	*TERM*	*DEF*	*TO*	*CSFBRF*	*HFRIRF*
CBRF	0.50	0.30	-0.03	-0.21	0.01	0.39	-0.48	0.32	0.48

With the exception of the *CSFBRF* correlations, coefficients greater than absolute 0.25, 0.19 and 0.17 are significant at the 1%, 5% and 10% levels respectively.
CSFBRF correlation coefficients greater than absolute 0.22, 0.17 and 0.14 are significant at the 1%, 5% and 10% levels respectively.

Table 4.3
Result of regressions on the HFRI Convertible Arbitrage Index excess returns from January 1990 to December 2002

This table reports results from regressions on HFRI Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	Q-Stat	Adj. R^2
0.5010	0.0763							79.76***	11.65%
(4.65)***	(4.00)***								
0.4860	0.0749	0.0820	0.0336					93.07***	18.37%
(4.75)***	(4.11)***	(4.06)***	(2.31)**						
0.4248	0.0932	0.0939	0.0715	0.0410				86.21***	20.13%
(3.73)***	(4.90)***	(4.21)***	(3.12)***	(2.17)**					
0.4326	0.0784	0.0792	0.0737	0.0453	-0.0392			86.0***	20.13%
(3.72)***	(3.02)***	(2.74)***	(3.17)***	(2.49)**	(-1.06)				
0.3958	0.0176					0.2016	0.2230	78.23***	26.41%
(3.56)***	(1.17)					(3.84)***	(4.08)***		
0.4040	0.0177	0.0517	0.0022			0.1738	0.2118	87.79***	28.40%
(3.78)***	(0.96)	(2.66)***	(0.12)			(3.08)***	(3.65)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 4.3 presents results of the estimation of the risk factor models discussed above on the HFRI Convertible Arbitrage Index excess returns from January 1990 to December 2002. The error term of the return regression is potentially heteroskedastic and autocorrelated. Although the conditional heteroskedasticity and autocorrelation are not formally treated in the OLS estimate of the parameter, the t-stats in parenthesis below the parameter estimates are heteroskedasticity and autocorrelation-consistent due to Newey and West (1987).[41]

[41] For all the time-series analysis in this chapter, adjusting the autocorrelation beyond a lag of 3 periods does not yield any material differences. A t-stat based on 3 lags is adopted for regressions.

The first result is from estimating the CAPM. The market coefficient, 0.07, and the intercept are significantly positive indicating that there is a positive relationship between convertible bond arbitrage returns and the market portfolio. This is a finding consistent with Capocci and Hübner (2004) who estimate a market coefficient for convertible arbitrage hedge funds of 0.06. Assuming this is a correctly specified factor model the α coefficient indicates abnormal returns of 0.50% per month. However the low adjusted R^2 indicates that this one factor model may not fully capture the risk in convertible bond arbitrage.

The second result is the estimate of the Fama and French (1993) three factor stock model. The factor loadings on all three factors are significantly positive, consistent with Capocci and Hübner's (2004) findings for convertible arbitrage, but the relatively low adjusted R^2 suggest that this model does not fully capture the risk in convertible bond arbitrage. It should be highlighted that the *SMB* coefficient indicates that convertible arbitrageurs appear to favour issues from smaller companies perhaps due to the greater arbitrage opportunities. Again the estimated α indicates abnormal returns.

The next result is from estimating the Carhart (1997) four factor model. The momentum factor adds little explanatory value to the regression and the negative correlation, highlighted earlier, between *HML* and *UMD* increases the significance of the *HML* coefficient. The Ecko and Norli (2005) *TO* factor adds no explanatory power to the model.

The penultimate result is from estimation of the Fama and French (1993) bond factor model. The coefficients on both factors, *DEF* and *TERM*, are highly significant, with coefficients greater than 0.10 and the overall explanatory power of the regression improves with an adjusted R^2 of 25.55%. The results indicate that convertible arbitrageurs have significant term structure and credit risk. Despite the improvement in model fit arbitrageurs appear to be able to generate abnormal returns of 0.40% per month. The final result is an estimation of the combined Fama and French's (1993) bond and stock factor models. The coefficients for *RMRF* and *HML* are no longer significantly different from zero. Arbitrageurs appear to be generating their returns from exposure to default risk, term structure risk and from investing in the issues of smaller companies.

Consistent with the evidence presented by Brooks and Kat (2001) of serial correlation in convertible arbitrage index returns the Q-stats are significant at the 1% level indicating that the residuals of the models presented in Table 4.3 are autocorrelated.

Table 4.3b reports results from estimating the same series of regression models on the HFRI index from 1993 to 2002. This is to allow for any potential survivor bias, pre 1993 when according to Ackerman, McEnally and Ravenscraft (1999) HFR did not keep data on dead funds. The results are almost identical with the exception of *TO*, the liquidity factor which is now significantly negative, consistent with expectations, in Eckbo and Norli's (2005) model. As in Table 4.3 the residuals of the estimated models presented in Table 4.3b display autocorrelation.

Table 4.3b
Result of regressions on the HFRI Convertible Arbitrage Index excess returns from January 1993 to December 2002

This table reports results from regressions on HFRI Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	Q Stat	Adj. R^2
0.5202	0.0752							47.09***	11.61%
(4.38)***	(3.38)***								
0.5025	0.0754	0.0765	0.0313					52.79***	17.60%
(4.45)***	(3.48)***	(3.48)***	(2.07)**						
0.4435	0.0941	0.0870	0.0658	0.0353				47.49***	18.69%
(3.47)***	(3.93)***	(3.56)***	(2.62)***	(1.71)*					
0.4583	0.0655	0.0597	0.0705	0.0432	-0.0744			45.97***	20.13%
(3.54)***	(2.08)**	(1.95)*	(2.77)***	(2.19)**	(-2.00)**				
0.4507	0.0256					0.1843	0.2055	46.88***	22.90%
(3.71)***	(1.53)					(2.95)***	(3.23)***		
0.4526	0.0287	0.0541	0.0054			0.1538	0.1929	50.12***	25.17%
(3.90)***	(1.31)	(2.40)**	(0.25)			(2.26)**	(2.84)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 4.4 reports results from the same series of regressions, only this time on the CSFB Tremont Convertible Arbitrage Index from January 1994 to December 2002. Results are similar to the HFRI Index but the explanatory power of the regressions is lower. Again the major risks faced by the arbitrageur are default risk, term structure risk and the risk from investing in the issues of small companies. Results from the estimation of the models characterises convertible arbitrage as producing abnormal returns of between 0.35% and 0.42% per month. Again the residuals of all six models exhibit autocorrelation.

Table 4.4
Result of regressions on the CSFB Tremont Convertible Arbitrage Index excess returns from January 1994 to December 2002

This table reports results from regressions on the CSFB Tremont Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	Q Stat	Adj. R^2
0.4212	0.0425							93.00***	1.23%
(2.08)**	(1.46)								
0.4055	0.0477	0.0927	0.0520					93.63***	5.76%
(2.08)**	(1.66)*	(2.69)***	(2.38)**						
0.3234	0.0783	0.1108	0.1092	0.0550				90.90***	6.86%
(1.44)	(2.21)**	(2.50)**	(2.03)**	(1.31)					
0.3460	0.0405	0.0752	0.1160	0.0656	-0.0984			83.74***	7.95%
(1.52)	(0.91)	(1.39)	(2.16)**	(1.60)	(-1.74)*				
0.3501	-0.0284					0.2587	0.2585	111.1***	11.88%
(1.66)*	(-0.84)					(2.59)***	(3.12)***		
0.3534	-0.0197	0.0564	0.0146			0.2200	0.2410	108.6***	12.03%
(1.72)*	(-0.44)	(2.08)**	(0.45)			(1.97)**	(2.64)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Overall the explanatory power of the risk factor models for both the HFRI Convertible Arbitrage Index and CSFB Tremont Convertible Arbitrage Index are low. The most important risk factors are *SMB*, *DEF* and *TERM*, a robust finding for both indices, but the inclusion of these factors in a convertible arbitrage factor model leads us to the conclusion that convertible arbitrageurs are able to generate significant abnormal returns.[42] The Q-stats of all of the models presented in this section are highly significant indicating that the residual of all of the models exhibit serial correlation. In the next

[42] This is a finding consistent with other studies. See for example Capocci and Hubner (2004)

section two hypotheses to explain the autocorrelation are presented followed by a univariate analysis of the Convertible Arbitrage indices.

4.4 Analysis of the hedge fund indices

4.4.1 Hypothesis to explain the observed autocorrelation

There are two non-competing hypotheses to explain the observed autocorrelation, illiquidity in the securities held by convertible arbitrageurs and time varying expected returns. Getmansky, Lo and Makarov (2004) argue that it is illiquidity (and possible return smoothing by hedge fund managers) that causes the perceived serial correlation. In the case where the securities held by a fund are not actively traded, the returns of the fund will appear smoother than true returns, be serially correlated, resulting in a downward bias in estimated return variance and a consequent upward bias in performance when the fund is evaluated using mean variance analysis. If Getmansky, Lo and Makarov's (2004) hypothesis is correct then a linear factor model analysis ignoring illiquidity will overstate performance. In the previous section a liquidity risk factor, *TO*, was employed but as this factor is derived from equities (which are more liquid than convertible bonds) this factor is unlikely to capture the full liquidity risk.[43] The alternate hypothesis is that autocorrelation is caused by time variation in expected return. This time variation could be caused by variation in hedge fund leverage or risk exposures. Time varying expected returns will be explored in Chapter 7. However, these are not competing hypotheses and the evidence presented by Getmansky, Lo and

[43] One potential solution would be to calculate the *TO* factor using convertible bond rather than equity data. Unfortunately there is extremely limited data available on convertible bond trading volume.

Makarov (2004) suggests that serial correlation in hedge fund returns is predominantly caused by illiquidity with time variation in expected returns being a secondary cause.

This study proposes the simple solution of using the lagged hedge fund index return as an explanatory variable. The lagged hedge fund index return acts as a proxy risk factor for the illiquidity in hedge fund security holdings. Specifying the lagged hedge fund index return as an explanatory variable also potentially addresses the serial correlation present in the risk factor models in that the serial correlation may be a product of a missing variable i.e. illiquidity. Assuming the liquidity hypothesis holds, if a hedge fund holds zero illiquid securities then hedge fund returns at time t should have no relationship with hedge fund returns at time $t-1$. If the fund holds illiquid securities then there will be a relationship between returns at time t and $t-1$, captured by a significant positive coefficient on the one period lag of the hedge fund index return. The larger the lagged hedge fund index return coefficient the greater the illiquidity exposure. A linear factor model can then be estimated using this illiquidity factor combined with the other market factors to assess hedge fund index and also individual hedge fund returns.

One potential difficulty with specifying the lagged hedge fund index returns as a risk factor is that for the sample period January 1990 to December 2002 hedge fund returns were mainly positive and trending upwards. Whether positive autocorrelation can be considered a risk factor depends upon the serial correlation being a symmetric effect. If the persistence only occurs in positive months then it cannot be considered a risk factor but is in fact a desirable attribute. If it persists in negative months then it can be considered a risk factor. Table 4.5 presents results of the following linear regression on the subdivided sample.

$$y_t = \alpha + \beta y_{t-1} + e \quad (4.7)$$

Where y_t is the excess return on the HFRI index at time t. Panel A presents results of estimating (4.7) for the entire sample, Panel B presents results of estimating (4.7) when lagged hedge fund returns are greater than zero and Panel C presents results of estimating (4.7) when lagged hedge fund returns are less than zero. It is clear in these results that the autocorrelation is symmetric being both positive, with a coefficient of approximately 0.50, in up and down months. As the sample is relatively small, with only thirty three negative observations, caution must remain in interpreting the lagged excess return as a risk factor.

Table 4.5
Regressing HFRI index returns on their one period lag

This table presents the results of regressing excess HFRI index returns at time t on the one period lag of excess HFRI index returns. The first reported result is for the entire sample. The second reported result is when the ample is restricted to $y_{t-1} \geq 0$ and the third reported result s when the sample is restricted to $y_{t-1} < 0$.

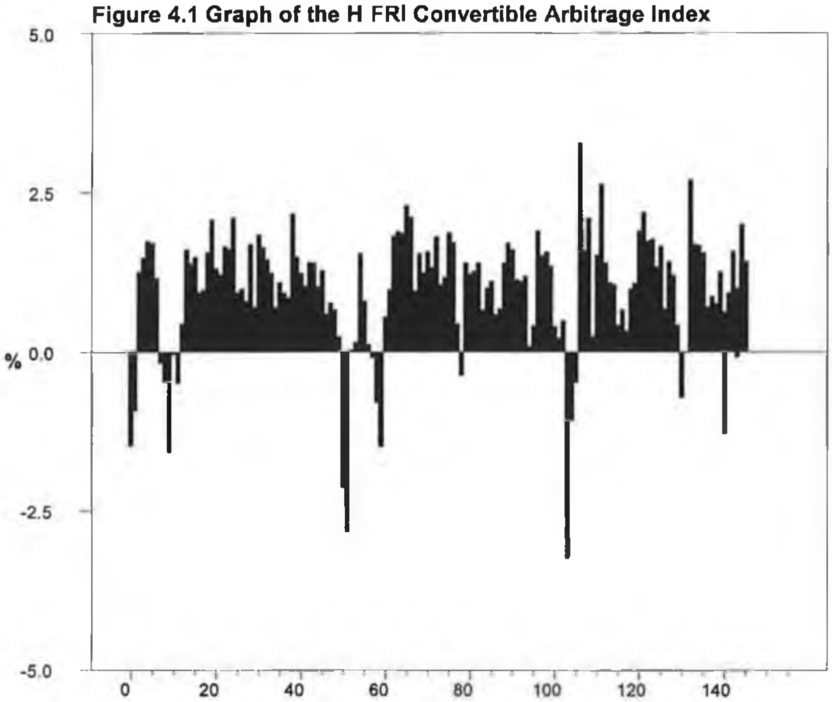
	α	$\beta_{Y_{t-1}}$	N	Adj. R^2
A: Entire sample	0.2754	0.5249	155	28.34%
	(3.69)***	(7.87)***		
B: $y_{t-1} \geq 0$	0.2365	0.5603	122	15.16%
	(1.90)*	(4.76)***		
C: $y_{t-1} < 0$	0.3059	0.5338	33	11.39%
	(0.98)	(2.26)***		

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

4.4.2 Univariate analysis

Before proceeding to estimate risk factor models incorporating the one period lag of the dependent variable as a risk factor it is useful to statistically examine the convertible arbitrage indices' return process. In this section the time plot of the series, the autocorrelation function and the partial correlation function are examined. Plotting the time path of the series provides useful information concerning outliers, missing values and structural breaks in the series. Nonstationary variables may have a pronounced trend or appear to meander without a constant mean or variance. Comparing the sample ACF and PACF to those of various theoretical AR and ARMA processes may indicate the statistical, as opposed to qualitative, relevance of incorporating a one period lag as a risk factor.

Figure 4.1 Graph of the H FRI Convertible Arbitrage Index



In Figure 4.1 the time plot of the HFRI Convertible Arbitrage Index return series is presented. Looking at this time plot yields two main insights. First the series is generally positive with nine periods with negative observations, lasting from one to five months. Second, the negative observation periods are reasonable evenly spread throughout the series so there is at least five months of positive observations between each period of negative observations.

Figure 4.2 ACF of the HFR I Convertible Arbitrage Index

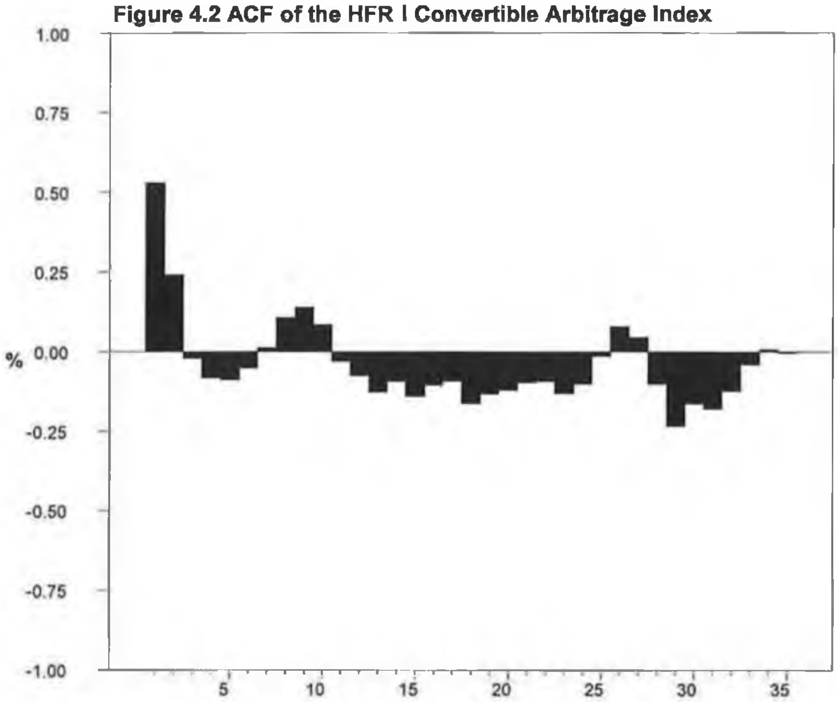
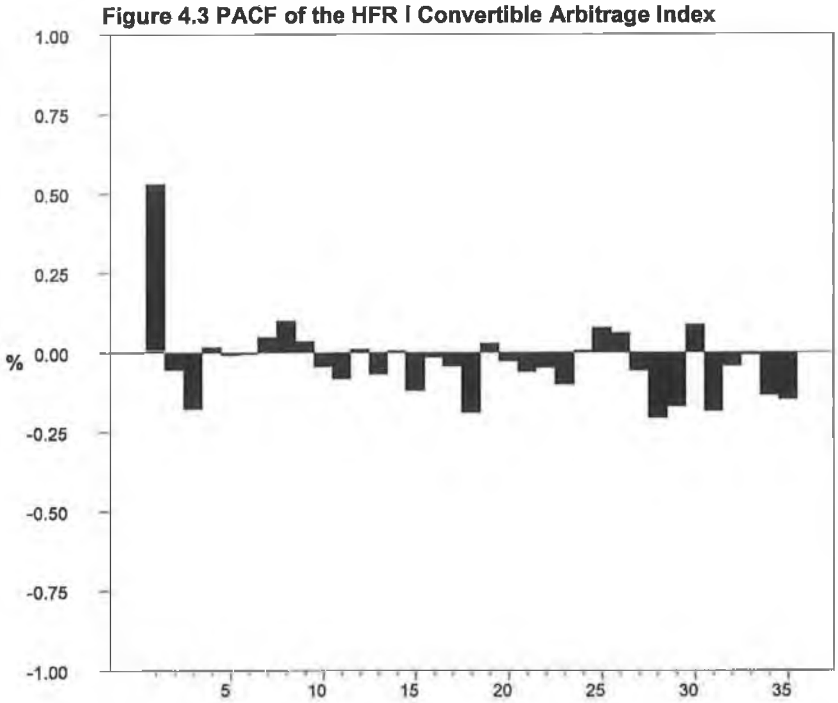


Figure 4.3 PACF of the HFR I Convertible Arbitrage Index



Figures 4.2 and 4.3 display the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the HFRI Convertible Arbitrage return series respectively. The rapid decay of the ACF and the single large spike at lag 1 suggest that the series may follow an AR(1) process supporting the inclusion of the one period lag of the index to reduce bias in the estimation of the alpha and beta coefficients in a linear factor model of convertible arbitrage returns.

Figure 4.4 Graph of the CSFB/Tremont Convertible Arbitrage Index

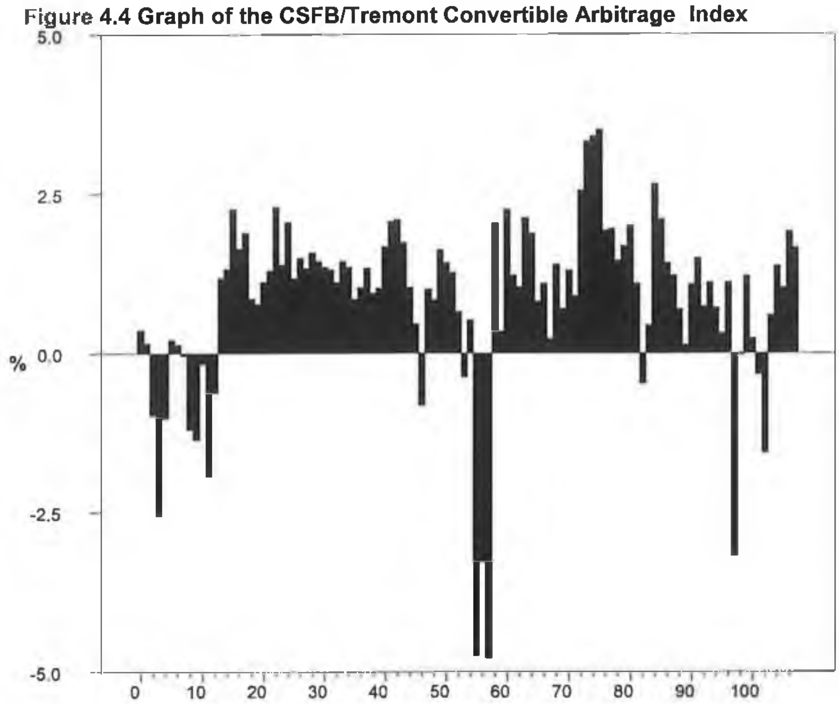


Figure 4.4 displays the time plot for the CSFB Tremont Convertible Arbitrage Index return series. Again the series is generally positive with eight periods with negative observations lasting from one to five months. The negative observation periods are not as well distributed as the HFRI series but are reasonably spread out, other than the first thirteen months of the series when eight of the observations are negative.

The ACF and PACF for the CSFB Tremont Convertible Arbitrage Index return series are displayed in Figures 4.5 and 4.6. The oscillating decay in the ACF and the single large spike in the PACF again suggest that the inclusion of the one period lag of the hedge fund index may improve the goodness of fit of the multi-factor risk models examined in the previous section, and lead to increased efficiency in the estimation of the alpha and risk factor coefficients.

Figure 4.5 ACF of the CSFB/Tremont Convertible Arbitrage Index

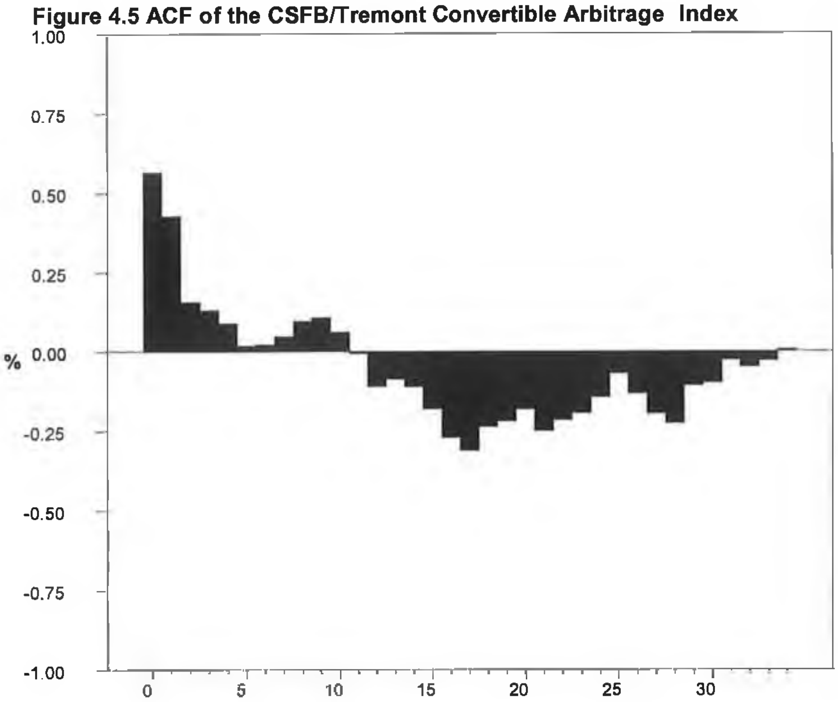
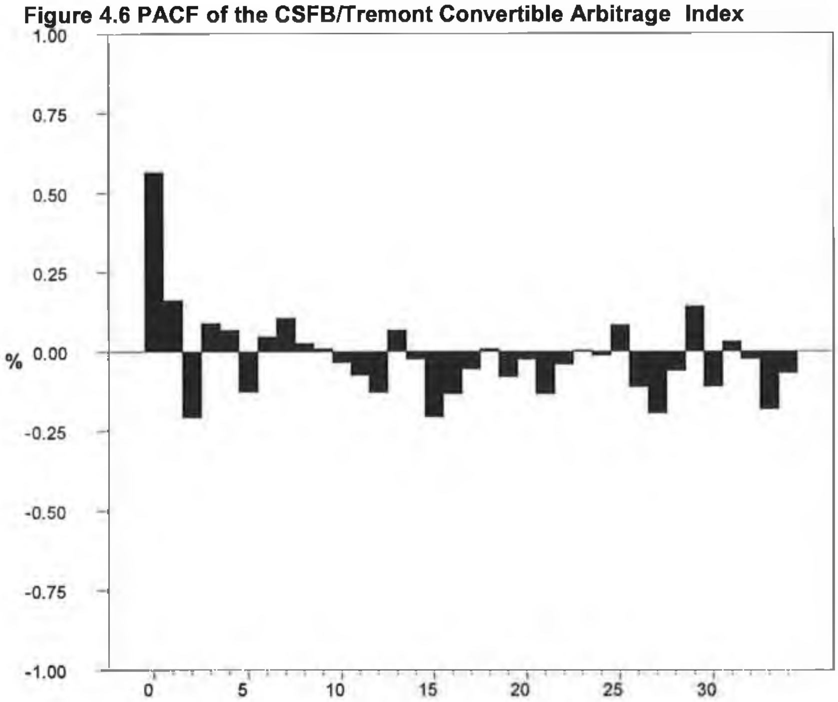


Figure 4.6 PACF of the CSFB/Tremont Convertible Arbitrage Index



Given both hedge fund indices approximate an AR(1) process, including the one period lag of the dependent variable as a regressor will reduce the bias in the estimates of coefficients, particularly the α which is interpreted as a measure of out performance. A similar result would be achieved by estimating the factor model using a statistical autocorrelation correction procedure such as the Corchane-Orcutt (1949) procedure. However, a disadvantage of this statistical procedure is that the results cannot be interpreted easily as functions of risk.

4.4.3 Specifying lagged hedge fund returns as a risk factor

To examine the effect of including the lag of hedge fund index returns in the risk factor model the analysis from Section 4.3 is repeated with the inclusion of a one period lag of the dependent variable as an explanatory variable as set out in equations (4.8) to (4.13).

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.8}$$

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.9}$$

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.10}$$

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_{TO} TO_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.11}$$

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.12}$$

$$y_t = \alpha + \beta_{RMRF} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t \tag{4.13}$$

Table 4.6 presents the results of this analysis for the HFRI Convertible Arbitrage Index. The introduction of y_{t-1}, the lagged HFRI excess return, has a substantial improvement in the explanatory power of the overall models without reducing the significance or magnitude of the coefficients on the individual factors. Moreover, the abnormal returns have reduced to 0.14% per month for the Fama and French (1993) bond market factor model and are only significant at the 10% level with the model explaining over 52% of HFRI Convertible Arbitrage returns.

Table 4.6
Result of regressions on the HFRI Convertible Arbitrage Index excess returns with a one period lag of the hedge fund index from February 1990 to December 2002

This table reports results from estimating (4.8) to (4.13) on HFRI Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity. y_{t-1} is the one period lagged excess return on the HFRI Convertible Arbitrage Index.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	β_y	Q Stat	Adj. R^2
0.2229	0.0777							0.5449	10.84	41.01%
(2.52)**	(3.92)***							(8.02)***		
0.2197	0.0759	0.0691	0.0264					0.5272	19.46	46.06%
(2.68)***	(4.06)***	(4.04)***	(1.95)*					(8.32)***		
0.2113	0.0791	0.0713	0.0329	0.0070				0.5224	20.26	45.76%
(2.51)**	(4.11)***	(4.15)***	(2.10)**	(0.54)				(8.17)***		
0.2205	0.0599	0.0522	0.0354	0.0122	-0.0504			0.5253	20.99	46.31%
(2.58)***	(2.34)**	(2.54)**	(2.21)**	(0.95)	(-1.53)			(8.13)***		
0.1366	0.0261					0.1783	0.2047	0.5257	16.65	53.61%
(1.71)*	(1.89)*					(4.44)***	(5.29)***	(9.13)***		
0.1457	0.0247	0.0429	-0.0013			0.1575	0.1974	0.5202	19.51	55.32%
(1.91)*	(1.67)*	(2.41)**	(-0.08)			(3.59)***	(4.91)***	(9.03)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 4.6b presents the results of this analysis for the HFRI Convertible Arbitrage Index from 1993 to 2002. Despite the inclusion of the lagged dependent variable and the exclusion of the pre 1993 period, the convertible arbitrage indices still appear to generate abnormal returns of 0.16% per month, albeit at the 10% significance level, or a compounded annual return of 1.9% per annum.

Table 4.6b
Result of regressions on the HFRI Convertible Arbitrage Index excess returns with a one period lag of the hedge fund index from January 1993 to December 2002

This table reports results from estimating (4.8) to (4.13) HFRI Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity. y_{t-1} is the one period lagged excess return on the HFRI Convertible Arbitrage Index.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	β_y	Q Stat	Adj. R^2
0.2379	0.0798							0.5093	9.28	37.04%
(2.26)**	(3.42)***							(6.29)***		
0.2306	0.0810	0.0693	0.0315					0.4964	14.08	42.15%
(2.35)**	(3.54)***	(3.53)***	(2.18)**					(6.49)***		
0.2038	0.0919	0.0760	0.0522	0.0204				0.4859	14.75	42.19%
(1.99)**	(3.84)***	(3.80)***	(2.89)***	(1.34)				(6.40)***		
0.2205	0.0599	0.0522	0.0354	0.0122	-0.0504			0.5253	15.53	46.31%
(2.58)***	(2.34)**	(2.54)**	(2.21)**	(0.95)	(-1.53)			(8.13)***		
0.1604	0.0292					0.1899	0.2243	0.5234	12.99	50.33%
(1.70)*	(1.95)*					(3.51)***	(4.42)***	(7.70)***		
0.1675	0.0320	0.0468	0.0051			0.1635	0.2135	0.5146	16.46	52.13%
(1.88)*	(1.91)*	(2.23)**	(0.29)			(2.82)***	(4.06)***	(7.66)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 4.7 presents the results for the CSFB Tremont Convertible Arbitrage Index. Adding the lagged dependent variable, y_{t-1}, improves the explanatory power of the overall models. Again, the significance of the individual factors is unaffected although the model intercepts are now statistically insignificant for all models.

Table 4.7
Result of regressions on the CSFB Tremont Convertible Arbitrage Index excess returns with a one period lag of the hedge fund index from January 1994 to December 2002

This table reports results from estimating (4.8) to (4.13) CSFB Tremont Convertible Arbitrage Index returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity. y_{t-1} is the one period lagged excess return on the CSFB Tremont Convertible Arbitrage Index.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	β_y	Q Stat	Adj. R^2
0.1652	0.0653							0.5830	17.20	34.16%
(1.22)	(2.24)**							(5.24)***		
0.1543	0.0685	0.0905	0.0455					0.5782	18.67	38.83%
(1.23)	(2.56)**	(3.68)***	(3.25)***					(5.57)***		
0.1135	0.0851	0.1005	0.0771	0.0303				0.5693	20.35	38.83%
(0.85)	(2.64)***	(3.68)***	(2.49)**	(1.14)				(5.64)***		
0.1350	0.0561	0.0733	0.0832	0.0390	-0.0762			0.5618	21.30	39.41%
(0.98)	(1.41)	(2.08)**	(2.77)***	(1.55)	(-1.91)*			(5.51)***		
0.0778	-0.0122					0.2881	0.2918	0.6078	22.22	48.58%
(0.60)	(-0.62)					(3.21)***	(4.04)***	(6.41)***		
0.0813	-0.0120	0.0456	-0.0003			0.2657	0.2844	0.6067	19.02	49.14%
(0.66)	(-0.41)	(1.91)*	(-0.01)			(2.54)**	(3.49)***	(6.50)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

After the inclusion of the lagged dependent variable the average convertible arbitrageur, represented by the convertible arbitrage indices, displays lower abnormal performance. This is despite the potential positive upward bias in hedge fund index returns. The robustness of the results is demonstrated by the remarkable similarity, both in coefficient significance and magnitude, for the two hedge fund indices and the similarity across different time periods.

4.5 Convertible bond arbitrage risk factor

One potential criticism of the analysis so far is the use of factors and models which were not formulated explicitly for the examination of convertible bond arbitrage factors. In this section of the paper, to improve understanding of hedge fund risk, a simulated convertible arbitrage portfolio is included acting as a risk factor. This is useful for examining whether arbitrageurs can generate abnormal returns relative to this factor and if so whether these abnormal returns are earned from taking on other risks. To construct this factor a convertible bond arbitrage portfolio is simulated using data from 1990 to 2002.

The convertible bond portfolio is an equally weighted portfolio of delta neutral hedged long convertible bonds and short stock positions. In order to initiate a delta neutral hedge for each convertible bond the delta for each convertible bond is estimated on the trading day it enters the portfolio. The delta estimate is then multiplied by the convertible bond's conversion ratio to calculate Δ_{it} the number of shares to be sold short in the underlying stock (the hedge ratio) to initiate the delta neutral hedge. On the following day the new hedge ratio, Δ_{it+1}, is calculated, and if $\Delta_{it+1} > \Delta_{it}$ then $\Delta_{it+1} - \Delta_{it}$ shares are sold, or if $\Delta_{it+1} < \Delta_{it}$, then $\Delta_{it} - \Delta_{it+1}$ shares are purchased maintaining the delta neutral hedge. The delta of each convertible bond is then recalculated daily and the hedge is readjusted maintaining the delta neutral hedge.

Daily returns were calculated for each position on each trading day up to and including the day the position is closed out. A position is closed out on the day the convertible bond is delisted from the exchange. Convertible bonds may be delisted for several reasons. The company may be bankrupt, the convertible may have expired or the convertible may have been fully called by the issuer.

The daily returns for a position *i* on day *t* are calculated as follows.

$$R_{it} = \frac{P_{it}^{CB} - P_{it-1}^{CB} + C_{it} - \Delta_{it-1}(P_{it}^{U} - P_{it-1}^{U} + D_{it}) + r_{t-1}S_{i,t-1}}{P_{it-1}^{CB} + \Delta_{it-1}P_{it-1}^{U}} \tag{4.14}$$

Where R_{it} is the return on position *i* at time *t*, P_{it}^{CB} is the convertible bond closing price at time *t*, P_{it}^{U} is the underlying equity closing price at time *t*, C_{it} is the coupon payable at time *t*, D_{it} is the dividend payable at time *t*, Δ_{it-1} is the delta neutral hedge ratio for position *i* at time *t-1* and $r_{t-1}S_{i,t-1}$ is the interest on the short proceeds from the sale of the shares. Daily returns are then compounded to produce a position value index for each hedged convertible bond over the entire sample period.

The value of the convertible bond arbitrage portfolios on a particular date is given by the formula.

$$V_t = \frac{\sum_{i=1}^{i=N_t} W_{it} PV_{it}}{F_t} \tag{4.15}$$

Where V_t is the portfolio value on day t, W_{it} is the weighting of position i on day t, PV_{it} is the value of position i on day t, F_t is the divisor on day t and N_t is the total number of position on day t. W_{it} is set equal to one for each live hedged position.

On the inception date of the portfolio, the value of the divisor is set so that the portfolio value is equal to 100. Subsequently the portfolio divisor is adjusted to account for changes in the constituents in the portfolio. Following a portfolio change the divisor is adjusted such that equation (4.16) is satisfied.

$$\frac{\sum_{i=1}^{i=N_t} W_{ib} PV_i}{F_b} = \frac{\sum_{i=1}^{i=N_t} W_{ia} PV_i}{F_a} \tag{4.16}$$

Where PV_i is the value of position i on the day of the adjustment, W_{ib} is the weighting of position i before the adjustment, W_{ib} is the weighting of position i after the adjustment, F_b is the divisor before the adjustment and F_a is the divisor after the adjustment.

Thus the post adjustment index factor F_a is then calculated as follows.

$$F_a = \frac{F_b x \sum_{i=1}^{i=N_t} W_{ia} PV_i}{\sum_{i=1}^{i=N_t} W_{ib} PV_i} \tag{4.17}$$

As the margins on the strategy are small relative to the nominal value of the positions, convertible bond arbitrageurs usually employ leverage. Calamos (2003) and Ineichen (2000) estimate that for an individual convertible arbitrage hedge fund this leverage may vary from two to ten times equity. However, the level of leverage in an efficiently run portfolio is not static and varies depending on the opportunity set and risk climate. Khan (2002) estimates that in mid 2002 convertible arbitrage hedge funds were at an average leverage level of 2.5 to 3.5 times, whereas he estimates that in late 2001 average leverage levels were approximately 5 to 7 times.

From a strategy analysis perspective it is therefore difficult to ascribe a set level of leverage to the portfolio. Changing the leverage applied to the portfolio has obvious effects on returns and risk as measured by standard deviation. It is decided to apply leverage of two times to the portfolio as this produces a portfolio with a similar average return to indices of convertible arbitrage hedge fund returns.[44] Finally, monthly returns were calculated from the index of convertible bond portfolio values.

The monthly returns in excess of the risk free rate of interest act as the convertible bond arbitrage risk factor *CBRF*. Summary statistics for *CBRF* are presented in Panel C of Table 4.1. The average return is 0.33% per month with a variance of 3.104. The average return is lower and the variance higher than the two convertible arbitrage hedge fund indices, *CSFBRF* and *HFRIRF*. *CBRF* is negatively skewed and has positive kurtosis as do the two hedge fund indices.

[44] For more detailed discussion of the portfolio construction and properties see Chapter 3.

Panel C of Table 4.2 displays the correlations between *CBRF*, the two hedge fund indices *HFRIRF* and *CSFBRF* and the various other explanatory variables. *CBRF* is positively correlated with both of the hedge fund indices though the correlation is stronger with *HFRIRF*. The correlation coefficients for *CBRF* and the explanatory variables all have the same sign as those of the two hedge fund indices and the explanatory variables. Analysis of the summary statistics and the correlation therefore suggests that the *CBRF* factor shares many characteristics with the hedge fund indices.

Table 4.8 provides further analysis of the relationship between *CBRF* the convertible bond arbitrage factor and the other explanatory variables. Overall the results are remarkably similar to the hedge fund indices, both in significance and coefficient magnitude, again demonstrating the robustness of the convertible arbitrage risk factor model. Like the two hedge fund indices *DEF* and *TERM* are the two most important factors in explaining the *CBRF* series. *CBRF* returns are also positively related to *SMB* the factor mimicking size. The principal difference between the results for *CBRF* and the two hedge fund indices is that *CBRF* is significantly positively related to *HML* the book to market factor, although both of the hedge fund indices are also positively related to *HML* when *DEF* and *TERM* are omitted.

Like the hedge fund indices Q-stats are significant, indicating serial correlation in the *CBRF* residuals, however it is not first order serial correlation as *CBRF* is a more dynamic series.

Table 4.8
Result of regressions on the simulated convertible arbitrage portfolio excess returns

This table reports results from regressions on simulated convertible arbitrage portfolio returns in excess of the risk free rate of interest. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity.

α	β_{RMRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{TO}	β_{DEF}	β_{TERM}	Q-Stat	Adj. R^2
0.2268	0.2028							52.06***	26.56%
(1.54)	(5.07)***								
0.1906	0.2186	0.1216	0.105					55.78***	33.46%
(1.40)	(5.21)***	(3.50)***	(4.84)***						
0.0974	0.2464	0.1397	0.1627	0.0624				52.65***	34.69%
(0.57)	(4.86)***	(3.95)***	(3.28)***	(1.48)					
0.0944	0.2522	0.1455	0.1618	0.0607	0.0152			49.13***	34.28%
(0.54)	(4.35)***	(3.44)***	(3.29)***	(1.45)	(0.32)				
0.0738	0.1174					0.2848	0.3656	50.99***	37.11%
(0.52)	(3.64)***					(4.10)***	(3.79)***		
0.0934	0.1528	0.1009	0.0758			0.1868	0.3070	42.46***	39.84%
(0.71)	(4.48)***	(2.92)***	(3.60)***			(3.18)***	(3.59)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

4.6 Results of the convertible arbitrage factor models

This section of the paper provides results of estimating parsimonious convertible arbitrage hedge fund index risk factor models. These models incorporate, *CBRF*, a factor mimicking the return in excess of the risk free rate of interest on a delta hedged long convertible bond arbitrage portfolio, *DEF*, the factor mimicking default risk and *TERM*, the factor mimicking term structure risk. This analysis aids an assessment of the performance of the convertible arbitrage hedge fund strategy.

Table 4.9 reports the results from estimating the following factor models on convertible bond hedge fund index excess returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_y y_{t-1} + \varepsilon_t \quad (4.18)$$

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t \quad (4.19)$$

Where, y_t is the excess return on the hedge fund index at time t, y_{t-1} is the one period lag of the excess return on the hedge fund index at time t, $CBRF_t$ is the excess return on the convertible bond arbitrage risk factor at time t. *DEF* and *TERM* are included as they are the most significant market risk factors in the multi-factor models of hedge fund indices reported above.

Panel A of Table 4.9 reports results of estimating equations (4.18) and (4.19) for the HFRI Convertible Arbitrage Index from 1990 to 2002. This sample includes the period up to December 1992 when dead funds were excluded from the HFRI indices. The overall regression has high explanatory power with 43.18% of convertible arbitrage excess returns explained by this two factor model. The individual coefficients are also highly significant. The alpha from this model is 0.2093% per month, or 2.54% per annum, significant at the 5% level. Arbitrageurs are therefore taking more risk than that captured by our two factor model. As discussed previously the main risks faced by arbitrageurs are default risk and term structure risk so these are included in model (4.19). The explanatory power of the model is high with an adjusted R^2 of 54.15%. All explanatory variable coefficients are significant and the alpha coefficient is no longer significant at the 5% level.

Table 4.9
Result of regressions on the HFRI and CSFB Tremont Convertible Arbitrage Index excess returns with a one period lag of the hedge fund index

This table reports results from estimating (4.18) and (4.19) on the HFRI Convertible Arbitrage Index excess returns and CSFB Tremont Convertible Arbitrage Index excess returns. *RMRF* is the excess return on Fama and French's (1993) market proxy, *SMB* and *HML* are Fama and French's factor-mimicking portfolios of size and market to book equity. *UMD* is the Carhart (1997) factor mimicking portfolio for one-year momentum. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *TO* is Eckbo and Norli's (2005) factor mimicking portfolio for liquidity. y_{t-1} is the one period lagged excess return of the hedge fund index excess return.

Panel A: HFRI Model 1990 – 2002

α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Q Stat	Adj. R^2
0.2093	0.2461	0.4668			14.03	43.18%
(2.45)**	(5.39)***	(7.01)***				
0.1343	0.0957	0.4961	0.1710	0.1930	15.31	54.15%
(1.67)*	(2.28)**	(8.51)***	(3.30)***	(4.30)***		

Panel B: HFRI Model 1994 – 2002

α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Q Stat	Adj. R^2
0.1615	0.3324	0.4304			15.38	39.97%
(1.48)	(4.05)***	(5.12)***				
0.1369	0.1434	0.4939	0.1808	0.2152	15.24	51.41%
(1.46)	(1.92)*	(6.74)***	(2.64)***	(3.74)***		

Panel C: CSFB Tremont Model 1994 – 2002

α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Q Stat	Adj. R^2
0.0872	0.3095	0.5355			23.27	37.36%
(0.63)	(3.21)***	(4.93)***				
0.0666	0.0456	0.6046	0.2584	0.2659	21.76	48.58%
(0.53)	(0.83)	(6.38)***	(2.82)***	(3.77)***		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Panel B of Table 4.9 reports results from estimating models (4.18) and (4.19) for the HFRI Convertible Arbitrage Index restricting the sample to January 1994 to December 2002, aiding comparison with the CSFB Tremont Index results. The two factor model explains 40% of convertible arbitrage returns and during this sample period the hedge fund indices are not generating statistically significant alpha. The inclusion of the *DEF* and *TERM* variables improves the explanatory power of the model (adjusted R^2 of 51.41%) and again with this model there is no statistically significant alpha.

Results for estimating the two and four factor models for the CSFB Tremont Convertible Arbitrage Index are reported in Panel C of Table 4.9. Again explanatory power is high with adjusted R^2 of 37.36% and 48.58% for the two factor and four factor models respectively. With both of these models the estimated alphas are not statistically significant at levels less than or equal to 10%.

In contrast to the results presented in this section previous studies have documented convertible arbitrage generating significant abnormal returns. Capocci and Hübner (2004) estimate that the average convertible arbitrage hedge fund generates an abnormal return of 0.42% per month. Fung and Hsieh (2002) estimate that the CSFB Tremont index generates abnormal returns of 0.74% per month. Agarwal and Naik (2004) augment a linear factor model with the payoff from an equity index put option, finding evidence that the HFRI and CSFB Tremont index generate abnormal returns of 0.24% and 0.59% respectively per month.

The results of these two factor and four factor convertible arbitrage risk factor models indicate that convertible arbitrageurs do not on average generate positive alpha in excess of their compensation for appropriate risk. The convertible arbitrage risk factor combined with a one period lag of the dependent variable capture much of the risk in convertible arbitrage returns. Where indices appear to generate abnormal returns relative to these models it is over a sample period incorporating the period where dead funds were excluded from the index.

4.7 Robustness: Estimating the linear model in sub-samples ranked and subdivided by time and risk factors

As a further robustness check of the risk factors and risk factor model the HFRI and CSFB Tremont samples were ranked and subdivided for five separate robustness checks. The HFRI sample is subdivided into five sub-sample periods as this gives sufficient data in each sub-sample to efficiently estimate coefficients. As the sample period is shorter for the CSFB Tremont series, here four rather than five sub-sample periods are estimated. Model (4.19) was re-estimated in each of the sub-samples and coefficient estimates were checked for consistency across sample periods. It is important to examine the persistence of the risk factor coefficients as the estimated alpha's efficiency depends upon stationary coefficients.[45] The sample was subdivided (1) by time, (2) by default risk factor, (3) by term structure risk factor, (4) by convertible arbitrage risk factor and (5) by the lag of the hedge fund index.

[45] The evidence on the persistence of risk factor coefficients in the literature is mixed. Kat and Menexe (2002) provide evidence that hedge funds correlation with equity market returns is strongly persistent. Fung and Hsieh (2004) provide evidence that the HFRI Fund of Funds Index displays time varying risk factor coefficients.

Table 4.10 presents results from subdividing the HFRI sample into five equal sized groups by time and re-estimating the linear factor model. If there is any time variation in the HFRI risk factors, there significance and magnitude should vary across the different sub-samples. There are three things to note in this table. First the *TERM* and y_{t-1} are significant across the entire sample period. *DEF* is significant except from June 2000 to December 2002. *CBRF* is only significant from April 1995 onward. There is little evidence of time variation in the risk factor coefficients and the model is robust across time.

Table 4.10
HFRI sample subdivided by time

Table 4.10 presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples by time.

$$y_t = \alpha + \beta_{CBRF}CBRF_t + \beta_{DEF}DEF_t + \beta_{TERM}TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where, y_t is the excess return on the HFRI convertible arbitrage index, *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

Time Period	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
2/90 : 8/92	0.0779	0.0474	0.5099	0.1522	0.1699	66.94%
	(0.64)	(1.02)	(5.69)***	(3.09)***	(3.71)***	
9/92 : 3/95	-0.2070	0.0964	0.5611	0.3645	0.3605	60.55%
	(-1.51)	(0.90)	(4.89)***	(2.64)***	(3.11)***	
4/95 : 10/97	0.2651	0.1935	0.2840	0.1676	0.1565	30.95%
	(1.87)*	(1.76)*	(3.60)***	(1.70)*	(1.89)*	
11/97 :5/00	0.2210	0.1668	0.5366	0.4600	0.4810	75.89%
	(1.81)*	(1.96)**	(6.00)***	(7.33)***	(7.58)***	
6/00 : 12/02	0.2966	0.2352	0.3006	0.0680	0.1193	36.51%
	(3.66)***	(2.07)**	(2.77)***	(1.28)	(3.71)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.11 presents the results from ranking the CSFB sample by time and subdividing into four equal sized sub-samples and estimating the risk factor model. The y_{t-1}, *DEF* and *TERM* coefficients are significantly positive across the entire sample period again demonstrating the robustness of the results.

Table 4.11
CSFB sample subdivided by time

Table 4.11 presents results from estimating the following regression on CSFB Tremont convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples by time.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB Tremont convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

Time Period	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
1/94 : 3/96	-0.1544	0.0810	0.6422	0.2081	0.2371	54.13%
	(-0.96)	(0.98)	(10.27)***	(1.96)**	(3.23)***	
4/96 : 6/98	-0.0483	-0.0175	0.4949	0.4148	0.3181	29.85%
	(-0.20)	(-0.31)	(2.89)***	(2.10)**	(2.28)**	
7/98 : 9/00	0.1912	0.2844	0.7568	0.6138	0.6170	69.06%
	(1.31)	(1.21)	(8.26)***	(3.31)***	(3.23)***	
10/00 : 12/02	0.2162	0.2836	0.2492	0.0913	0.1703	25.82%
	(1.60)	(2.19)**	(1.70)*	(1.87)*	(8.12)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.12 presents the results from ranking the HFRI sample by *DEF* and subdividing into five equal sized sub-samples and estimating the risk factor model. Ranking by *DEF* results in relatively more variation across the sample period but the results are robust. *TERM* is significant in all but the lowest sub-sample. The coefficients on *CBRF* and *DEF* are significant in three of the *DEF* sub-samples. y_{t-1} is significant in all but the highest *DEF* sub-sample.

Table 4.12
HFRI sample subdivided by default risk factor

Table 4.12 presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by default risk.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 31	0.6089	0.1779	0.5212	0.1702	0.0116	61.34%
	(1.43)	(3.13)***	(9.15)***	(3.80)***	(0.09)	
Next lowest 31	0.1498	0.0853	0.4728	0.1829	0.1773	41.17%
	(0.99)	(1.10)	(5.35)***	(0.96)	(3.03)***	
Middle 31	-0.3934	0.0465	0.8229	0.4946	0.2249	73.16%
	(-2.43)**	(0.71)	(13.93)***	(2.13)**	(3.75)***	
Next highest 31	-0.2526	0.1037	0.3656	0.5759	0.2869	55.86%
	(-0.58)	(2.24)**	(5.47)***	(2.13)**	(3.79)***	
Highest 31	1.0616	0.1321	-0.0394	0.0450	0.1854	32.49%
	(4.50)***	(1.69)*	(-0.26)	(0.98)	(4.05)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.13 presents the results from ranking the CSFB sample by *DEF* and subdividing into four equal sized sub-samples and estimating the risk factor model. *TERM* is significantly positive in all but the lowest *DEF* sub-sample and *DEF* is significant at extreme values of *DEF*. The y_{t-1} coefficient is significantly positive across the entire sample period.

Table 4.13
CSFB sample subdivided by default risk factor

Table 4.13 presents results from estimating the following regression on CSFB Tremont convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples by *DEF*.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB Tremont convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 27	0.2535	0.3497	0.7612	0.1801	0.0422	44.34%
	(0.36)	(1.56)	(8.69)***	(1.92)*	(0.24)	
Next lowest 27	-0.0478	-0.1012	0.5310	-0.1884	0.2414	39.32%
	(-0.27)	(-1.13)	(5.55)***	(-0.92)	(2.55)**	
Next highest 27	-0.4367	0.0997	0.9139	0.6642	0.3266	78.32%
	(-0.82)	(1.69)*	(5.94)***	(1.44)	(2.36)**	
Highest 27	0.8186	-0.2393	0.2982	0.3152	0.4502	36.65%
	(5.68)***	(-1.63)	(3.54)***	(3.98)***	(4.83)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.14 presents the results from ranking the HFRI sample by *TERM* and subdividing into five equal sized sub-samples and running the risk factor model. y_{t-1} and *DEF* are significant across each of the sub-samples. *TERM* is only significant in the highest and lowest *TERM* sub-samples. *CBRF* is significant in four of the five *TERM* sub-samples.

Table 4.14
HFRI sample subdivided by term structure risk factor

Table 4.14 presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by term structure risk.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 31	0.3925	0.1574	0.7315	0.1222	0.3006	71.34%
	(1.23)	(1.70)*	(3.54)***	(2.17)**	(3.60)***	
Next lowest 31	-0.0923	0.1418	0.3798	0.2280	-0.1320	43.91%
	(-0.35)	(1.84)*	(4.58)***	(3.04)***	(-0.84)	
Middle 31	0.2745	0.0399	0.5292	0.1407	0.0275	33.45%
	(1.40)	(0.56)	(2.74)***	(3.08)***	(0.11)	
Next highest 31	0.0242	0.1312	0.5259	0.0783	0.1613	43.36%
	(0.07)	(1.66)*	(4.69)***	(1.84)*	(0.76)	
Highest 31	0.2897	0.1328	0.4917	0.2785	0.1934	70.89%
	(1.35)	(2.34)**	(12.81)***	(4.05)***	(4.38)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.15 presents the results from ranking the CSFB sample by *TERM* and subdividing into four equal sized sub-samples and running the risk factor model. The *DEF* and y_{t-1} coefficients are significantly positive across the entire sample period. *TERM* is significantly positive in all but the second highest *TERM* sub-sample and *CBRF* is only significant at the lowest value of *TERM.*

Table 4.15
CSFB sample subdivided by term structure risk factor

Table 4.15 presents results from estimating the following regression on CSFB Tremont convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples by *TERM.*

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB Tremont convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	α	β_{CBRF}	β_{Y}	β_{DEF}	β_{TERM}
Lowest 27	-0.0360	0.2012	0.7290	0.1128	0.1649	64.65%
	(-0.14)	(1.72)*	(3.67)***	(1.83)*	(1.99)**	
Next lowest 27	0.7757	0.0909	0.3800	0.2200	0.6165	32.83%
	(3.68)***	(0.54)	(1.99)**	(2.75)***	(2.99)***	
Next highest 27	-0.0020	0.0346	0.5366	0.1494	0.2517	5.61%
	(-0.00)	(0.38)	(2.89)***	(2.08)**	(0.59)	
Highest 27	0.6060	-0.0118	0.7710	0.4187	0.1697	69.88%
	(2.49)**	(-0.22)	(12.99)***	(3.99)***	(2.06)**	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.16 presents the results from ranking the HFRI sample by *CBRF* and subdividing into five equal sized sub-samples and running the risk factor model. y_{t-1} is significant in every sample period. *CBRF* is only significant in the middle sub-sample (with a coefficient of 1.0). *DEF* and *TERM* are only insignificant in the second highest sub-sample.

Table 4.16
HFRI sample subdivided by convertible bond arbitrage risk factor

Table 4.16 presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by convertible bond arbitrage risk.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 31	-0.1190	0.0194	0.7334	0.1874	0.1730	51.94%
	(-0.59)	(0.23)	(5.63)***	(4.52)***	(2.57)**	
Next lowest 31	0.2213	0.2158	0.5324	0.1182	0.1879	50.40%
	(1.95)*	(1.26)	(6.99)***	(2.84)***	(4.81)***	
Middle 31	-0.1405	0.9955	0.3539	0.1529	0.1663	46.84%
	(-1.19)	(3.91)***	(5.65)***	(2.98)***	(4.11)***	
Next highest 31	0.6453	-0.1691	0.3521	0.1641	0.2073	14.17%
	(1.55)	(-0.44)	(3.90)***	(1.10)	(1.50)	
Highest 31	0.5649	-0.1221	0.6558	0.1774	0.1550	32.20%
	(2.25)**	(-1.69)*	(3.81)***	(2.71)***	(2.06)**	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.17 presents the results from ranking the CSFB sample by *CBRF* and subdividing into four equal sized sub-samples and running the risk factor model. The *DEF* and *TERM* coefficients are significantly positive across the entire sample period. y_{t-1} is significantly positive in all but the second highest *CBRF* sub-sample and *CBRF* is significant in the lowest sub-sample of *CBRF*.

Table 4.17
CSFB sample subdivided by convertible bond arbitrage risk factor

Table 4.17 presents results from estimating the following regression on CSFB Tremont convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples by *CBRF*.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB Tremont convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 27	0.3924	0.4786	0.9131	0.2258	0.1932	63.53%
	(1.41)	(2.18)**	(7.54)***	(4.25)***	(2.27)**	
Next lowest 27	0.0370	0.5054	0.7857	0.3158	0.3953	40.63%
	(0.17)	(0.80)	(11.94)***	(2.16)**	(3.48)***	
Next highest 27	0.1319	0.3270	0.2594	0.2642	0.2580	10.82%
	(0.24)	(0.59)	(1.56)	(1.69)*	(2.00)**	
Highest 27	0.2857	0.0100	0.4860	0.1665	0.1890	27.99%
	(0.86)	(0.12)	(4.98)***	(2.52)**	(2.58)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.18 presents results of ranking the entire sample from 1990 to 2002 by y_{t-1}, the one period lag of the HFRI index excess return, subdividing into five equal sized sub-samples and re-estimating equation (7.1) for each sub-sample period. Ranking the sample allows the identification of whether the factor loadings are constant.

Table 4.18
HFRI sample subdivided by one month lag of HFRI excess returns

This table presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by one month lagged HFRI excess returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 31	-0.0810	-0.1424	0.4782	0.3876	0.4066	52.28%
	(-0.37)	(-1.61)	(4.40)***	(4.53)***	(7.14)***	
Next lowest 31	-0.2634	0.1618	1.6926	0.1697	0.2281	46.42%
	(-0.95)	(2.23)**	(2.29)**	(1.78)*	(3.01)***	
Middle 31	0.9397	0.0755	-0.4953	0.1450	0.1814	37.03%
	(1.33)	(1.28)	(-0.53)	(4.76)***	(4.92)***	
Next highest 31	0.1897	0.1371	0.4883	0.0428	0.0720	17.06%
	(0.35)	(4.18)***	(0.92)	(1.52)	(2.19)**	
Highest 31	1.0516	0.1257	-0.0265	0.0027	0.0373	6.61%
	(5.05)***	(1.72)*	(-0.23)	(0.08)	(1.31)	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Three results should be noted from this table. The first is that the adjusted R^2 of regression model reduces across the sub-sample periods. In the lowest y_{t-1} period the adjusted R^2 is greatest and in the highest y_{t-1} period the adjusted R^2 is lowest. The second is that both the magnitude and significance of the *DEF* and *TERM* factors gradually decreases from the lowest y_{t-1} period to the highest y_{t-1} period. The final results to be noted are that the *CBRF* coefficient is significantly negative in the lowest y_{t-1} period and significantly positive in the highest y_{t-1} period. This provides weak evidence that arbitrageurs' portfolio risk exposure may not be constant.

Table 4.19
CSFB sample subdivided by one month lag of CSFB excess returns

This table presents results from estimating the following regression on CSFB convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by one month lagged CSFB excess returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB convertible arbitrage excess returns, *DEF* is the factor proxy for default risk and *TERM* is the factor proxy for *TERM* structure risk.

	α	β_{CBRF}	β_Y	β_{DEF}	β_{TERM}	Adj. R^2
Lowest 27	-0.1585	-0.1368	0.5920	0.5534	0.5718	49.49%
	(-0.78)	(-1.06)	(7.95)***	(3.58)***	(4.44)***	
Next lowest 27	-0.6326	0.2052	2.3284	0.1661	0.0590	43.20%
	(-1.75)*	(1.42)	(2.56)**	(2.16)**	(0.50)	
Next highest 27	0.6074	0.0827	-0.1037	0.2044	0.2330	7.10%
	(0.61)	(0.79)	(-0.09)	(1.55)	(2.14)**	
Highest 27	-0.0487	-0.1001	0.8039	0.0652	0.1028	32.66%
	(-0.12)	(-1.46)	(3.71)***	(1.93)*	(2.12)**	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 4.19 presents results from a similar analysis of the CSFB Tremont Convertible Arbitrage index. For this analysis the sample is ranked from 1994 to 2002 by $CSFBRF_{t-1}$, subdividing into four equal sized sub-samples and equation (4.19) is re-estimated for each sub-sample. The results for the CSFB Tremont index again point to non-linearity in the relationship between convertible arbitrage returns and risk factors. In the lowest y_{t-1} period the adjusted R^2 is greatest and in the highest y_{t-1} period the adjusted R^2 is lower, although in the second highest period the adjusted R^2 is lowest. Again both the magnitude and significance of the *DEF* and *TERM* factors decreases from the lowest y_{t-1} period to the highest y_{t-1} period.

The evidence presented in this section of the chapter further demonstrate the robustness of the default risk factor, term structure risk factor and convertible arbitrage risk factors in explaining convertible arbitrage hedge fund index returns. With the exception of rankings on previous months' hedge fund index returns these results are remarkably robust across different time periods and ranked sub-samples.

4.8 Conclusions

This chapter contributes through the definition and specification of a range of risk factors drawn from the asset pricing literature which explain a large proportion of the returns in convertible arbitrage hedge fund indices. Default and term structure risk factors are highly significant in explaining the returns of convertible arbitrage indices' returns. The inclusion of a one period lag of convertible arbitrage index excess returns correcting for serial correlation, but also interpretable as a proxy for illiquidity risk, improves the explanatory power of these models. A univariate analysis of the convertible arbitrage index data generating process is also carried out which provides statistical evidence to support the inclusion of the one period lag of the hedge fund index in the model. The alpha or perceived out-performance generated by the convertible arbitrage indices is much smaller relative to a model omitting the lag of hedge fund index returns and is significant only for the HFRI index for a time period biased upward by the exclusion of dead funds.

A convertible arbitrage factor is also specified which is important in explaining convertible arbitrage returns. This factor is constructed by combining long positions in convertible bonds with short positions in the underlying stocks into a portfolio and using the excess returns from this portfolio as an explanatory variable. This factor is highly significant in explaining convertible arbitrage index returns and combined with a lag of hedge fund index returns and factors mimicking default and term structure risk, this four factor model should serve as an appropriate model for examining individual convertible arbitrage hedge fund performance. These risk factors are remarkably consistent in explaining hedge fund index returns across time and sub-samples ranked by risk factors.

4.9 Limitations of this analysis

4.9.1 Addressing potential non-linearity in the relationships

Although it is clear that the default risk, term structure risk and convertible arbitrage risk factors are significant in explaining convertible arbitrage returns, it is not clear whether these relationships are linear. Correct specification of the functional relationship will eliminate biases in the coefficient estimates.

In Chapter 7 this potential bias will be addressed. A relatively new non-linear model which allows for a smooth transition between different states will be tested against the linear model.

4.9.2 Distribution of the factor model residuals

The statistics in Table 4.1 suggest that the returns from the hedge fund strategy indices are not normally distributed with positive kurtosis and negative skewness. Although several of the factors also display these characteristics it is likely that the residuals from the factor models may be non-Gaussian.

If this is the case then OLS may not be the most efficient estimation technique. In Chapter 9 this issue will be explored in greater detail and an alternative estimation technique explicitly allowing for the non-normality inherent in hedge fund returns will be employed and its performance will be compared relative to OLS.

Chapter 5: The risk and return of convertible arbitrage hedge funds: a multi-factor analysis

5.1 Introduction

Through the identification of individual fund's exposures to variations in the returns of the asset classes in a multi-factor model, the effectiveness of a hedge fund manager's activities can be compared with that of other managers and a passive investment in the asset mixes. In the previous chapter several alternative factors were defined and the historical exposure of convertible arbitrage benchmark indices to these risk factors was estimated. For the convertible arbitrage indices and a simulated convertible bond arbitrage portfolio, default risk and term structure risk are highly significant risk factors. With the specification of term structure and default risk factors, a factor proxy for illiquidity in the securities held by funds, and a convertible bond arbitrage risk factor, the abnormal return estimates of the hedge fund indices were not significantly different from zero at the 10% level for the indices[46], providing evidence that this factor specification captures the central risks in the convertible arbitrage strategy. In this chapter analysing the returns of individual hedge funds using multi-factor risk models yields evidence on individual convertible arbitrage hedge funds' risk exposures and historical performance relative to other funds and a passive investment in the asset mixes.

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[46] With the exception of the HFRI index over the sample period including January 1990 to December 1992, a period where HFRI excluded dead funds with a resulting upward bias on performance.

When a linear factor model is specified with term structure, default and convertible bond arbitrage risk factors, the explanatory power of the models is low with a mean adjusted R^2 of 2.4%. The coefficients on the default risk, term structure risk and convertible bond arbitrage risk factors are significant for between fourteen and eighteen funds. Surprisingly, the sign for the majority of significant coefficients on the default risk and term structure risk factors are negative, inconsistent with findings for the hedge fund indices. Given these results few conclusions can be drawn on performance from this model.

To further explore the anomalous coefficients of the default risk and term structure risk factors, a model is specified allowing for potential non-synchrony between the hedge fund returns and the risk factors, caused by illiquidity in the securities held by the funds. This model specifies lagged and contemporaneous observations of the market factors. The explanatory power of the model is higher than the contemporaneous model[47] and each risk factor is significant for up to twenty five of the hedge funds. Results from estimating this model suggest that convertible arbitrage hedge funds generate abnormal return of thirty basis points per month or 3.7% per annum. A third model is specified which allows for non-synchrony in the data and incorporates an explicit illiquidity factor proxy. The mean explanatory power of this model is 29% and results from estimating this model suggest that convertible arbitrage funds generate significant abnormal returns of approximately 2.4% per annum.

Some evidence is also presented on hedge fund performance persistence, suggesting persistence in under performance, though given data limitations conclusions are

[47] Mean adjusted R^2 of 21% compared to 2.4% for the contemporaneous model.

tentative. The remainder of the chapter is organised as follows. Section 5.2 examines the individual hedge fund data, Section 5.3 presents results from estimating a contemporaneous multi-factor model for individual hedge funds and Section 5.4 presents results from estimating a multi-factor model allowing for non-synchrony in the data. Section 5.5 concludes.

5.2 Data

The individual fund data was sourced from the HFR database. The original database consisted of 113 funds. However, many funds have more than one series in the database. Often this appears to be due to a dual domicile. (E.g. Fund X *Ltd* and Fund X *LLC* with almost identical returns.) To ensure that no fund was included twice, the cross correlations between the individual funds' returns are estimated. If two funds have high correlation coefficients, then the details of the funds are examined in depth. In two cases high correlation coefficients are reported due to a fund reporting twice, in USD and in EUR. In this situation the EUR series is deleted. Finally, in order to have adequate data to run the factor model tests, any fund which does not have 24 consecutive monthly returns between 1990 and 2002 is excluded. The final sample consisted of fifty five hedge funds. Of these fifty five funds, twenty five are still alive at the end of December 2002 and thirty are dead.

Table 5.1
Statistics on individual hedge fund returns

This table presents descriptive statistics on the fifty five hedge funds included in the sample. For each fund *N* is the number of monthly return observations, *Min* and *Max* are the minimum and maximum monthly return, *Skewness* and *Kurt* are the skewness and kurtosis of the hedge funds return distribution and *Q-Stat* is the Ljung and Box (1978) Q-Statistic jointly testing the series' ten lags of autocorrelation are significantly different from zero.

	N	*Mean*	*Min*	*Max*	*Skewness*	*Kurt*	*Q-Stat*
HF1	69	1.01	-4.41	4.95	-0.65	3.05	6.94
HF2	69	1.04	-8.07	9.77	0.32	2.80	13.11
HF3	38	1.74	-1.57	11.21	1.92	6.66	7.68
HF4	60	1.55	-1.62	11.74	2.08	8.85	9.46
HF5	69	1.31	-10.27	12.08	-0.64	4.44	12.36
HF6	69	1.33	-8.99	9.31	-1.19	4.37	16.39*
HF7	58	0.98	-2.49	3.43	-0.61	1.78	8.82
HF8	82	1.28	0.00	4.54	1.12	1.96	83.37***
HF9	57	0.80	-5.70	9.03	0.01	0.02	6.66
HF10	27	1.23	-1.69	5.48	0.25	-0.02	14.13
HF11	52	0.59	-0.74	3.00	1.73	7.62	10.65
HF12	58	0.82	-2.38	3.95	0.40	1.55	25.39***
HF13	30	0.33	-0.77	0.95	-1.11	3.49	4.24
HF14	55	1.02	-0.81	2.88	0.27	0.13	26.07***
HF15	42	1.05	-0.81	3.38	0.54	0.02	28.55***
HF16	38	1.18	0.00	2.87	0.46	-0.55	16.40*
HF17	25	0.45	-0.59	1.65	0.20	-0.49	9.33
HF18	36	1.27	-2.51	7.08	0.90	2.65	11.88
HF19	69	0.92	-5.20	3.17	-2.34	5.87	37.27***
HF20	69	1.02	-4.31	3.64	-1.71	3.99	10.88
HF21	37	0.24	-34.16	3.84	-5.72	34.05	0.76
HF22	69	1.37	-2.77	5.08	0.32	0.18	21.23**
HF23	69	0.68	-1.88	2.75	-0.58	1.09	18.23*
HF24	69	0.85	-2.17	6.53	1.27	6.12	7.50
HF25	69	1.02	-4.31	3.64	-1.71	3.99	10.88
HF26	69	0.96	-4.41	4.95	-0.53	2.56	7.94
HF27	69	1.05	-2.13	3.11	-0.55	1.20	18.14*
HF28	25	0.92	-0.88	2.60	-0.10	-0.73	14.13
HF29	24	-0.40	-5.52	4.00	-0.21	-0.66	18.33**
HF30	38	1.21	-2.68	6.88	0.56	1.14	9.43
HF31	69	1.06	-8.96	5.54	-2.04	6.49	23.27***
HF32	69	0.82	-1.70	3.86	0.36	-0.07	12.58
HF33	69	0.41	-24.68	23.25	-0.17	2.22	6.66
HF34	69	1.24	-3.98	6.77	-0.14	0.50	23.27***
HF35	69	1.00	-11.88	7.14	-1.29	4.62	17.20*
HF36	69	0.69	-1.61	1.78	-1.21	3.22	57.12***
HF37	36	0.83	-1.78	2.92	-0.19	1.49	13.55
HF38	69	0.87	-4.82	4.07	-1.22	5.80	11.67

HF39	51	0.94	-2.30	3.95	0.03	1.07	14.97
HF40	51	0.92	-1.60	2.41	-0.85	1.78	17.50*
HF41	69	1.25	-9.19	4.10	-3.01	12.59	24.62***
HF42	24	1.02	-2.09	2.94	-0.82	1.63	13.19
HF43	69	0.75	-2.16	2.80	-0.86	1.54	7.28
HF44	69	1.66	-9.56	5.20	-2.86	11.47	30.42***
HF45	41	1.45	-8.13	8.30	-0.20	1.78	39.69***
HF46	69	1.03	-2.02	3.45	-0.84	1.87	8.89
HF47	69	0.95	-2.30	4.16	0.43	3.25	24.78***
HF48	69	0.98	-1.32	4.83	0.45	1.73	10.20
HF49	69	0.82	-1.08	2.22	-0.49	0.97	13.15
HF50	67	0.80	-3.29	3.37	-0.77	1.51	17.65*
HF51	57	0.93	-8.34	4.21	-2.34	10.54	14.35
HF52	52	0.94	-2.40	3.40	-0.39	-0.02	8.26
HF53	69	1.02	-3.70	6.05	-0.51	4.32	23.33***
HF54	57	0.72	-2.00	2.28	-0.84	2.89	19.30**
HF55	69	0.82	-0.98	2.01	-0.53	1.09	18.54**
Mean	57	0.96	-4.47	5.06	-0.47	3.48	
Min	24	-0.40	-34.16	0.95	-5.72	-0.73	
Max	82	1.74	0.00	23.25	2.08	34.05	

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Statistics are generated using RATS 5.0

Descriptive statistics on each hedge fund are reported in Table 5.1. The mean number of observations is fifty seven months up to a maximum of eighty two. The mean monthly return[48] is 0.90% and the minimum monthly return by a fund over the sample period was -34%. The maximum monthly return was 23%. The mean skewness is -0.47 and the mean kurtosis is 3.48. The Ljung and Box (1978) Q-Statistic tests the joint hypothesis that the first ten lagged autocorrelations are all equal to zero. The results reject this hypothesis for twenty four of the hedge funds.

5.3 Individual fund empirical results

In this section results are presented from estimating a linear multi-factor model with default risk, term structure risk and convertible bond arbitrage risk factors. Table 5.2

[48] Returns are logarithmic.

reports results from estimating the following three factor model on excess individual hedge fund returns:

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \varepsilon_t \qquad (5.1)$$

Where $CBRF_t$ is the excess return on the convertible bond arbitrage risk factor at time t[49], DEF_t, the default risk factor, is the return on a portfolio of long term corporate bonds minus the return on a portfolio of long term government bonds at time t, $TERM_t$, the term structure risk factor, is the return on a portfolio of long term government bonds minus the return on a portfolio of short term government bonds at time t.

Eighty percent of funds have positive estimates of the alpha coefficient significantly different from zero.[50] *DEF* the default risk factor is significant for fourteen of the funds but the coefficient is negative for twelve of the fourteen. This is a result inconsistent with the hedge fund indices where the *DEF* coefficient is positive. *TERM* the term structure risk factor is significantly different from zero for eighteen hedge funds. Fourteen of the significant *TERM* coefficients are negative with four positive. Like *DEF* this is a finding inconsistent with the hedge fund indices where the *TERM* coefficient is positive. *CBRF* the convertible arbitrage risk factor is significantly positive for fifteen of the hedge funds. There is no significantly negative coefficient for *CBRF*. This is consistent with the finding for the hedge fund indices. The mean adjusted R^2 for the fifty five hedge funds is 2.4% with a minimum of -14.4% and a maximum of 24.2%.

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49 For details on the construction of the convertible bond arbitrage risk factor see Chapters 3 and 4.

50 In discussions in the text statistical significance indicates t-stats are significant from zero at least at the 10% level unless reported.

Given the low explanatory power of the model few conclusions on hedge fund performance can be drawn from these results.

Table 5.2
Individual fund factor model

This table presents results from estimating the factor model on individual fund returns where $r_i - r_f$ is the mean excess return for that fund and N is the number of monthly observations for that fund.

Fund	$r_i - r_f$	α	β_{DEF}	β_{TERM}	β_{CBRF}	Q Stat	Adj. R^2	N
1	0.65	0.6218	0.0062	-0.0762	0.1048	6.27	-1.8%	69
		(3.68)***	(0.11)	(-0.84)	(0.75)			
2	0.69	0.3883	-0.2023	-0.5714	0.6849	12.62**	12.0%	69
		(1.00)	(-1.22)	(-2.64)***	(2.39)**			
3	1.38	1.4620	-0.1793	-0.1973	-0.0719	10.37	-0.6%	38
		(3.12)***	(-2.14)**	(-1.28)	(-0.15)			
4	1.19	1.2308	-0.2103	-0.2863	0.0184	9.42	3.3%	60
		(3.85)***	(-3.37)***	(-2.43)**	(0.06)			
5	0.95	0.9355	-0.3794	-0.4512	0.3970	19.66***	0.1%	69
		(2.06)**	(-1.73)*	(-1.94)*	(1.65)*			
6	0.97	0.9325	-0.2845	-0.3143	0.3369	18.08***	-0.1%	69
		(2.58)***	(-1.79)*	(-1.60)	(1.61)			
7	0.62	0.5756	-0.1396	-0.1179	0.3923	14.78**	7.8%	58
		(3.45)***	(-2.93)***	(-1.65)*	(2.41)**			
8	0.92	0.8454	0.0356	0.0393	-0.0131	10.88*	-3.3%	82
		(5.68)***	(0.71)	(0.73)	(-0.16)			
9	0.44	-0.4604	0.8532	0.5063	-0.1945	10.47	20.4%	57
		(-1.10)	(5.26)***	(2.76)***	(-1.23)			
10	0.87	0.9045	-0.0396	-0.1714	0.3980	7.29	7.9%	27
		(2.56)**	(-0.59)	(-2.57)**	(1.76)*			
11	0.23	0.2650	-0.0020	-0.0029	0.0091	10.60	-6.2%	52
		(3.57)***	(-0.08)	(-0.10)	(0.15)			
12	0.46	0.4617	-0.0643	-0.0606	0.1171	10.59	-3.5%	58
		(2.32)**	(-1.20)	(-0.90)	(0.73)			
13	-0.03	0.0098	-0.0543	-0.0602	0.1546	11.45*	18.2%	30
		(0.21)	(-2.23)**	(-1.88)*	(2.78)***			
14	0.66	0.6782	0.0047	-0.0221	0.0543	10.01	-3.2%	55
		(5.23)***	(0.16)	(-0.45)	(0.71)			
15	0.69	0.6742	-0.0625	-0.0887	0.2671	9.28	1.2%	42
		(2.90)***	(-1.21)	(-1.48)	(1.71)*			
16	0.82	0.8150	-0.0255	-0.0096	0.1797	8.77	-3.4%	38
		(4.72)***	(-0.56)	(-0.13)	(1.49)			

17	0.09	0.1972	-0.0071	0.0034	0.0932	9.22	-10.5%	25
		(1.39)	(-0.13)	(0.05)	(0.67)			
18	0.91	0.9691	-0.1533	-0.3553	0.2721	5.68	6.5%	36
		(4.26)***	(-2.02)**	(-3.67)***	(1.62)			
19	0.56	0.5030	-0.0479	0.0041	0.1284	9.53	-3.0%	69
		(1.84)*	(-0.26)	(0.02)	(0.82)			
20	0.66	0.6216	-0.1819	-0.1928	0.1741	6.86	-1.3%	69
		(2.30)**	(-1.03)	(-1.23)	(1.14)			
21	-0.12	-0.6108	-0.3909	0.6541	0.4547	5.44	13.8%	37
		(-0.48)	(-1.21)	(1.32)	(0.79)			
22	1.11	1.0363	0.0674	0.1154	-0.1271	4.57	-3.2%	69
		(3.20)***	(0.34)	(0.76)	(-0.81)			
23	0.38	0.2691	-0.0665	0.0306	0.1359	5.67	6.8%	69
		(1.48)	(-0.59)	(0.32)	(1.61)			
24	0.38	0.1448	0.2890	0.3434	0.0266	5.29	7.3%	69
		(0.82)	(1.72)*	(2.29)**	(0.20)			
25	0.66	0.6216	-0.1819	-0.1928	0.1741	4.11	-1.3%	69
		(2.30)**	(-1.03)	(-1.23)	(1.14)			
26	0.60	0.5757	-0.0368	-0.1067	0.1061	8.85	-2.7%	69
		(3.34)***	(-0.50)	(-1.03)	(0.70)			
27	0.69	0.5320	0.0320	-0.0348	0.1604	13.35**	2.1%	69
		(3.70)***	(0.38)	(-0.38)	(1.47)			
28	0.56	0.5538	0.0513	0.1055	0.2973	13.06**	24.2%	25
		(3.32)***	(0.90)	(1.81)*	(2.46)**			
29	-0.76	-0.6165	-0.0400	-0.3713	0.2301	10.16	6.6%	24
		(-1.02)	(-0.27)	(-1.51)	(0.46)			
30	0.85	0.6473	-0.2464	-0.2139	0.8261	9.96	8.8%	38
		(1.72)*	(-3.00)***	(-1.43)	(2.64)***			
31	0.70	0.6135	-0.2337	-0.3270	0.3900	17.38***	0.6%	69
		(1.63)	(-1.23)	(-1.53)	(1.50)			
32	0.33	0.3298	0.1660	0.1390	-0.0464	20.52***	-3.7%	69
		(1.29)	(0.89)	(0.98)	(-0.38)			
33	0.05	-0.7147	0.0056	0.2823	1.5005	14.29**	4.7%	69
		(-0.62)	(0.01)	(0.44)	(1.89)*			
34	0.67	0.4604	0.2972	0.1737	0.0439	32.29***	0.6%	69
		(1.09)	(1.44)	(0.88)	(0.23)			
35	0.64	0.4180	-0.0630	-0.2155	0.4237	17.19***	-0.7%	69
		(0.98)	(-0.27)	(-1.07)	(1.60)			
36	0.13	0.2446	0.0581	0.1025	-0.0407	21.09***	2.7%	69
		(2.03)**	(1.45)	(2.50)**	(-0.92)			
37	0.47	0.5520	0.0115	-0.0027	-0.0420	25.74***	-9.2%	36
		(2.27)**	(0.23)	(-0.04)	(-0.24)			
38	0.52	0.3927	-0.1049	-0.1036	0.3385	24.51***	2.0%	69

		(1.80)*	(-1.37)	(-1.58)	(1.94)*			
39	0.58	0.4716	-0.1560	-0.1739	0.5883	14.12**	19.6%	51
		(2.94)***	(-3.68)***	(-2.08)**	(4.82)***			
40	0.52	0.4236	0.1001	0.0360	-0.0208	12.34*	1.5%	51
		(2.56)**	(1.14)	(0.50)	(-0.42)			
41	0.89	0.8783	-0.3959	-0.4306	0.4158	54.59***	5.9%	69
		(2.32)**	(-1.81)*	(-2.21)**	(1.41)			
42	0.66	0.8387	0.0023	-0.0054	-0.0624	57.64***	-14.4%	24
		(2.35)**	(0.04)	(-0.08)	(-0.28)			
43	0.39	0.4156	-0.0285	-0.0769	0.0019	5.37	-2.7%	69
		(4.03)***	(-0.65)	(-1.26)	(0.01)			
44	1.30	1.2274	-0.3922	-0.3749	0.5269	46.51***	4.6%	69
		(2.83)***	(-1.19)	(-1.34)	(1.97)**			
45	1.09	1.1904	-0.0805	-0.3313	0.0400	82.97***	-3.4%	41
		(1.55)	(-0.58)	(-1.92)*	(0.10)			
46	0.67	0.6504	0.0104	0.0021	-0.1329	30.09***	-2.8%	69
		(6.31)***	(0.19)	(0.03)	(-0.97)			
47	0.36	0.5872	0.0333	0.1177	-0.0710	30.11***	0.0%	69
		(2.85)***	(0.35)	(1.32)	(-0.89)			
48	0.62	0.5277	-0.0802	-0.0634	0.2316	34.04***	-0.2%	69
		(3.64)***	(-1.14)	(-0.70)	(1.93)*			
49	0.46	0.4305	-0.1033	-0.1299	0.0753	49.80***	2.3%	69
		(3.71)***	(-1.58)	(-2.01)**	(1.03)			
50	0.44	0.4092	-0.1932	-0.2794	0.3862	26.33***	13.9%	67
		(2.60)***	(-3.08)***	(-2.95)***	(2.95)***			
51	0.57	0.5668	-0.0951	-0.1386	0.2175	18.89***	-3.2%	57
		(2.02)**	(-0.68)	(-1.19)	(1.02)			
52	0.58	0.6100	-0.0923	-0.2010	0.0824	24.15***	0.2%	52
		(2.73)***	(-1.28)	(-2.21)**	(0.39)			
53	0.66	0.5912	0.0810	0.1414	-0.0506	20.52***	-2.2%	69
		(3.19)***	(0.92)	(1.08)	(-0.26)			
54	0.36	0.3364	-0.0892	-0.0853	0.3140	26.15***	12.7%	57
		(3.33)***	(-3.39)***	(-1.84)*	(3.35)***			
55	0.46	0.3504	0.0216	-0.0166	0.0901	27.84***	2.1%	69
		(4.27)***	(0.43)	(-0.31)	(1.42)			
Mean		0.52	-0.05	-0.07	0.20	2.4%		
P- Value		(0.00)	(0.04)	(0.02)	(000)			

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

5.3 Results of regressions incorporating lags of the risk factors

Considering their significance in the hedge fund index data generating process it is surprising that the returns of so few of the individual hedge funds are positively related to the default and term structure risk factors. Where there is a significant relationship with individual hedge funds the coefficient is generally negative, whereas the risk factors are significantly positive for the two hedge fund indices and the simulated convertible bond arbitrage portfolio. It is probable, given the illiquidity of the securities held by these hedge funds, that including only contemporaneous risk factors fails to capture the true relationship between individual hedge funds and risk factors. Asness, Krail and Liew (2001) find that the returns on convertible arbitrage, event driven, fixed income arbitrage, long/short equity and global macro hedge fund indices at time t are related to the S&P500 at lags one, two and three and regressing hedge fund returns only on contemporaneous S&P500 understates risk exposure. The effect is most pronounced for the convertible arbitrage, event driven and fixed income arbitrage hedge fund indices. Asness, Krail and Liew (2001) attribute their findings to the illiquid securities held by hedge funds.

In this section, results from estimating two risk factor models are presented, a model incorporating lags of the risk factors, and a model incorporating lags of the risk factors augmented with a one period lag of the hedge fund return. The model incorporating lags of the risk factors is specified following Asness, Krail and Liew (2001) to better estimate the risk factor coefficients. This model is then augmented with the one period lag of the hedge fund return as a proxy illiquidity risk factor. If hedge funds hold only liquid securities then the returns at time t should be unrelated to returns at time $t-1$. A positive coefficient on the one period lag of the hedge fund index indicates that the manager is receiving a risk premium for bearing liquidity risk.

Table 5.3 presents results from estimating (5.2) for individual convertible arbitrage hedge funds.

$$y_t = a + \beta_0' DEF + \beta_1' TERM + \beta_2' CBRF + \varepsilon \qquad (5.2)$$

Where y_t is the excess return on the hedge fund at time $t-1$, $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$ and $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$. The β coefficient is the sum of the contemporaneous β and lagged β s. Figures in parenthesis are P-Values from the joint test of $\beta_{jt} + \beta_{jt-1} + \beta_{jt-2} = 0$ for DEF, $TERM$ and $CBRF$.

Table 5.3

Results of estimating non-synchronous regressions of individual fund risk factors

This table presents the results of estimating the excess returns of individual hedge funds on the following model of hedge fund returns.

$$y_t = a + \beta_0' DEF + \beta_1' TERM + \beta_2' CBRF + \varepsilon$$

Where y_t is the excess return on the portfolio at time $t-1$, $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$ and $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$. The β coefficient is the sum of the contemporaneous β and lagged β s. Figures in parenthesis are P-Values from the joint test of $\beta_{jt} + \beta_{jt-1} + \beta_{jt-2} = 0$ for DEF, $TERM$ and $CBRF$.

Fund	$r_i - r_f$	α	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	Adj R^2	Q stat	N
1	0.65	0.51	0.08	0.00	0.42	10.3%	7.90	69
		(0.00)	(0.60)	(0.98)	(0.11)		(0.25)	
2	0.69	-0.01	0.04	-0.41	1.18	17.0%	21.01	69
		(0.98)	(0.91)	(0.42)	(0.07)		(0.00)	
3	1.38	1.28	-0.47	-0.70	1.34	21.8%	24.80	38
		(0.00)	(0.09)	(0.15)	(0.04)		(0.00)	
4	1.19	1.09	-0.46	-0.73	1.40	30.0%	24.20	60
		(0.00)	(0.01)	(0.01)	(0.00)		(0.00)	

5	0.95	0.15	1.01	0.76	0.97	52.4%	33.92	69
		(0.71)	(0.01)	(0.01)	(0.15)		(0.00)	
6	0.97	0.43	0.56	0.38	1.13	30.2%	18.00	69
		(0.19)	(0.15)	(0.19)	(0.11)		(0.01)	
7	0.62	0.58	0.18	0.25	0.50	32.0%	23.47	58
		(0.00)	(0.02)	(0.01)	(0.02)		(0.00)	
8	0.92	0.80	0.05	0.18	0.04	-1.1%	26.58	82
		(0.00)	(0.69)	(0.13)	(0.85)		(0.00)	
9	0.44	-0.01	0.28	0.62	0.54	46.7%	21.71	57
		(0.97)	(0.19)	(0.02)	(0.06)		(0.00)	
10	0.87	1.04	0.40	0.43	0.05	17.6%	15.84	27
		(0.00)	(0.05)	(0.15)	(0.89)		(0.01)	
11	0.23	0.28	0.03	0.01	-0.03	-9.0%	22.31	52
		(0.00)	(0.57)	(0.88)	(0.85)		(0.00)	
12	0.46	0.40	-0.06	0.23	0.49	-1.4%	20.22	58
		(0.01)	(0.65)	(0.18)	(0.07)		(0.00)	
13	-0.03	-0.10	-0.09	0.01	0.46	48.6%	21.00	30
		(0.04)	(0.01)	(0.78)	(0.00)		(0.00)	
14	0.66	0.63	-0.01	0.07	0.44	2.9%	19.87	55
		(0.00)	(0.89)	(0.35)	(0.01)		(0.00)	
15	0.69	0.65	-0.05	0.05	0.32	-11.1%	20.68	42
		(0.00)	(0.62)	(0.72)	(0.24)		(0.00)	
16	0.82	0.66	-0.10	0.12	0.76	12.5%	18.54	38
		(0.00)	(0.33)	(0.39)	(0.00)		(0.01)	
17	0.09	0.08	-0.20	-0.20	0.33	4.6%	19.95	25
		(0.51)	(0.00)	(0.00)	(0.07)		(0.00)	
18	0.91	1.10	0.28	0.20	-0.21	25.0%	14.42	36
		(0.00)	(0.22)	(0.52)	(0.64)		(0.03)	
19	0.56	-0.22	0.89	0.88	0.13	42.6%	7.61	69
		(0.22)	(0.00)	(0.00)	(0.59)		(0.27)	
20	0.66	0.33	0.31	0.27	0.12	7.4%	7.76	69
		(0.31)	(0.30)	(0.20)	(0.45)		(0.26)	
21	-0.12	-0.47	0.61	1.91	0.25	29.4%	17.67	37
		(0.62)	(0.26)	(0.05)	(0.76)		(0.01)	
22	1.11	0.86	0.21	0.49	-0.12	7.5%	20.69	69
		(0.02)	(0.57)	(0.10)	(0.73)		(0.00)	
23	0.38	-0.20	0.51	0.53	0.03	25.7%	22.65	69
		(0.25)	(0.00)	(0.00)	(0.85)		(0.00)	
24	0.38	-0.05	0.60	0.71	-0.20	26.3%	22.83	69
		(0.79)	(0.00)	(0.00)	(0.35)		(0.00)	
25	0.66	0.33	0.31	0.27	0.12	7.4%	23.10	69
		(0.31)	(0.30)	(0.20)	(0.45)		(0.00)	
26	0.60	0.47	0.08	0.06	0.36	7.5%	7.05	69

		(0.01)	(0.62)	(0.74)	(0.18)		(0.32)	
27	0.69	0.20 (0.09)	0.66 (0.00)	0.51 (0.00)	0.02 (0.88)	40.3%	12.81 (0.05)	69
28	0.56	0.47 (0.00)	0.09 (0.39)	0.23 (0.06)	0.50 (0.03)	39.5%	17.22 (0.01)	25
29	-0.76	0.09 (0.78)	0.49 (0.00)	-0.98 (0.00)	-1.69 (0.00)	73.9%	18.18 (0.01)	24
30	0.85	0.70 (0.04)	0.09 (0.53)	0.08 (0.51)	0.97 (0.03)	47.4%	18.85 (0.00)	38
31	0.70	0.45 (0.23)	-0.31 (0.37)	-0.80 (0.06)	1.02 (0.03)	11.6%	24.15 (0.00)	69
32	0.33	-0.05 (0.85)	0.26 (0.28)	0.19 (0.28)	0.37 (0.10)	5.0%	28.35 (0.00)	69
33	0.05	-1.58 (0.20)	-0.96 (0.30)	-1.12 (0.34)	4.52 (0.00)	10.1%	17.50 (0.01)	69
34	0.67	-0.37 (0.32)	0.51 (0.05)	0.33 (0.31)	0.78 (0.05)	29.0%	38.28 (0.00)	69
35	0.64	-0.61 (0.12)	1.03 (0.06)	0.51 (0.27)	1.03 (0.05)	41.1%	7.22 (0.30)	69
36	0.13	0.18 (0.08)	0.13 (0.03)	0.32 (0.00)	-0.14 (0.10)	21.0%	12.74 (0.05)	69
37	0.47	0.40 (0.01)	-0.16 (0.21)	0.05 (0.72)	0.09 (0.78)	16.2%	34.31 (0.00)	36
38	0.52	0.10 (0.62)	0.38 (0.03)	0.26 (0.09)	0.52 (0.04)	38.3%	23.62 (0.00)	69
39	0.58	0.43 (0.01)	0.05 (0.59)	0.08 (0.45)	0.82 (0.00)	49.9%	6.73 (0.35)	51
40	0.52	0.25 (0.00)	0.19 (0.01)	0.16 (0.04)	0.14 (0.18)	53.4%	5.24 (0.51)	51
41	0.89	0.55 (0.25)	-0.01 (0.98)	-0.22 (0.33)	0.77 (0.07)	17.0%	47.83 (0.00)	69
42	0.66	0.58 (0.04)	-0.24 (0.08)	0.07 (0.71)	0.40 (0.13)	-1.8%	50.38 (0.00)	24
43	0.39	0.38 (0.00)	0.12 (0.20)	0.10 (0.44)	0.10 (0.47)	-1.7%	11.20 (0.08)	69
44	1.30	0.67 (0.25)	0.22 (0.65)	0.03 (0.92)	0.89 (0.00)	22.0%	26.23 (0.00)	69
45	1.09	1.15 (0.14)	-0.06 (0.88)	-0.10 (0.86)	0.08 (0.94)	-18.8%	91.61 (0.00)	41
46	0.67	0.56 (0.00)	0.14 (0.33)	0.10 (0.43)	0.00 (0.99)	-2.0%	29.48 (0.00)	69
47	0.36	0.44 (0.03)	0.14 (0.39)	0.39 (0.04)	-0.09 (0.62)	19.3%	29.79 (0.00)	69

48	0.62	0.29 (0.00)	0.21 (0.10)	0.21 (0.18)	0.59 (0.00)	30.4%	37.23 (0.00)	69
49	0.46	0.19 (0.03)	0.18 (0.02)	0.14 (0.04)	0.16 (0.09)	43.3%	53.46 (0.00)	69
50	0.44	0.33 (0.01)	0.00 (1.00)	-0.07 (0.53)	0.61 (0.00)	35.8%	18.30 (0.01)	67
51	0.57	0.66 (0.03)	0.07 (0.79)	-0.15 (0.66)	-0.47 (0.30)	-5.2%	11.81 (0.07)	57
52	0.58	0.64 (0.00)	0.15 (0.44)	0.13 (0.63)	0.11 (0.73)	7.1%	20.65 (0.00)	52
53	0.66	0.22 (0.17)	0.72 (0.00)	0.66 (0.01)	-0.25 (0.58)	13.4%	26.31 (0.00)	69
54	0.36	0.32 (0.00)	0.01 (0.89)	0.12 (0.26)	0.46 (0.01)	16.2%	40.07 (0.00)	57
55	0.46	0.17 (0.02)	0.38 (0.00)	0.29 (0.00)	0.01 (0.91)	38.0%	22.84 (0.00)	69
Mean *P*-Value		0.34 (0.00)	0.17 (0.00)	0.14 (0.03)	0.42 (0.00)	21%		

The mean explanatory power of the model is 21% (adjusted R^2) higher than results for the contemporaneous model where the mean adjusted R^2 was 2.4%. The coefficients on *DEF*, *TERM* and *CBRF* are significantly different from zero for twenty two, twenty one and twenty five hedge funds respectively. The mean coefficient on *DEF* was 0.17, compared to a range of 0.17 to 0.25 for the hedge fund indices. The mean coefficient of *TERM* was 0.14 compared to a range of 0.19 to 0.26 for the hedge fund indices and the mean coefficient on *CBRF* was 0.42 compared to a range of 0.05 to 0.35 for the hedge fund indices. The alphas are significantly positive for thirty two hedge funds and significantly negative for one hedge fund. The mean estimated alpha is a statistically significant[51] 0.34% per month. Although lagged risk factors will capture illiquidity there is no factor specified in this model explicitly for illiquidity risk and estimates of performance may be biased upward.

[51] The mean estimated coefficients are significant at the 1% level with the exception of the mean estimate of the *TERM* coefficient which is significant at the 5% level.

Table 5.4 presents the results of repeating this analysis with the inclusion of the time *t-1* factor mimicking illiquidity in the securities held by convertible arbitrage hedge funds.

$$y_t = \text{a} + \beta_0{'}\, DEF + \beta_1{'}TERM + \beta_2{'}CBRF + \beta_3 y_{t-1} + \varepsilon \quad (5.3)$$

Where y_t is the excess return on the individual hedge fund at time *t-1*, $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$ and y_{t-1} is the one period lag of the excess return on the individual hedge fund. The β coefficient is the sum of the contemporaneous β and lagged β s. Figures in parenthesis are *P*-Values from the joint test of $\beta_{jt} + \beta_{jt-1} + \beta_{jt-2} = 0$ for *DEF*, *TERM* and *CBRF* and $\beta_3 = 0$ for y_{t-1}.

Table 5.4
Results of estimating non-synchronous regressions of individual fund risk factors augmented with a liquidity risk factor proxy

This table presents the results of estimating the excess returns of individual hedge funds on the following model of hedge fund returns.

$$y_t = \alpha + \beta_0{'}\, DEF + \beta_1{'}TERM + \beta_2{'}CBRF + \beta_3 y_{t-1} + \varepsilon$$

Where y_t is the excess return on the portfolio at time *t-1*, $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$ and y_{t-1} is the one period lag of the excess return on the portfolio. The β coefficient is the sum of the contemporaneous β and lagged β s. Figures in parenthesis are *P*-Values from the joint test of $\beta_{jt} + \beta_{jt-1} + \beta_{jt-2} = 0$ for *DEF*, *TERM* and *CBRF* and $\beta_3 = 0$ for y_{t-1}.

Fund	$r_i - r_f$	α	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	β_Y	Adj R^2	Q Stat (10)	N
1	0.65	0.49	0.08	0.03	0.39	0.08	9.3%	9.49	69
		(0.00)	(0.57)	(0.85)	(0.13)	(0.38)		(0.15)	
2	0.69	-0.10	0.07	-0.25	1.00	0.26	20.8%	6.40	69
		(0.72)	(0.84)	(0.58)	(0.08)	(0.01)		(0.38)	
3	1.38	1.08	-0.46	-0.70	1.33	0.16	19.1%	12.07	38
		(0.04)	(0.12)	(0.17)	(0.04)	(0.32)		(0.06)	
4	1.19	0.87	-0.43	-0.66	1.36	0.20	31.2%	11.63	60

		(0.00)	(0.05)	(0.07)	(0.01)	(0.22)		(0.07)	
5	0.95	0.07	0.99	0.82	0.78	0.18	53.3%	9.91	69
		(0.83)	(0.01)	(0.01)	(0.23)	(0.23)		(0.13)	
6	0.97	0.26	0.64	0.60	0.91	0.25	35.7%	4.83	69
		(0.38)	(0.09)	(0.05)	(0.16)	(0.03)		(0.57)	
7	0.62	0.45	0.22	0.31	0.41	0.29	40.8%	9.77	58
		(0.00)	(0.02)	(0.01)	(0.01)	(0.04)		(0.13)	
8	0.92	0.24	0.02	0.12	0.01	0.70	51.0%	16.35	82
		(0.02)	(0.74)	(0.13)	(0.95)	(0.00)		(0.01)	
9	0.44	1.55	-1.12	0.21	0.68	0.24	21.9%	31.14	57
		(0.01)	(0.19)	(0.81)	(0.61)	(0.38)		(0.00)	
10	0.87	0.83	0.42	0.51	-0.24	0.26	11.5%	23.43	27
		(0.01)	(0.02)	(0.04)	(0.58)	(0.20)		(0.00)	
11	0.23	0.28	0.02	0.02	-0.05	0.08	-18.0%	44.78	52
		(0.00)	(0.70)	(0.78)	(0.79)	(0.29)		(0.00)	
12	0.46	0.24	-0.06	0.20	0.43	0.38	13.6%	18.99	58
		(0.04)	(0.53)	(0.12)	(0.01)	(0.00)		(0.00)	
13	-0.03	-0.07	-0.07	0.02	0.40	0.03	51.3%	25.39	30
		(0.11)	(0.18)	(0.71)	(0.00)	(0.88)		(0.00)	
14	0.66	0.34	-0.03	0.07	0.33	0.44	17.5%	32.71	55
		(0.00)	(0.60)	(0.39)	(0.01)	(0.00)		(0.00)	
15	0.69	0.33	0.01	0.12	0.02	0.54	15.3%	22.63	42
		(0.08)	(0.93)	(0.42)	(0.94)	(0.00)		(0.00)	
16	0.82	0.23	0.02	0.27	0.38	0.60	38.5%	27.13	38
		(0.09)	(0.77)	(0.02)	(0.00)	(0.00)		(0.00)	
17	0.09	0.04	-0.24	-0.20	0.40	0.21	10.0%	29.01	25
		(0.66)	(0.00)	(0.01)	(0.00)	(0.07)		(0.00)	
18	0.91	1.12	0.28	0.17	-0.21	0.02	21.6%	22.07	36
		(0.00)	(0.24)	(0.58)	(0.62)	(0.85)		(0.00)	
19	0.56	-0.35	0.67	0.66	0.19	0.47	60.3%	10.09	69
		(0.00)	(0.00)	(0.00)	(0.21)	(0.00)		(0.12)	
20	0.66	0.21	0.28	0.24	0.11	0.28	13.6%	11.52	69
		(0.43)	(0.29)	(0.18)	(0.33)	(0.10)		(0.07)	
21	-0.12	-0.49	0.70	1.97	0.17	0.17	29.4%	19.56	37
		(0.55)	(0.18)	(0.04)	(0.82)	(0.03)		(0.00)	
22	1.11	0.30	0.60	0.69	-0.16	0.35	20.0%	19.09	69
		(0.33)	(0.11)	(0.02)	(0.57)	(0.01)		(0.00)	
23	0.38	-0.11	0.41	0.43	0.07	0.11	24.6%	21.34	69
		(0.51)	(0.01)	(0.00)	(0.63)	(0.38)		(0.00)	
24	0.38	-0.09	0.48	0.55	-0.05	0.17	30.5%	21.41	69
		(0.61)	(0.02)	(0.00)	(0.74)	(0.18)		(0.00)	
25	0.66	0.21	0.28	0.24	0.11	0.28	13.6%	20.75	69
		(0.43)	(0.29)	(0.18)	(0.33)	(0.10)		(0.00)	

26	0.60	0.42 (0.01)	0.08 (0.62)	0.07 (0.66)	0.31 (0.22)	0.12 (0.23)	7.3%	8.36 (0.21)	69
27	0.69	0.20 (0.16)	0.61 (0.00)	0.46 (0.00)	0.00 (0.97)	0.09 (0.53)	42.9%	15.18 (0.02)	69
28	0.56	0.31 (0.00)	0.01 (0.89)	0.24 (0.01)	0.51 (0.01)	0.29 (0.03)	47.5%	11.54 (0.07)	25
29	-0.76	0.07 (0.77)	0.19 (0.28)	-0.97 (0.00)	-1.27 (0.00)	0.35 (0.00)	77.4%	12.60 (0.05)	24
30	0.85	0.39 (0.08)	0.03 (0.84)	0.12 (0.47)	0.83 (0.02)	0.36 (0.02)	50.5%	9.92 (0.13)	38
31	0.70	0.30 (0.37)	-0.29 (0.35)	-0.71 (0.09)	0.91 (0.02)	0.28 (0.05)	17.2%	13.79 (0.03)	69
32	0.33	-0.47 (0.02)	0.79 (0.00)	0.58 (0.00)	0.14 (0.43)	-0.34 (0.00)	15.7%	18.43 (0.01)	69
33	0.05	-1.51 (0.17)	-0.96 (0.28)	-1.14 (0.29)	4.33 (0.00)	0.16 (0.27)	10.7%	10.19 (0.12)	69
34	0.67	-1.46 (0.00)	1.75 (0.00)	1.04 (0.00)	0.62 (0.06)	0.28 (0.03)	41.0%	19.22 (0.00)	69
35	0.64	-0.57 (0.16)	0.97 (0.12)	0.47 (0.35)	1.04 (0.04)	0.04 (0.78)	40.2%	8.54 (0.20)	69
36	0.13	-0.30 (0.00)	0.50 (0.00)	0.57 (0.00)	-0.04 (0.78)	-0.23 (0.25)	47.0%	11.03 (0.09)	69
37	0.47	0.27 (0.01)	-0.03 (0.76)	0.13 (0.16)	-0.19 (0.53)	0.44 (0.00)	30.8%	34.03 (0.00)	36
38	0.52	0.06 (0.73)	0.33 (0.06)	0.22 (0.14)	0.53 (0.02)	0.22 (0.01)	44.3%	16.09 (0.01)	69
39	0.58	0.39 (0.00)	0.06 (0.56)	0.10 (0.38)	0.66 (0.08)	0.15 (0.33)	49.4%	4.65 (0.59)	51
40	0.52	0.10 (0.06)	0.40 (0.00)	0.36 (0.00)	0.45 (0.00)	0.00 (0.97)	62.2%	5.46 (0.49)	51
41	0.89	0.16 (0.64)	0.06 (0.78)	-0.05 (0.81)	0.59 (0.00)	0.53 (0.00)	41.4%	5.04 (0.54)	69
42	0.66	0.46 (0.07)	-0.12 (0.23)	0.23 (0.27)	0.31 (0.16)	0.27 (0.03)	11.0%	7.05 (0.32)	24
43	0.39	0.49 (0.00)	0.10 (0.32)	0.04 (0.78)	0.09 (0.57)	-0.20 (0.03)	0.7%	12.29 (0.06)	69
44	1.30	0.25 (0.54)	0.31 (0.37)	0.14 (0.55)	0.49 (0.01)	0.47 (0.00)	40.2%	6.33 (0.39)	69
45	1.09	0.50 (0.37)	-0.20 (0.52)	0.00 (1.00)	0.13 (0.88)	0.50 (0.01)	4.7%	17.75 (0.01)	41
46	0.67	0.73 (0.00)	0.12 (0.45)	0.07 (0.60)	0.01 (0.97)	-0.25 (0.01)	4.0%	21.42 (0.00)	69
47	0.36	-0.06	0.30	0.38	0.08	0.30	58.0%	22.80	69

		(0.72)	(0.10)	(0.02)	(0.31)	(0.02)		(0.00)	
48	0.62	0.28	0.22	0.24	0.54	0.08	30.9%	36.59	69
		(0.00)	(0.05)	(0.10)	(0.01)	(0.53)		(0.00)	
49	0.46	0.09	0.14	0.11	0.16	0.32	48.9%	45.23	69
		(0.20)	(0.04)	(0.08)	(0.02)	(0.00)		(0.00)	
50	0.44	0.29	0.03	0.01	0.55	0.14	37.1%	16.64	67
		(0.02)	(0.69)	(0.91)	(0.00)	(0.44)		(0.01)	
51	0.57	0.62	0.08	-0.14	-0.49	0.10	-6.4%	6.23	57
		(0.03)	(0.77)	(0.67)	(0.25)	(0.39)		(0.40)	
52	0.58	0.50	0.13	0.15	0.14	0.17	7.2%	17.23	52
		(0.01)	(0.48)	(0.56)	(0.63)	(0.12)		(0.01)	
53	0.66	0.14	0.65	0.63	-0.27	0.24	17.4%	25.69	69
		(0.31)	(0.00)	(0.01)	(0.50)	(0.03)		(0.00)	
54	0.36	0.24	0.04	0.14	0.32	0.32	21.7%	43.27	57
		(0.01)	(0.66)	(0.17)	(0.02)	(0.00)		(0.00)	
55	0.46	0.17	0.35	0.26	0.00	0.09	41.6%	11.14	69
		(0.05)	(0.00)	(0.00)	(0.99)	(0.53)		(0.08)	
Mean		0.20	0.19	0.19	0.37	0.22	29%		
P-Value		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			

The *DEF* coefficients are significant for twenty hedge funds (mean coefficient of 0.19 compared to 0.17 for the model omitting y_{t-1}), the coefficients on *TERM* (mean coefficient 0.19 compared to 0.14 for the model omitting y_{t-1}) and *CBRF* (mean coefficient of 0.37 compared to 0.42 for the model omitting y_{t-1}) are significant for approximately half of hedge funds and the y_{t-1} coefficients (mean coefficient 0.22) are significant for thirty hedge funds. The mean adjusted R^2 of the model is 29%. Despite the inclusion of the factor mimicking illiquidity in the securities held by hedge funds the alphas generated by the convertible bond hedge funds are significantly positive for twenty eight hedge funds with a mean alpha of 0.49% and significantly negative for four hedge funds with a mean alpha of -0.64%. However, for all fifty five hedge funds the mean alpha is a statistically significant 0.20% per month, 2.4% per annum, compared to a significantly positive alpha of 0.34% per month for the lagged model omitting the lag of y_t. All coefficients are significant at the 1% level. These estimates of abnormal return are lower than those reported in previous studies. Capocci and Hübner (2004), Fung and Hsieh (2004) utilising linear factor models estimate that convertible arbitrage generates abnormal returns of 0.42% and 0.73% per month respectively.

5.4 Fund performance persistence

To examine performance persistence funds were divided up into four equally weighted portfolios, following Carhart (1997), from 1993 to 2002 based on the previous twelve months of returns.[52] As there were too few funds in the HFR database before 1993 this period is excluded. If a fund's previous twelve months' returns were in the top quartile of fund performance the fund goes into Portfolio 1 for the next twelve months. If a fund's previous twelve months' returns were in the bottom quartile then that fund goes into Portfolio 4 for the following twelve months. The middle ranking funds go into Portfolios 2 and 3. Portfolios were resorted at the beginning of each year. Forming portfolios in this manner allows the examination of persistence in performance of convertible arbitrage hedge funds.

[52] Here four portfolios are used rather than the ten used by Carhart (1997) due to the small sample size. In 1993 there are only three funds in each portfolio. This is the minimum number of funds in each of the ten years from 1993 to 2002.

Table 5.5
Summary statistics of the four HFR performance persistence portfolios

This table presents summary statistics on the four performance persistence portfolios and factors. Portfolio 1 is made up of funds with the highest previous twelve months of returns, with Portfolio 4 being made up of funds with the lowest previous twelve months of returns.

	Mean	Std Dev	Skewness	Kurt	Q-Stat
$r_{Port1} - r_f$	0.71	1.65	-0.23	1.32	13.56
$r_{Port2} - r_f$	0.61	0.97	-1.31	5.76	30.51***
$r_{Port3} - r_f$	0.60	0.91	-0.85	2.59	43.58***
$r_{Port4} - r_f$	0.39	1.88	-1.94	6.69	39.91***

Table 5.5 provides summary statistics of the four portfolios. There is little difference in the returns of Portfolios 1, 2, and 3, although Portfolio 1 has a higher standard deviation. Portfolio 4, the portfolio formed of funds with the worst previous month's returns is by far the poorest performer underperforming by between 21 and 32 basis points per month. This provides some weak evidence of persistence in poor performance by convertible arbitrage hedge funds.

Table 5.6
Cross correlations

This table presents the cross correlations between the four performance persistence portfolios and various market factors over the sample period 1993 to 2002.

	$r_{Port1} - r_f$	$r_{Port2} - r_f$	$r_{Port3} - r_f$	$r_{Port4} - r_f$	*DEF*	*TERM*	*CBRF*
$r_{Port1} - r_f$	1.00						
$r_{Port2} - r_f$	0.45	1.00					
$r_{Port3} - r_f$	0.38	0.58	1.00				
$r_{Port4} - r_f$	0.45	0.56	0.53	1.00			
DEF	-0.09	-0.05	0.06	0.01	1.00		
TERM	0.16	0.01	-0.09	-0.02	-0.71	1.00	
CBRF	0.18	0.15	0.13	0.15	0.35	0.04	1.00

Coefficients greater than absolute 0.22, 0.17 and 0.14 are significant at the 1%, 5% and 10% levels respectively.

Table 5.6 provides cross correlations between the four performance persistence hedge fund portfolios and factors. $HFRIRF_{t-1}$ and *CBRF* are positively correlated with the four hedge fund portfolios. However, *DEF* and *TERM* have little correlation with the portfolios.

Table 5.7
Results of estimating the factor model on the HFR performance persistence portfolios

This table presents the results of estimating the following model of hedge fund returns for the four performance persistence portfolios. Portfolio 1 is made up of funds with the highest previous twelve months of returns, with Portfolio 4 being made up of funds with the lowest previous twelve months of returns.

$$y_t = \alpha + \beta_0' DEF + \beta_1' TERM + \beta_2' CBRF + \beta_3 y_{t-1} + \varepsilon$$

Where y_t is the excess return on the portfolio at time t-1, $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$ and y_t is the one peiod lag of the excess return on the portfolio. The β coefficient is the sum of the contemporaneous β and lagged β s. Figures in parenthesis are P-Values from the joint test of $\beta_{jt} + \beta_{jt-1} + \beta_{jt-2} = 0$ for *DEF*, *TERM* and *CBRF* and $\beta_3 = 0$ for y_{t-1}.

Panel A: Portfolio 1

$r_i - r_f$	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	$\beta_{DEF(t\ to\ t-2)}$	β_y	Adj. R^2	Q-Stat
0.71	0.30	0.07	0.11	0.85	0.05	21.0%	5.35
	(0.05)	(0.59)	(0.54)	(0.00)	(0.76)		(0.50)

Panel B: Portfolio 2

$r_i - r_f$	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	$\beta_{DEF(t\ to\ t-2)}$	β_y	Adj. R^2	Q-Stat
0.61	0.21	0.09	0.17	0.23	0.43	35.7%	8.66
	(0.04)	(0.22)	(0.08)	(0.08)	(0.00)		(0.19)

Panel C: Portfolio 3

$r_i - r_f$	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	$\beta_{DEF(t\ to\ t-2)}$	β_y	Adj. R^2	Q-Stat
0.60	0.23	0.00	0.01	0.28	0.42	37.0%	4.47
	(0.00)	(1.00)	(0.94)	(0.00)	(0.00)		(0.61)

Panel D: Portfolio 4

$r_i - r_f$	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	$\beta_{DEF(t\ to\ t-2)}$	β_y	Adj. R^2	Q-Stat
0.39	-0.02	0.21	0.27	0.37	0.42	29.7%	6.24
	(0.94)	(0.27)	(0.10)	(0.05)	(0.00)		(0.40)

Table 5.7 reports results from estimating the non-synchronous model augmented with the one period lag of the portfolio excess return, equation (5.3) on the four performance persistence portfolios. *CBRF*, the convertible bond arbitrage factor is significant for all

of the portfolios. *TERM*, the term structure risk factor is significant for portfolios two and three. The one period lag of the performance persistence portfolio excess return, y_{t-1}, is significant for Portfolios 2, 3 and 4. The estimated alphas for Portfolios 1, 2 and 3 range from 0.21 to 0.30 and are significant at the 5% level. The estimated alpha for Portfolio 4 is insignificant from zero providing further evidence of persistence in the performance of under performing convertible arbitrage hedge funds. Previous research on performance persistence in hedge fund returns has documented weak performance persistence in quarterly data (Agarwal and Naik, 2000b). Kat and Menexe (2002), Brown, Goetzmann and Ibbotson (1999) and Capocci, Corhay and Hübner (2005) find little evidence to support persistence in performance by hedge funds.

5.5 Conclusion

Evidence from examining individual hedge funds finds support for the default risk factor, term structure risk factor and the convertible bond risk factor being significant in hedge fund returns, particularly if both lagged and contemporaneous observations of the risk factors are specified. This is a finding which supports the evidence of Asness, Krail and Liew (2001) that to properly estimate the risks faced by individual hedge funds a model which includes lags of the explanatory variables should be specified. When a non-synchronous model of hedge fund performance is estimated omitting an explicit illiquidity factor results indicate that convertible arbitrage hedge funds generate a statistically significant alpha of 0.34% per month or 4.1% per annum. However, illiquidity in the securities held by convertible arbitrage hedge funds also appears to be a key risk factor. Here y_{t-1}, the one period lag of the hedge fund or portfolio of hedge fund's return is employed as a proxy risk factor for illiquidity. When this illiquidity factor is specified in a four factor model the mean estimate of abnormal performance is lower (0.20% per month) though remains statistically significant from zero. Evidence is also presented on persistence in convertible arbitrage hedge fund performance.

5.6 Limitations and avenues for further research

5.6.1 Suitability of the lag of the hedge fund as an explanatory variable

Evidence presented here suggests that if an illiquidity factor is specified in a multi-factor model containing lagged and contemporaneous risk factors, then estimates of abnormal performance will be reduced to 2.5% per annum. Omitting the illiquidity factor from the model leads to the conclusion that convertible arbitrage hedge funds generate abnormal returns of 4.1% per annum. These results are sensitive to the specification of an illiquidity factor and may be sensitive to the illiquidity factor specified.

Getmansky, Lo and Makarov (2004) discuss the possibility that the serial correlation in hedge fund returns is partially caused by deliberate performance smoothing in addition to the illiquidity in the securities held by the funds. In this case, as including the lag of the dependent variable as an explanatory variable reduces the estimated alpha for convertible arbitrage funds, performance may be understated. However, if the serial correlation is caused by an omitted illiquidity variable, and the effect is symmetric, it must be accounted for in the risk factor model. If an illiquidity factor is not specified then estimates of performance will be over stated. The specification of the lag of the hedge fund return as a dependent variable should lead to an estimate of performance closer to the true value than a risk factor model omitting an illiquidity variable.

If all of the autocorrelation is caused by smoothing the estimated mean hedge fund return should be unchanged, but the standard deviation should be larger, having a resulting negative effect on performance evaluation, through the larger variance using mean variance analysis. In the present analysis, stripping out past returns and failing to include the portion of current real returns which will not be reported until future months, will lower the mean return leading to an understatement of performance. However, it would be difficult to rebuff an argument that deliberate performance smoothing is not an additional risk for an investor, and investors would favour funds that do not performance smooth over funds that do, in the same way that investors prefer funds that hold securities with greater liquidity than funds who hold illiquid securities *ceteris paribus*. In relative performance evaluation, the inclusion of a lagged convertible arbitrage return as a risk factor, even if it slightly reduces estimates of overall performance is superior to a factor model which does not differentiate between funds who engage in deliberate performance smoothing and those that do not. Nonetheless, when data becomes available on turnover in the convertible bond market, an illiquidity risk factor derived from this data is likely to be a more direct model of illiquidity risk while avoiding the potential biases from including a lag of a hedge fund benchmark index as a risk factor.

Chapter 6: A review of non-linear time series models

6.1 Introduction

This chapter provides a review of non-linear models focusing in detail on the smooth transition autoregressive (STAR) and smooth transition regressive (STR) family of models first proposed by Chan and Tong (1986) and extended by Teräsvirta and Anderson (1992) for modelling non-linearities in the business cycle. Several studies of hedge funds have noted the non-linearity inherent in the returns of dynamic trading strategies.[53] Given these characteristics, a linear model may be functionally misspecified when examining the data generating process of a dynamic trading strategy. Mitchell and Pulvino (2001) and Agarwal and Naik (2004) note that the payoff to dynamic trading strategies share characteristics with short positions in equity put options implying that there are two regimes; one regime with little equity exposure and one with a high correlation with equities. In Chapter 3 of this study, evidence was presented which indicated that the relationship between convertible bond arbitrage and equities has three regimes. When equity returns were extremely negative there is a strong positive correlation with convertible bond arbitrage returns; when equity returns were within one standard deviation of the mean there is a weak positive correlation with equities; and when equity returns were extremely positive there is a negative relationship with equities.

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[53] Agarwal and Naik (2004), Fung and Hsieh (2001), Fung and Hsieh (2002) and Mitchell and Pulvino (2001) amongst others document this feature of hedge fund returns.

An innovation of the STAR models discussed later in this chapter is that they allow for a smooth transition from one regime to another, rather than a jump, a characteristic better suited to examining dynamic trading strategies where portfolios are rebalanced, by various market participants at different intervals and by varying degrees, in reaction to evolving market conditions.

The remainder of this chapter is organised as follows. Section 6.2 presents a general review of non-linear time series models. Section 6.3 proceeds to look in detail at the specification and estimation of STAR models. Section 6.4 concludes.

6.2 Review of non-linear models

Several econometrics texts offer reviews of non-linear time series models. Enders (2003) provides an accessible comprehensive review of non-linear models. Granger and Teräsvirta (1993) provide a detailed review of smooth transition non-linear models.

6.2.1 Extensions of AR and ARMA models

The simplest form of a non-linear autoregressive model is a first order non-linear autoregressive [NLAR(1)] model given by equation (6.1) where y_t is a function of y_{t-1}.

$$y_t = f(y_{t-1}) + e_t \tag{6.1}$$

Equation (6.2) sets out a particular form of the NLAR(1) model where α_1, the autoregressive coefficient is a function of the value of y_{t-1}.

$$y_t = \alpha_1(y_{t-1}) \cdot y_{t-1} + e_t \tag{6.2}$$

The NLAR(p) model is given by (6.3).

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) + e_t \tag{6.3}$$

As the functional form of (6.3) is unknown, to estimate this type of model Enders suggests using a Taylor series approximation of the unknown functional form. For the general NLAR(p) model the annotation for a Taylor series approximation must be simplified. This is often called a generalized autoregressive (GAR) model.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p}\sum_{j=1}^{p}\sum_{k=1}^{r}\sum_{l=1}^{s} \alpha_{ijkl} y_{t-i}^{k} y_{t-j}^{l} + e_t \tag{6.4}$$

In the absence of a theoretical foundation for the relationship a GAR model is useful as it is capable of mimicking the functional form of a variety of models, but one drawback is that with such a range of variables the model is likely to be overparameterized.

The general form of a bilinear (BL) model is given by (6.5). The bilinear model uses moving average terms and the interactions of autoregressive and moving average terms to approximate a higher order GAR model. The BL model is a simple ARMA model including an additional term which allows for the interaction of moving average and autoregressive terms.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + e_t + \sum_{i=1}^{q} \beta_i e_{t-i} + \sum_{i=1}^{r} \sum_{j=1}^{s} c_{ij} y_{t-i} e_{t-j} \tag{6.5}$$

6.2.2 Threshold models

A threshold, or regime switching model, allows the behaviour of y to depend on the state of the system. For example, in a recession the unemployment rate often rises sharply and then slowly decline to its mean, however in an economic expansion the unemployment rate is unlikely to fall sharply. The adjustment of the unemployment rate depends upon whether the economy is in recession or in an expansionary state. Similarly when the economy is in a gradual expansion, central banks are unlikely to raise or cut interest rates aggressively. However, in a sharp recession or extreme expansion central banks are likely to aggressively cut or increase interest rates respectively. The attraction of TAR models is that they are employed to follow a hypothesised adjustment mechanism, unlike GAR or BL models, which are specified in the absence of a theoretical relationship.

$$y_t = \alpha_0 + \lambda_t \alpha_1 y_{t-1} + (1 - \lambda_t) \alpha_2 y_{t-1} + e_t \tag{6.6}$$

Equation (6.6) describes a simple TAR model. Below a set level of y_{t-1}, $\lambda_t = 1$, and the relationship between y and y_{t-1} is explained by α_1 in equation (6.7) above this level $\lambda_t =$

0, and the relationship between y and y_{t-1} is explained by α_2 in equation (6.8). This straightforward methodology allows for two different regimes, depending on the level of y_{t-1}.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + e_t \tag{6.7}$$

$$y_t = \alpha_0 + \alpha_2 y_{t-1} + e_t \tag{6.8}$$

Threshold models do not necessarily need an autoregressive component. It seems reasonable that the relationship between security prices may be different when returns are extremely positive or negative. A good example is a convertible bond, where if the price of the stock increases beyond a certain point the convertible bond begins to act like a stock and below this point acts more like a bond and less like a stock. In order to model the returns to these types of instruments it is necessary to use a model which allows for a change in behaviour of the security. A straightforward method to model the relationship between the return on a convertible bond y_t and the return on a stock x_t is to use a simple bivariate threshold model incorporating a dummy variable λ into the model as shown in equation (6.9).

$$y_t = \alpha_0 + \lambda_t \alpha_1 x_t + (1 - \lambda_t)\alpha_2 x_t + e_t \tag{6.9}$$

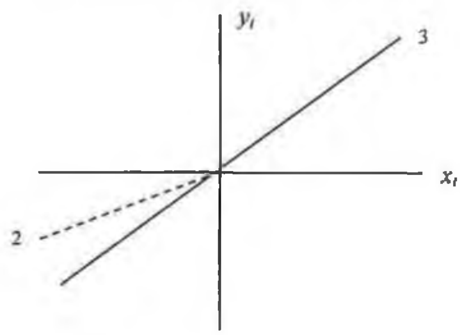
Below a set level of x_t, $\lambda_t = 1$, and the relationship between y and x is explained by α_1, above this level $\lambda_t = 0$, and the relationship between y and x is explained by α_2. This methodology allows for two different regimes, depending on the level of x_t.

$$y_t = \alpha_0 + \alpha_1 x_t + e_t \qquad (6.10)$$

$$y_t = \alpha_0 + \alpha_2 x_t + e_t \qquad (6.11)$$

Consider an example where the threshold of x_t is 0, and α_1 is greater than α_2. Looking at Figure 1, you can see the solid black line is equation (6.11) and the broken black line is equation (6.10). There is a kink in the relationship when $x_t = 0$ and as a result when $x_t < 0$, the relationship between x_t and y_t is given by α_2 and when $x_t > 0$ the relationship between the two is given by α_1.

Figure 6.1 Threshold model



Obviously this is a simplification of the true relationship between convertible bonds and equities as in reality the relationship is more complex and there is convexity or curvature in the move from equity to non-equity instrument. This highlights the shortcomings of this kind of model as it jumps from one regime to another. In reality financial time series relationship changes are likely to be much smoother (unless of course there is a jump in the underlying asset price).

In most situations the value of the threshold is not zero, is unknown and must be estimated. Chan (1993) shows how to obtain a consistent estimate of the threshold. Simply eliminate the highest and lowest 15% of observations from the sample, and then estimate the model for the full sample using each of the other 70% of the sample as an estimate of the threshold τ. Simply choose τ to minimise the residual sum of squares.

The threshold model discussed so far has a binary adjustment, with the process being either one or the other depending on the level relative to τ. Some processes may not adjust in this way. Consider the following NLAR model.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_1 y_{t-1} f(y_{t-1}) + e_t \tag{6.12}$$

If $f(\ )$ is a smooth continuous function the autoregressive coefficient ($\alpha_1 + \beta_1$) will change smoothly along with the value of y_{t-1}. This type of model is known as a smooth transition autoregressive (STAR) model. The two particularly useful forms of the STAR model that allow for a varying degree of autoregressive decay are the LSTAR (Logistic-STAR) and ESTAR (Exponential-STAR) models.

The LSTAR model generalises the standard autoregressive model such that the autoregressive coefficient is a logistic function.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \theta[\beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p}] + e_t \tag{6.13}$$

Where $\theta = [1+\exp(-\gamma(y_{t-1}-c))]^{-1}$, γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit as γ approaches zero or infinity, the LSTAR model becomes an AR(p) model since the value of θ is constant. For intermediate values of γ, the degree of autoregressive decay depends upon the value of y_{t-1}. As y_{t-1} approaches -∞, θ approaches 0 and the behaviour of y_t is given by $\alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + e_t$. As y_{t-1} approaches +∞, θ approaches 1 and the behaviour of y_t is given by $(\alpha_0 + \beta_0) + (\alpha_1 + \beta_1)y_{t-1} + ... + e_t$.

The exponential form of the model is similar but $\theta = 1 - \exp(-\gamma(y_{t-1}-c)^2)$. For the ESTAR model as γ approaches infinity or zero the model becomes a linear AR(p) model as θ becomes constant. Otherwise the model displays non-linear behaviour. It is important to note that the coefficients for the ESTAR model are symmetric around $y_{t-1} = c$. As y_{t-1} approaches c, θ approaches 0 and the behaviour of y_t is given by $\alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + e_t$. As y_{t-1} moves further from c, θ approaches 1 and the behaviour of y_t is given by $(\alpha_0 + \beta_0) + (\alpha_1 + \beta_1)y_{t-1} + ... + e_t$

The smooth transition models discussed so far contain an autoregressive component. It is also possible to specify a smooth transition model using one of the explanatory variables or an external variable as the transition variable and this type of model is known as a smooth transition regressive (STR) model. This allows for the situation where the transition from one regime to another depends upon one of the explanatory variables or an external variable, say z_t, rather than the first lag of the dependent variable y_{t-1}. In this case $f(z_t)$ is substituted for $f(y_{t-1})$.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \tag{6.14}$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$, $x_t = (y_t, \ldots, y_{t-p}\ ; x_{1t,\ldots}, x_{kt})$ and the variable z_t may be any element of x_t, or another variable not included in x_t or a lag of y_t. For convenience from this point forward the term STR is used to capture models with or without an autoregressive component.

As discussed in Van Dijk, Teräsvirta and Franses (2002) the STR model in its basic form cannot accommodate more than two regimes. At any given point in time y_t is determined as a weighted average of two models, where the weights assigned to the two models depend on the value of the transition function $f(z_t,\gamma,c)$. To obtain a STR model that accommodates more than two regimes, depends on whether the regimes can be characterized by a single transition variable z_t, or by a combination of several variables $x_{1t},\ldots,x_{mt}$. In the situation where there is a combination of several variables the model can be extended to contain 2^m regimes. For example a four-regime model can be obtained by encapsulating two different two-regime LSTR models. Van Dijk and Franses (1999) discuss in detail this multiple regime STR (MRSTR) model.

However, in the situation where there is more than two regimes characterised by a single transition variable, z_t, a three regime STR model can be obtained relatively easily by adding a second non-linear component to give.

$$y_t = \alpha' x_t + \beta' x_t f(z_t, \gamma_1, c_1) + \delta' x_t f(z_t, \gamma_2, c_2) + e_t \tag{6.15}$$

It is assumed that $c_1 < c_2$, the parameters in the model change smoothly from regime 1 via 2 to 3, as z_t increases, as first function f_1 changes from 0 to 1, followed by a similar change of f_2.

In a situation where there is a non-linear process with an unknown functional form, or the non-linear relationship is difficult to fit, the Artificial Neural Network (ANN) can be useful. The simple form of the logistic function ANN is (6.16).

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{n} \alpha_i [1 + \exp(-\gamma_i (y_{t-1} - c_i))]^{-1} + e_t \qquad (6.16)$$

The ANN model only allows the intercept α_0 to time vary and uses n different logistic functions. This allows the model to approximate any AR(1) non-linear model closely. The main drawback to the model is that it has little clear economic interpretation.

The Markov switching model posits that regime switches are exogenous. Rather than being triggered by reaching a certain level of the dependent or explanatory variables, there are fixed probabilities of a regime change. For example in a first-order Markov process, if p11 is the probability of remaining in regime 1, then 1 - p11 is the probability of leaving regime 1 and switching to regime 2. If p22 is the probability of remaining in regime 2, then 1 - p22 is the probability of leaving regime 2 and switching to regime 1. In a Markov switching model no attempt is made to explain the timing of regime changes, the probabilities are estimated with the coefficients in the different regimes.

Markov switching models are useful for modelling systems where there are large shocks which push a system from e.g. low volatility to extremely high volatility.

6.3 Specification and estimation of STR models

In this section the specification and estimation methodology of the smooth transition regressive (STR) model as set out by Granger and Teräsvirta (1993) is reviewed. The methodology for formally testing linearity and if non-linearity is selected, the methodology for selecting from the STR family of models is also described.

A two regime (one-threshold) STR model with m = p + k + 1 independent variables can be written as

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \tag{6.17}$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$, $x_t = (y_t, \ldots, y_{t-p} ; x_{1t, \ldots}, x_{kt})$ and the variable z_t may be any element of x_t, another variable not included in x_t or a lag of y_t.

Choosing $f(z_t) = [1 + \exp(-\gamma(z_t - c))]^{-1}$ yields the logistic STR (LSTR) model where γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit as γ approaches zero or infinity, the LSTR model becomes a linear model since the value of $f(z_t)$ is constant. For intermediate values of γ, the degree of decay depends upon the value of z_t. As z_t approaches $-\infty$, θ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t approaches $+\infty$, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

Choosing $f(z_t) = 1 - \exp(-\gamma(z_t - c)^2)$ yields the exponential STR (ESTR) model. For the ESTR model, as γ approaches infinity or zero the model becomes a linear model as $f(z_t)$ becomes constant. Otherwise the model displays non-linear behaviour. It is important to note that the coefficients for the ESTR model are symmetric around $z_t = c$. As z_t approaches c, $f(z_t)$ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t moves further from c, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

The estimation of STR models consists of three stages following Granger and Teräsvirta (1993):

(a) Specification of a linear model.

The initial step requires a complete specification of a linear model. The maximum lag length of the dependent and independent variables must be determined. Granger and Teräsvirta (1993) recommend a preference for an over-specified model to underspecification as serial correlation in the error term may affect the outcome of linearity tests.

(b) Testing linearity

The second step involves testing linearity against STR models using the linear model specified in (a) as the null. To carry out this test the auxiliary regression is estimated:

$$u_t = \beta_0 ' x_t + \beta_1 ' x_t z_t + \beta_2 ' x_t z_t^2 + \beta_3 ' x_t z_t^3 \qquad (6.18)$$

Where the values of u_t are the residuals of the linear model specified in the first step. The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$. In the absence of theory equation (6.18) can be used to select the transition variable z_t. The test can be carried for each possible candidate for the transition variable. If linearity is rejected for more than one transition variable (whether different lags of y in the autoregressive case, values of x_t or an external variable) then the hypothesis cannot be rejected and the choice of z_t that leads to the smallest P-value is selected.

(c) Choosing between LSTR and ESTR

If linearity is rejected the selection between LSTR and ESTR models is based on the following series of nested F tests.

$$\text{H3: } \beta_3 = 0 \qquad (6.19)$$

$$\text{H2: } \beta_2 = 0 | \ \beta_3 = 0 \qquad (6.20)$$

$$\text{H1: } \beta_1 = 0 | \ \beta_2 = \beta_3 = 0 \qquad (6.21)$$

Accepting (6.19) and rejecting (6.20) implies selecting an ESTR model. Accepting both (6.19) and (6.20) and rejecting (6.21) leads to an LSTR model as well as a rejection of (6.19). The estimation of LSTR models is then carried out by non-linear least squares. Granger and Teräsvirta (1993) argue that strict application of this sequence of tests may lead to incorrect conclusions and suggest the computation of the P-values of the F-tests of (6.19) to (6.21) and make the choice of the STR model on the basis of the lowest *P*-value.

STR models are usually estimated by non-linear least squares although they can also be estimated using maximum likelihood methods. In this research project the STR models are estimated using non-linear least squares in the RATS programme. RATS uses the Marquardt variation of the Gauss-Newton to solve the non-linear least squares regression. Joint estimation of the smoothness parameter, γ, and the transition variable, c, can be difficult, as discussed by Teräsvirta (1994). When γ is large the slope of the transition function at c is steep and a large number of observations in the region of c would be needed to estimate γ accurately. Relatively large changes in γ can have only minor effects on the transition function $f(z_t)$. If γ is large and c is sufficiently close to 0 and estimation is proving difficult Teräsvirta (1994) suggests rescaling the parameters (scaling γ down and c up) or alternatively Teräsvirta (1994) proposes that γ be fixed and estimated only after the final specification has been found.

If convergence is reached then the validity of the model must be evaluated. The first step is to ensure that the estimates seem reasonable. For example, the estimate of c should be within the observed range of z_t and should be consistent with financial theory. Insignificant coefficients suggest that the parameter may be redundant and a more parsimonious model may be more correctly specified. To assess the improvement in specification of the model over the linear counterpart the ratio of the residual standard deviations in the STR and corresponding linear models should be examined. The Akraike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) can also be compared. Finally, evaluation of the model's residuals and residual autocorrelations should be conducted. Teräsvirta (1994) suggests examining the residual standard deviation, the McLeod and Li (1983) test of no Autoregressive Conditional Heteroscedascticity (ARCH) of order k, the skewness and kurtosis of the residual and a Jacque and Bera (1980) test of normality in the errors. In the presence of ARCH or Generalized Autoregressive Conditional Heteroscedasctic (GARCH) effects Lundbergh and Teräsvirta (1999) and Gallagher and Taylor (2001) propose estimating a STR-GARCH model, allowing e_t, the error term, in equation (6.12) to follow a GARCH(p, q) process as in (6.22).

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{6.22}$$

Where $\alpha_0 > 0$, $\alpha_i \geq 0$ for all $i = 1,\ldots, q$, $\beta_i \geq 0$ for all $i = 1,\ldots, p$ are sufficient conditions for $h_t > 0$ for all $t = 1,\ldots, T$. If $\beta_i = 0$ for all $i = 1,\ldots, p$ then GARCH(p, q) reduces to ARCH(q).

6.4 Conclusion

This chapter provided a review of non-linear time series models with particular focus on the smooth transition autoregressive (STAR) and smooth transition regressive (STR) family of models. These models seem particularly useful for examining dynamic trading strategies where non-linearity in the relationship between the returns on these strategies and the returns on common market factors is likely to be characterised by a gradual shift in the relationship rather than a jump.

Chapter 7: Smooth transition models in convertible arbitrage returns

7.1 Introduction

Academic literature on dynamic trading strategies has generally focused on linearly modelling the relationship between the returns of hedge funds which follow such strategies and the asset markets and contingent claims on those assets in which hedge funds operate (see for example Fung and Hsieh (1997), Liang (1999), Schneeweis and Spurgin (1998), Capocci and Hübner (2004) and Agarwal and Naik (2004)). Several studies of hedge funds have documented non-linearity in hedge fund returns. Fung and Hsieh (2001, 2002b) present evidence of hedge fund strategy payoffs sharing characteristics with lookback straddles, and Mitchell and Pulvino (2001) document the returns from a merger arbitrage portfolio exhibiting similar characteristics to a short position in a stock index put option. Financial theory suggests that the relationship between convertible arbitrage returns and risk factors will also be non-linear. By being long a convertible bond and short an underlying stock, funds are hedged against equity market risk but are left exposed to a degree of downside default and term structure risk. When the convertible bond is above a certain threshold it acts more like equity than bond. However, when the convertible bond falls in value it acts more like bond than equity. Effectively, the convertible arbitrageur is short a credit put option.[54] Previous research by Agarwal and Naik (2004) provides evidence that convertible arbitrage hedge fund indices' returns are positively related to the payoff from a short equity index option but

[54] Some convertible arbitrage funds hold credit default swaps to hedge credit risk, however these hedges are likely to be imprecise.

the authors do not consider the relationship between convertible arbitrage and default and term structure risk.

In this chapter evidence is presented of a non-linear relationship between convertible arbitrage hedge fund index returns and default and term structure risk factors. This non-linear relationship is modelled using logistic smooth transition autoregressive (LSTAR) models. These models were developed by Teräsvirsta and Anderson (1992) for modelling non-linearities in the business cycle. To date these models have not been applied in the hedge fund literature. The models have interesting properties which make them very applicable to hedge fund research. In financial markets with many participants operating independently and at different time horizons, movements in asset prices are likely to be smooth.[55] In contrast with the Threshold Autoregressive (TAR) and the Hamilton (1989) Markov regime-switching models the STAR models allow for a gradual shift from one risk regime to another. Evidence is presented here that non-linear models of convertible arbitrage hedge fund index returns are more efficient than their linear alternatives in explaining the relationship between convertible arbitrage returns and risk factors. To test the robustness of these results a similar model is specified for a simulated convertible arbitrage portfolio and again evidence is presented supporting the hypothesis of non-linearity in the relationship between the returns of convertible arbitrage and default and term structure risk factors.

The remainder of the chapter is organised as follows. Section 7.2 outlines the theoretical foundation for the non-linear relationship between convertible arbitrage returns and risk

[55] With the exception of jumps in asset prices in reaction to announcements or major events.

factors. Section 7.3 discusses the data and provides a preliminary analysis. Section 7.4 provides details of the linear models and preliminary evidence of non-linearity in the relationship between convertible arbitrage returns and risk factors. Section 7.5 discusses the empirical results of the non-linear STAR models. Section 7.6 provides conclusions and Section 7.7 highlights any limitations in the analyses and avenues for further research.

7.2 Theoretical foundation for a non-linear relationship

A convertible bond can be divided into a fixed income component and a call option on the equity of the issuer component, which when exercised converts the convertible bond with the underlying equity. Convertible arbitrage derives returns from two principal areas; income from the fixed income component of the convertible bond, and long volatility exposure from the equity option component. Income comes from the coupon paid periodically by the issuer to the holder of the bond. As this coupon is generally fixed it leaves the holder of the convertible bond exposed to term structure risk. As the convertible bond remains a debt instrument until converted, the holder of the convertible bond is also exposed to the risk of default by the issuer.[56] The return from the long volatility exposure comes from the equity option component of the convertible bond. To capture the long volatility exposure, the arbitrageur initiates a dynamic hedging strategy. The hedge is rebalanced as the stock price and/or convertible price move. In order for the volatility exposure to generate positive returns the actual volatility over the life of the

[56] In Chapters 4 and 5 it was demonstrated that default risk and term structure risk are two of the key risks faced by convertible arbitrageurs.

position must be greater than the implied volatility of the convertible bond at the initial set up of the hedge. If the actual volatility is equal to the implied volatility you would expect little return to be earned from the long volatility exposure. If the actual volatility over the life of the position is less than the implied volatility at setup then you would expect the position to have negative non-income returns.

Depending on the delta of the convertible bond, the hedged convertible bond behaves more like a fixed income instrument or a hedged equity option. As the stock price moves below the conversion price of the convertible bond the delta approaches zero and the convertible bond shares the risk characteristics of a corporate bond combined with an out-of-the-money call option, principally default and term structure risk. As the stock price moves toward the conversion price the convertible bond's delta increases and the arbitrageur will begin dynamic hedging to capture volatility. At this stage the relative default and term structure risks of the strategy will lessen and the arbitrageur will face volatility risk.[57]

The empirical analyses presented in Chapters 4 and 5 of this study assumed a linear relationship between convertible arbitrage returns and risk factors. Theory suggests that this relationship is in fact likely to be non-linear. As the stock price moves below the conversion price of the bond and the delta of the convertible bond decreases, a hedged convertible bond's fixed income security characteristics, specifically default and term structure risk, will increase. As the stock price moves above the conversion price the delta of the convertible bond will increase and the hedged convertible bond will act more

[57] In Chapters 4 and 5 this volatility risk was captured by *CBRF* the convertible bond arbitrage risk factor.

like a combination of a hedged option combined and a fixed income security, and the relative fixed income security characteristics, default and term structure risk, will decrease.

To model this relationship for a convertible arbitrage index it is necessary to take an aggregate view of the deltas of convertible bonds held by constituent hedge funds. As the aggregate convertible bond delta decreases, then the convertible arbitrage index will become gradually more exposed to fixed income risk characteristics. As the aggregate convertible bond delta increases the convertible arbitrage index will be gradually less exposed to default and term structure risk and more exposed to volatility risk. As there is no source of aggregate convertible bond deltas, this study proposes using the one period lag of the convertible arbitrage benchmark return, relative to a threshold level, as a proxy. The convertible arbitrage benchmarks represent an aggregate of hedged convertible bonds. If the benchmark generates negative returns then aggregate hedged convertible bonds held by arbitrageurs have fallen in value. This fall in value is caused either by a decrease in the value of the short stock position in excess of the increase in the value of the long corporate bond position or, more likely, a decrease in the value of the long convertible bond position in excess of the increase in the value of the short stock position. When the one period lag of the convertible arbitrage benchmark return is below the threshold level, convertible bond prices and deltas have decreased. As convertible bond prices fall the arbitrageur's portfolio is more exposed to fixed income risk characteristics, and default and term structure risk weightings should increase. When the one period lag of the convertible arbitrage benchmark return is above the threshold level, convertible bond prices and deltas have increased and the portfolio should behave less like a fixed income instrument.

7.3 Data and preliminary analysis

To examine the relationship between convertible arbitrage and its risk factors in a non-linear framework two indices of convertible arbitrage are employed: the CSFB Tremont Convertible Arbitrage Index and the HFRI Convertible Arbitrage Index. The CSFB Tremont Convertible Arbitrage Index is an asset weighted index (rebalanced quarterly) of convertible arbitrage hedge funds beginning in 1994, whereas the HFRI Convertible Arbitrage Index is equally weighted with a start date of January 1990.[58] When looking at the returns to an index of hedge funds, the issue of survivor bias must be addressed.

Survivor bias exists where managers with poor track records exit an index, while managers with good records remain. If survivor bias is large, then the historical returns of an index that studies only survivors will overestimate historical returns. Brown, Goetzmann and Ibbotson (1999) and Fung and Hsieh (1997) have estimated this bias to be in the range of 1.5 per cent to 3 per cent per annum. Although the HFRI and CSFB Tremont indices now control for survivor bias, according to Ackerman, McEnally and Ravenscraft (1999) HFR did not keep data on dead funds before January 1993. This may bias upwards the performance of the HFRI index pre 1993.

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[58] For details on the construction of the CSFB Tremont Convertible Arbitrage Index see www.hedgeindex.com. For details on the construction of the HFRI Convertible Arbitrage Index see www.hfr.com.

Table 7.1, Panel A presents summary statistics of the returns on the two convertible arbitrage indices in excess of the risk free rate of interest.[59] Where *CSFBRF* is the excess return on the CSFB Tremont Convertible Arbitrage Index and *HFRIRF* is the excess return on the HFRI Convertible Arbitrage Index. First note the significantly positive mean monthly excess returns and the relatively low variances of the two indices.[60] This suggests that convertible arbitrage produces high returns relative to risk. Second, the negative skewness and positive kurtosis of the two indices suggests that their returns are non-normally distributed.

Table 7.1
Summary statistics

CSFBRF is the excess return on the CSFB Tremont Convertible Arbitrage index, HFRIRF is the excess return on the HFRI Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio. All of the variables are monthly from January 1990 to December 2002 except the CSFB Tremont Convertible Arbitrage Index which is from January 1994 to December 2002.

	Mean	T-Stat	Variance	Std Error	Skewness	Kurtosis	Jarque-Bera
Panel A: Dependent Variables							
CSFBRF	0.440***	3.291	1.930	1.744	-1.76***	4.61***	151.16***
HFRIRF	0.538***	6.818	0.972	0.986	-1.42***	3.28***	122.46***
Panel B: Explanatory Returns							
DEF	0.540***	3.064	9.391	2.453	-0.37*	2.59***	47.20***
TERM	0.112	0.577	5.825	2.413	-0.36*	0.22	3.65
CBRF	0.325**	2.307	3.104	1.762	-1.36***	9.00***	573.96***

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Statistics are generated using RATS 5.0

[59] For the risk free rate of interest the yield on a 3 month treasury bill, sourced from the Federal Reserve website, www.federalreserve.org, is used.
[60] In discussions in the text statistical significance indicates t-stats are significant from zero at least at the 10% level unless reported.

Table 7.1, Panel B presents summary statistics of the explanatory factor returns. DEF_t, the proxy for default risk, is the difference between the overall return on a market portfolio of long-term corporate bonds (here the return on the CGBI Index of high yield corporate bonds is used) minus the long term government bond return at month t (here the return on the Lehman Index of long term government bonds is used). $TERM_t$ is the factor proxy for unexpected changes in interest rates at time t, or term structure risk. It is constructed as the difference between monthly long term government bond return and the short term government bond return (here the return on the Lehman Index of short term government bonds is used). Evidence is presented in Chapter 4 that convertible arbitrage index returns are positively related to both of these factors. The final factor *CBRF* is a factor proxy for convertible bond arbitrage risk. It is constructed by combining long positions in convertible bonds with short positions in the underlying stock.[61] Hedges are then rebalanced daily. These delta neutral hedged convertible bonds are then combined to create an equally weighted convertible bond arbitrage portfolio. $CBRF_t$ is the monthly return on this portfolio in excess of the risk free rate of interest at time t. Evidence is also presented in Chapter 4 highlighting the positive significant relationship between convertible arbitrage index returns and *CBRF*.

The two market factors *DEF* and *TERM* have low standard errors, but of the two, only *DEF* produces an average return (0.54%) significantly different from zero at the 1% level. *CBRF*'s average return is a significant 0.33%[62] per month with a variance of 3.104. The average return of *CBRF* is lower and the variance higher than the two

[61] For a more detailed discussion of the construction of the *CBRF* factor see Chapters 3 and Chapter 4.
[62] At the 5% level.

convertible arbitrage hedge fund indices, *CSFBRF* and *HFRIRF*. *CBRF* is negatively skewed and has positive kurtosis as do the two hedge fund indices.

Table 7.2
Cross correlations January 1990 to December 2002

CSFBRF is the excess return on the CSFB Tremont Convertible Arbitrage index, HFRIRF is the excess return on the HFRI Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio. All of the correlations cover the period January 1990 to December 2002 except for correlations with the CSFB Tremont Convertible Arbitrage Index which cover the period January 1994 to December 2002.

	TERM	*DEF*	*CSFBRF*	*HFRIRF*	*CBRF*
TERM	1.00				
DEF	-0.71	1.00			
CSFBRF	0.04	0.23	1.00		
HFRIRF	0.09	0.27	0.80	1.00	
CBRF	0.01	0.39	0.32	0.48	1.00

With the exception of the *CSFBRF* correlations, coefficients greater than 0.25, 0.19 and 0.17 are significant at the 1%, 5% and 10% levels respectively.
CSFBRF correlation coefficients greater than 0.22, 0.17 and 0.14 are significant at the 1%, 5% and 10% levels respectively.

Table 7.2 presents the correlations between the two dependent variables, *CSFBRF* and *HFRIRF* and the explanatory variables. Both of the variables are highly correlated with a coefficient of 0.80. Both are positively related to *DEF* the default risk factor and *CBRF* the factor proxy for convertible bond arbitrage risk. *CBRF* is positively correlated with *DEF* and *TERM* is negatively correlated with *DEF*.

7.4 Estimating the linear model

This section reviews the linear specification of the risk factor model defined and estimated in Chapters 4 and 5. In Chapter 4 a broad set of asset classes was defined and the exposure of hedge fund indices to those assets was identified. The most significant factors, default risk, *DEF*, term structure risk, *TERM*, and convertible bond arbitrage risk, *CBRF*, were combined in a linear risk factor model. As the residuals of the linear factor model were first order autocorrelated a lag of the hedge fund index, y_{t-1}, was included, primarily to ensure unbiased estimates of the alpha and beta coefficients, but the y_{t-1} coefficient can also be interpreted as a measure of illiquidity in the securities held by hedge funds. Following the identification of individual fund risk exposures in Chapter 5, the effectiveness of the individual funds' activities was compared with that of a passive investment in the asset mixes. In this section results from estimating the linear model for the hedge fund indices are presented. Initially the model is estimated for the entire sample period. Results are then presented for sub-samples ranked by the one period lag of the hedge fund benchmark returns, providing initial evidence of non-linearity in the relationship between convertible arbitrage and risk factors.

7.4.1 Estimating the model for the full sample

Table 7.3 presents the results of estimating the following linear model of HFRI convertible arbitrage index returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t \qquad (7.1)$$

Where y_t is the excess return on the HFRI Convertible Arbitrage index at time t. $TERM_t$ and DEF_t are term structure and default risk factors at time t. $CBRF_t$ is the excess return on the simulated convertible arbitrage portfolio at time t. y_{t-1} is the excess return on the HFRI Convertible Arbitrage index at time $t-1$.

Table 7.3
HFRI linear model

This table presents the results from estimating the following model of convertible arbitrage returns

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where y is the excess return on the HFRI Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio. Panel A covers the entire sample period from January 1990 to December 2002 whereas Panel B covers the period free from survivor bias, January 1993 to December 2002.

Panel A: HFRI Linear Multi Factor Model 1990 – 2002

α	β_{CBRF}	β_{DEF}	β_{TERM}	β_Y	Adj. R^2	AIC	SBC
0.1343	0.0957	0.1710	0.1930	0.4961	54.15%	654.82	670.04
(1.67)*	(2.28)**	(3.30)***	(4.30)***	(8.51)***			

Panel B: HFRI Linear Multi Factor Model 1993 – 2002

α	β_{CBRF}	β_{DEF}	β_{TERM}	β_Y	Adj. R^2	AIC	SBC
0.1393	0.1338	0.1831	0.2120	0.4947	51.22%	484.37	498.26
(1.47)	(2.11)**	(2.81)***	(3.89)***	(7.00)***			

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Panel A covers the entire sample period from January 1990 to December 2002. This includes the period from 1990 to 1992 when HFRI excluded failed funds. The coefficients are all positive and significantly different from zero. Panel B covers the period free from survivor bias, January 1993 to December 2002. Again all coefficients, with the exception of α, are positive and significantly different from zero and the magnitude of the coefficients is almost identical to the results for the entire sample period.

Table 7.4
CSFB linear model

This table presents the results from estimating the following models of convertible arbitrage returns

$$j_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_j j_{t-1} + \varepsilon_t$$

$$j_t = \alpha + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_j j_{t-1} + \varepsilon_t$$

Where *j* is the excess return on the CSFB Tremont Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio.

Panel A: CSFB Linear Multi Factor Model 1994 – 2002

α	β_{CBRF}	β_{DEF}	β_{TERM}	β_J	Adj. R^2	AIC	SBC
0.0666	0.0456	0.2584	0.2659	0.6046	48.58%	505.03	518.39
(0.53)	(0.83)	(2.82)***	(3.77)***	(6.38)***			

Panel B: CSFB Linear Multi Factor Model omitting *CBRF* 1994 – 2002

α	β_{CBRF}	β_{DEF}	β_{TERM}	β_J	Adj. R^2	AIC	SBC
0.0771		0.2734	0.2799	0.6104	48.96%	503.28	513.97
(0.75)		(6.40)***	(5.06)***	(8.70)***			

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 7.4 presents results of estimating two linear models of CSFB convertible arbitrage index returns. Panel A presents the results from estimating equation (7.2) while Panel B presents the results from estimating equation (7.3).

$$j_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_j j_{t-1} + \varepsilon_t \quad (7.2)$$

$$j_t = \alpha + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_j j_{t-1} + \varepsilon_t \quad (7.3)$$

Where j_t is the excess return on the CSFB Tremont Convertible Arbitrage index at time *t* and j_{t-1} is the excess return on the CSFB Tremont Convertible Arbitrage index at time *t-1*. All of the factors other than *CBRF* are positive and significantly different from zero. Excluding *CBRF* in Panel B leads to a slight improvement in the explanatory power of the model.

7.4.2 Re-estimating the linear model in sub-samples ranked and subdivided by previous month's returns

In this section preliminary evidence of the non-linearity in hedge fund index returns is presented. Ranking the sample and estimating the linear risk factor model in the different sub-samples provides a simple analysis of the default and term structure risk factor coefficients' constancy. Table 7.5 presents results of ranking the entire sample from 1990 to 2002 by the one period lag of the excess hedge fund benchmark return, y_{t-1}, subdividing into five equal sized sub-samples and re-estimating equation (7.1) for each sub-sample period. Under the hypothesised non-linearity the default and term structure coefficients, β_{DEF} and β_{TERM} should increase in magnitude and significance as the one period lag of the hedge fund benchmark return decreases.

Table 7.5
HFRI sample subdivided by one month lag of HFRI excess returns

This table presents results from estimating the following regression on HFRI convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by one month lagged HFRI excess returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_y y_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, y_{t-1} is the one moth lag of the HFRI convertible arbitrage excess returns, *DEF* is the factor proxying for default risk and *TERM* is the factor proxying for term structure risk.

	α	β_{CBRF}	β_{DEF}	β_{TERM}	β_Y	Adj. R^2
Lowest 31	-0.0810	-0.1424	0.3876	0.4066	0.4782	52.28%
	(-0.37)	(-1.61)	(4.53)***	(7.14)***	(4.40)***	
Next lowest 31	-0.2634	0.1618	0.1697	0.2281	1.6926	46.42%
	(-0.95)	(2.23)**	(1.78)*	(3.01)***	(2.29)**	
Middle 31	0.9397	0.0755	0.1450	0.1814	-0.4953	37.03%
	(1.33)	(1.28)	(4.76)***	(4.92)***	(-0.53)	
Next highest 31	0.1897	0.1371	0.0428	0.0720	0.4883	17.06%
	(0.35)	(4.18)***	(1.52)	(2.19)**	(0.92)	
Highest 31	1.0516	0.1257	0.0027	0.0373	-0.0265	6.61%
	(5.05)***	(1.72)*	(0.08)	(1.31)	(-0.23)	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Three results should be noted from this table. The first is that the adjusted R^2 of regression model reduces across the sub-sample periods from lowest y_{t-1} period to highest. In the lowest y_{t-1} period the adjusted R^2 is greatest and in the highest y_{t-1} period the adjusted R^2 is lowest. The second is that both the magnitude and significance of the *DEF* and *TERM* factor coefficients gradually decreases from the lowest y_{t-1} period to the highest y_{t-1} period. The final result to be noted is that the *CBRF* coefficient is negative in the lowest y_{t-1} period (significant at the 15% level) and significantly positive in the highest y_{t-1} period.[63] This provides initial evidence in support of the hypothesis that arbitrageurs' portfolio risk exposure varies depending on previous month's returns.

Table 7.6
CSFB sample subdivided by one month lag of CSFB excess returns

This table presents results from estimating the following regression on CSFB convertible arbitrage excess returns. The sample has been subdivided into five equal sized sub-samples ranked by one month lagged CSFB excess returns.

$$j_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_j j_{t-1} + \varepsilon_t$$

Where *CBRF* is the convertible bond arbitrage factor, j_{t-1} is the one moth lag of the CSFB convertible arbitrage excess returns, *DEF* is the factor proxying for default risk and *TERM* is the factor proxying for term structure risk.

	α	β_{CBRF}	β_{DEF}	β_{TERM}	β_J	Adj. R^2
Lowest 27	-0.1585	-0.1368	0.5534	0.5718	0.5920	49.49%
	(-0.78)	(-1.06)	(3.58)***	(4.44)***	(7.95)***	
Next lowest 27	-0.6326	0.2052	0.1661	0.0590	2.3284	43.20%
	(-1.75)*	(1.42)	(2.16)**	(0.50)	(2.56)**	
Next highest 27	0.6074	0.0827	0.2044	0.2330	-0.1037	7.10%
	(0.61)	(0.79)	(1.55)	(2.14)**	(-0.09)	
Highest 27	-0.0487	-0.1001	0.0652	0.1028	0.8039	32.66%
	(-0.12)	(-1.46)	(1.93)*	(2.12)**	(3.71)***	

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 7.6 presents results from a similar analysis of the CSFB Tremont Convertible Arbitrage index. For this analysis the sample is ranked from 1994 to 2002 by the one period lag of the CSFB Tremont excess return, j_{t-1}, subdivided into four equal sized sub-samples and equation (2) is re-estimated for each sub-sample.[64] The results for the CSFB Tremont index again point to non-linearity in the relationship between convertible

[63] This process was repeated, limiting the sample from January 1993 to December 2002, the period free from survivor bias, with similar results.
[64] As the sample period is shorter for the CSFB Tremont series, four rather than five sub-sample period is used.

arbitrage returns and risk factors. In the lowest j_{t-1} period the adjusted R^2 is greatest and in the highest j_{t-1} period the adjusted R^2 is lower, although in the second highest period the adjusted R^2 is lowest. Again both the magnitude and significance of the *DEF* and *TERM* factors decreases from the lowest j_{t-1} period to the highest j_{t-1} period providing further evidence in support of the hypothesis that convertible arbitrage risk factor coefficients vary.

7.5 Results of estimating STAR models

The previous section has provided initial evidence of a non-linear relationship between convertible bond arbitrage and risk factors supporting the theoretical relationship of two alternative risk regimes. When the convertible arbitrage index returns are below a threshold level, due to decreases in convertible bond prices, in the following month the index exhibits relatively large default and term structure risk; whereas in the alternate regime when the convertible arbitrage index returns are above a threshold level, the index exhibits relatively lower default and term structure risk. In this section this non-linearity is modelled using a smooth transition autoregressive (STAR) model. Initially the two convertible arbitrage hedge fund indices are modelled. As a robustness check the analysis is repeated for the simulated convertible arbitrage portfolio.

STAR models are specified for three principle reasons. (1) They incorporate two alternate regimes, corresponding with the theoretical relationship between convertible arbitrage returns and risk factors. One regime where the portfolio is more exposed to default and term structure risk and a second regime where the portfolio is less exposed to default and term structure risk and more exposed to the convertible arbitrage risk factor. (2) They incorporate a smooth transition from one risk regime to another. In financial markets with many participants operating independently and at different time horizons, movements in asset prices and risk weightings are likely to be smooth rather than sharp. (3) When estimating the STAR model no *ex ante* knowledge of the threshold variable c is required. This threshold is estimated simultaneously with the coefficients of the model. The only *ex ante* expectation of the level of the threshold is that it lies between the minimum and maximum of the threshold variable, the one period lag of the hedge fund benchmark return series.[65] Below the threshold it is hypothesised that the index will have more fixed income risk characteristics. Above the threshold it will have less fixed income risk characteristics.

7.5.1 STAR analysis of the hedge fund indices

A two regime (one-threshold) STAR model with m = p + k + 1 independent variables can be written as

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \qquad (7.4)$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$, $x_t = (y_t, \ldots, y_{t-p}\,; x_{1t,\ldots}, x_{kt})$ and the variable z_t is a lag of y_t.

[65] Although it is likely to be less than zero.

Choosing $f(z_t) = [1 + \exp(-\gamma(z_t - c))]^{-1}$ yields the logistic STAR (LSTAR) model where γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit as γ approaches zero or infinity, the LSTAR model becomes a linear model since the value of $f(z_t)$ is constant. For intermediate values of γ, the degree of decay depends upon the value of z_t. As z_t approaches $-\infty$, θ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t approaches $+\infty$, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

Choosing $f(z_t) = 1 - \exp(-\gamma(z_t - c)^2)$ yields the exponential STAR (ESTAR) model. For the ESTAR model, as γ approaches infinity or zero the model becomes a linear model as $f(z_t)$ becomes constant. Otherwise the model displays non-linear behaviour. It is important to note that the coefficients for the ESTR model are symmetric around $z_t = c$. As z_t approaches c, $f(z_t)$ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t moves further from c, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

The estimation of STAR models for the hedge fund indices consists of three stages:

(a) Specification of a linear autoregressive (AR) model. In Chapter 4 an AR model is estimated for both the CSFB Tremont and HFRI Convertible Arbitrage Indices. This specification is used here:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{7.5}$$

Where y_t is the excess return on the hedge fund index, and x_t is a matrix of convertible bond arbitrage risk factors (y_{t-1}, DEF_t, $TERM_t$, $CBRF_t$).

(b) Testing linearity, for different values of the delay parameter d, against STAR models using the linear model specified in (a) as the null. To carry out this test the auxiliary regression is estimated:

$$u_t = \beta_0 z_t + \beta_1 x_t z_t + \beta_2 x_t z_t^2 + \beta_3 x_t z_t^3 \tag{7.6}$$

Where the values of u_t are the residuals of the linear model specified in the first step. The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$. If linearity is accepted the hypothesis of non-linearity in the relationship between convertible arbitrage returns and risk factors must be rejected. If however, linearity is rejected for more than one value of d then the hypothesis is not rejected and the lag that leads to the smallest P-value is selected.

(c) The selection between LSTAR and ESTAR models is based on the following series of nested F tests.

$$\text{H3: } \beta_3 = 0 \tag{7.7}$$

$$\text{H2: } \beta_2 = 0 | \beta_3 = 0 \tag{7.8}$$

$$\text{H1: } \beta_1 = 0 | \beta_2 = \beta_3 = 0 \tag{7.9}$$

Accepting (7.7) and rejecting (7.8) implies selecting an ESTAR model. Accepting both (7.7) and (7.8) and rejecting (7.9) leads to an LSTAR model as well as a rejection of (7.7). The estimation of LSTAR models is then carried out by non-linear least squares. Granger and Teräsvirsta (1993) argue that strict application of this sequence of tests may lead to incorrect conclusions and suggest the computation of the *P*-values of the *F*-tests of (7.7) to (7.9) and make the choice of the STAR model on the basis of the lowest *P*-value. Given the theoretical relationship between convertible arbitrage returns and risk factors it would be expected that the LSTAR model would be chosen over the ESTAR.

The linearity tests for the HFRI Convertible Arbitrage Index for the period January 1990 to December 2002 are displayed in the first row of Table 7.7, Panel A. In carrying out linearity tests the values for the delay parameter d over the range $1 \leq d \leq 8$ were considered, and the *P*-values for the linearity test were calculated in each case. The delay parameter d is chosen by the lowest *P*-value. Linearity is rejected at levels of $d = 1$, 2 and 3 but the lowest *P*-value is for $d = 1$ so, consistent with expectations, y_{t-1}, the one period lag of the hedge fund benchmark return, is chosen as the transition variable z_t. When the sample is restricted to the survivor bias free January 1993 to December 2002, in Table 7.7, Panel B, the results are almost identical and again the lowest *P*-value is for $d = 1$. The linearity tests of the CSFB Tremont index are presented in the first row of Table 7.8. Linearity is rejected at levels of $d = 1$, 2 and 3 and the lowest *P*-value is again at $d = 1$ so y_{t-1}, the one period lag of the hedge fund benchmark return, is chosen as the transition variable z_t.

Table 7.7
Results for *F*-Tests of non-linearity and tests of L-STAR against E-STAR for HFRI

This table presents the results from a series of *F*-tests carried out after estimating the following auxiliary regression.

$$u_t = \beta_0 z_t + \beta_1 z_t x_t + \beta_2 z_t x_t^2 + \beta_3 z_t x_t^3$$

Where the values of u_t are the residuals of the HFRI linear model in Table 7.3.
The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$.
The selection between L-STAR and E-STAR models is based on the following series of nested *F* tests.

$$H_3 : \beta_3 = 0$$
$$H_2 : \beta_2 = 0 | \beta_3 = 0$$
$$H_1 \; \beta_1 = 0 | \beta_2 = \beta_3 = 0$$

Panel A covers the entire sample from January 1990 to December 2002 while Panel B covers the period January 1993 to December 2002 free from survival bias.

Panel A: *F*-Tests Results for HFRI 1990 – 2002

	d = 1	d = 2	d = 3	d = 4	d = 5	d = 6	d = 7	d = 8
H_0	0.0001***	0.0240**	0.0511*	0.2297	0.4432	0.6431	0.1587	0.0455**
H_3	0.0661*	0.2425	0.2038	0.9502	0.2791	0.9952	0.9550	0.7983
H_2	0.0450**	0.4380	0.0960*	0.1751	0.7251	0.5509	0.0232**	0.1077
H_1	0.0003***	0.0059***	0.1273	0.0783*	0.2994	0.1566	0.2973	0.0145**

Panel B: *F*-Tests Results for HFRI 1993 – 2002

	d = 1	d = 2	d = 3	d = 4	d = 5	d = 6	d = 7	d = 8
H_0	0.0001***	0.0009***	0.2945	0.3252	0.8820	0.8770	0.2610	0.0167**
H_3	0.3331	0.2905	0.8692	0.6301	0.4502	0.7554	0.9233	0.7146
H_2	0.0220**	0.0216**	0.3251	0.2443	0.9003	0.7746	0.0208**	0.2095
H_1	0.0001***	0.0017***	0.0759*	0.2212	0.7741	0.5480	0.6926	0.0017***

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 7.8
Results for *F*-Tests of non-linearity and tests of L-STAR against E-STAR for CSFB

This table presents the results from a series of *F*-tests carried out after estimating the following auxiliary regression.

$$u_t = \beta_0 z_t + \beta_1 z_t x_t + \beta_2 z_t x_t^2 + \beta_3 z_t x_t^3$$

Where the values of u_t are the residuals of the linear model in Table 7.4 Panel A.
The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$.
The selection between L-STAR and E-STAR models is based on the following series of nested *F* tests.

$$H_3: \beta_3 = 0$$
$$H_2: \beta_2 = 0 | \beta_3 = 0$$
$$H_1\ \beta_1 = 0 | \beta_2 = \beta_3 = 0$$

***F*-Tests Results for CSFB 1994 – 2002**

	d = 1	d = 2	d = 3	d = 4	d = 5	d = 6	d = 7	d = 8
H_0	0.0004***	0.0006***	0.0152**	0.4380	0.8441	0.2624	0.9022	0.7411
H_3	0.9955	0.9465	0.4655	0.3073	0.8608	0.8414	0.6531	0.4209
H_2	0.5868	0.1778	0.3780	0.5128	0.6201	0.4107	0.6314	0.4447
H_1	0.0000***	0.0000***	0.0046***	0.3901	0.3710	0.7377	0.9387	0.6834

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

The tests for the choice between ESTAR and LSTAR for the HFRI index are shown in Table 7.7 Panel A and B rows 2 to 4. Although not clear cut, at $d = 1$ for the entire sample period, the lowest *P*-value is for H_1 indicating an LSTAR model. The *F*-test results for the sample period 1993 to 2002 support this with again the lowest *P*-value for $d = 1$. Table 7.8 rows 2 to 4 presents the nested *F*-tests for the CSFB Tremont index and the statistics indicate an LSTAR model.

Table 7.9
Linear AR models of convertible arbitrage hedge fund index returns

This table presents results of the linear autoregressive model convertible arbitrage returns. Panel A covers the HFRI entire sample period from January 1990 to December 2002 whereas Panel B covers the period HFRI free from survivor bias, January 1993 to December 2002. Panel C presents results from estimating the CSFB model. σ_e is the residual standard deviation, SK is skewness, EK is kurtosis, JB is the Jacque-Bera test of normality in the residuals, JB Sig. is the *P*-Value of the Jacque-Bera statistic, ARCH(q) is the LM test of no ARCH effects up to order *q*, ARCH Sig is the *P*-Value of the LM test statistic, AIC is the Akraike Information Criteria and SBC is the Schwartz Bayesian Criterion.

	A. HFRI 1990 -2002		B. HFRI 1993 - 2002		C. CSFB 1994 – 2002	
α_0	0.13	(1.67)*	0.14	(1.47)	0.07	(0.53)
α_{yt-1}	0.50	(8.51)***	0.49	(7.00)***	0.60	(6.38)***
α_{CBRF}	0.10	(2.28)**	0.13	(2.11)**	0.05	(0.83)
α_{DEF}	0.17	(3.30)***	0.18	(2.81)***	0.26	(2.82)***
α_{TERM}	0.19	(4.30)***	0.21	(3.89)***	0.27	(3.77)***
σ_e	0.21		0.34		0.83	
SK	-0.19		-1.16		-1.38	
EK	2.09		2.75		3.68	
JB	29.06***		64.69***		95.07***	
JB Sig	(0.00)		(0.00)		(0.00)	
ARCH(4)	12.01***		8.10***		27.84***	
ARCH Sig	(0.02)		(0.09)		(0.00)	
AIC	654.82		484.37		505.03	
SBC	670.04		498.26		518.39	

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Following the results of the series of *F*-tests the LSTAR model (7.4) of convertible arbitrage index returns was then specified and estimated for the hedge fund indices.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \quad (7.4)$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$ and $x_t = (1, y_{t-1}, DEF_t, TERM_t, CBRF_t)$ and $f(z_t) = [1+\exp(-\gamma(y_{t-d} - c))]^{-1}$ where $d = 1$ for the HFRI index and the CSFB Tremont index.

Table 7.10
Results of L-STAR model for HFRI and CSFB

This table presents results from estimating the following logistic smooth transition regression models L-STAR of convertible arbitrage returns.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$ and $x_t = (1, y_{t-1}, DEF_t, TERM_t, CBRF_t)$ and $f(z_t) = [1+\exp(-\gamma(y_{t-d} - c))]^{-1}$ where $d = 1$ for the HFRI index and the CSFB Tremont index. σ_{nl}/σ_{lin} is the ratio of the residual standard deviations in the estimated non-linear and linear models, σ_e is the residual standard deviation, SK is skewness, EK is kurtosis, JB is the Jacque-Bera test of normality in the residuals, JB Sig. is the *P*-Value of the Jacque-Bera statistic, ARCH(q) is the LM test of no ARCH effects up to order *q*, ARCH Sig is the *P*-Value of the LM test statistic, AIC is the Akraike Information Criteria and SBC is the Schwartz Bayesian Criterion.

	A. HFRI 1990 -2002		B. HFRI 1993 - 2002		C. CSFB 1994 – 2002	
α_0	-0.31	(-2.05)**	-0.36	(-1.84)*	-0.61	(-1.41)
α_{yt-1}	0.40	(3.10)***	0.43	(2.75)***	0.65	(4.06)***
α_{CBRF}	-0.22	(-1.61)	0.08	(0.82)	-0.11	(-0.63)
α_{DEF}	0.51	(6.37)***	0.55	(7.25)***	0.97	(7.07)***
α_{TERM}	0.49	(5.70)***	0.50	(7.40)***	0.84	(6.65)***
β_0	0.81	(3.76)***	0.86	(3.23)***	0.57	(1.14)
β_{yt-1}	-0.13	(-0.74)	-0.15	(-0.71)	0.10	(0.62)
β_{CBRF}	0.36	(2.27)**	0.06	(0.38)	0.14	(0.72)
β_{DEF}	-0.48	(-5.22)***	-0.53	(-6.08)***	-0.78	(-5.39)***
β_{TERM}	-0.41	(-4.11)***	-0.42	(-4.44)***	-0.64	(-4.62)***
c	0.10	(1.00)	0.07	(0.66)	-0.76	(-2.32)**
γ	4.85	(2.54)***	4.34	(3.20)***	2.66	(3.94)***
σ_{nl}/σ_{lin}	0.80		0.50		0.47	
σ_e	0.17		0.17		0.39	
SK	-0.17		-0.16		-1.24	
EK	0.93		0.45		4.87	
JB	6.32		1.54		133.10	
JB Sig	0.04		0.46		0.00	
ARCH(4)	6.03		3.03		0.25	
ARCH Sig	0.20		0.55		0.99	
AIC	633.99		462.97		497.72	
SBC	670.52		496.32		529.80	

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

The LSTAR models are estimated by non-linear least squares. As discussed in Chapter 6 with a limited number of observations around c, the LSTAR model can be difficult to estimate. Following Teräsvirta (1994) the models were initially estimated with γ fixed and when the model was fully specified γ was re-estimated.[66] The parameter estimates together with the diagnostic statistics are reported in Table 7.10. For convenient comparison the results of the linear AR models and the relevant test statistics are presented in Table 7.9. The ARCH(4) test statistic indicates the presence of autoregressive conditional heteroscedascticity in the error term of the estimated linear models.

To eliminate redundant parameters in the LSTAR modes a series of F-tests was next carried out on insignificant parameters. Coefficients were set equal to zero if F-tests failed to reject that the coefficient was equal to zero. Table 7.11 reports results from estimating parsimonious LSTAR models following F-Tests of redundant parameters. The ratio of the residual standard deviations in the estimated non-linear and linear models, σ_{nl}/σ_{lin}, gives an indication of the efficiency gain of the non-linear model over the linear model. This ranges from 0.48 to 0.80, providing evidence of the large efficiency gain from estimating the non-linear model relative to the linear model. The ARCH(4) test statistics indicate that the autoregressive conditional heteroscedascticity present in the linear models has disappeared. Kurtosis and skewness in the residuals is now smaller

[66] To ensure the robustness of the estimated coefficients the estimation procedure was repeated using a range of initial lambda estimates from 0 to 10.

with the exception of kurtosis in the CSFB Tremont residuals. The residuals of two of the models remain non-normal.

The $y_{t-1} < c$ regime *DEF* coefficients are all significantly positive ranging from 0.55 to 0.99. The *DEF* coefficients range from 0.05 for the HFRI index, in the upper $y_{t-1} > c$ regime to 0.22 for the CSFB index. The alphas are significantly negative in the $y_{t-1} < c$ regime and significantly positive in the $y_{t-1} > c$ regime with the exception of the CSFB alphas which are not significantly different from zero. *CBRF* the convertible arbitrage risk factor is significantly negative in the $y_{t-1} < c$ regime and significantly positive in the $y_{t-1} > c$ regime in the HFRI 1990 to 2002 sample period. The y_{t-1} coefficients are lower relative to the linear model for the HFRI index. In the $y_{t-1} < c$ regime the coefficient is 0.40 and the coefficient is equal to 0.25 in the $y_{t-1} > c$ regime. In the linear model the coefficient on y_{t-1} is 0.50 for the HFRI index. Relaxing the restriction of linearity appears to reduce the estimated serial correlation. The threshold point, *c*, for the two HFRI sample periods is not significantly different from zero. For the CSFB Tremont index the threshold ranges from -0.7% to -1.0%, though Teräsvirta (1994) acknowledges the difficulty in estimating *c* precisely when there are few observations in the vicinity. The relatively low estimate of *c* for the CSFB Tremont index leaves fewer observations in the $y_{t-1} < c$ regime relative to the $y_{t-1} > c$ regime. As discussed in Teräsvirta (1994) symmetry in the division of observations between the regimes increases confidence in the model.

The results from the HFRI and CSFB Tremont indices provide evidence to support the existence of two risk regimes for convertible arbitrage. Consistent with theoretical expectations, in the $y_{t-1} < c$ regime when convertible arbitrage returns are below the threshold level the convertible arbitrage indices have increased default and term structure risk coefficients. In the $y_{t-1} > c$ regime when convertible arbitrage returns are above the threshold level the default and term structure risk coefficients decrease. In this regime the portfolio exhibits less fixed income risk characteristics and in the case of the HFRI 1990-2002 sample exhibits an increase in exposure to the convertible bond arbitrage risk factor.

There is clear evidence of the existence of two regimes. The coefficients on *DEF* and *TERM* are far larger when previous month's returns are negative in each of the three models. When previous month's returns become positive the risk factor weightings become smaller. The existence of these two regimes provides evidence to support the hypothesis of variation in portfolio risk depending on previous month's returns.

Table 7.11
Results of parsimonious L-STAR model for HFRI and CSFB

This table presents results from estimating the following logistic smooth transition regression models L-STAR of convertible arbitrage returns.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$ and $x_t = (1, y_{t-1}, DEF_t, TERM_t, CBRF_t)$ and $f(z_t) = [1+\exp(-\gamma(y_{t-d} - c))]^{-1}$ where $d = 1$ for the HFRI index and $d = 2$ for the CSFB Tremont index. σ_{nl}/σ_{lin} is the ratio of the residual standard deviations in the estimated non-linear and linear models, σ_e is the residual standard deviation, SK is skewness, EK is kurtosis, JB is the Jacque-Bera test of normality in the residuals, JB Sig. is the *P*-Value of the Jacque-Bera statistic, ARCH(q) is the LM test of no ARCH effects up to order *q*, ARCH Sig is the *P*-Value of the LM test statistic, AIC is the Akraike Information Criteria and SBC is the Schwartz Bayesian Criterion.

	A. HFRI 1990 -2002		B. HFRI 1993 - 2002		C. CSFB 1994 – 2002	
α_0	-0.40	(-1.83)*	-0.44	(-1.90)*	-0.24	(-0.69)
α_{yt-1}	0.34	(2.61)***	0.38	(2.76)***	0.77	(8.48)***
α_{CBRF}	-0.25	(-2.11)**				
α_{DEF}	0.55	(6.45)***	0.60	(10.38)***	0.99	(8.28)***
α_{TERM}	0.49	(4.14)***	0.53	(5.48)***	0.86	(7.03)***
β_0	0.80	(2.44)**	0.87	(2.33)**	0.19	(0.45)
β_{yt-1}						
β_{CBRF}	0.39	(2.77)***				
β_{DEF}	-0.50	(-5.19)***	-0.52	(-6.83)***	-0.77	(-6.19)***
β_{TERM}	-0.39	(-2.98)***	-0.39	(-3.51)***	-0.63	(-4.94)***
c					-1.04	(-4.13)***
γ	5.07	(3.13)***	5.02	(2.45)**	2.08	(4.45)***
σ_{nl}/σ_{lin}	0.80		0.53		0.48	
σ_e	0.17		0.18		0.40	
SK	-0.27		-0.06		-1.17	
EK	1.20		0.38		4.67	
JB	11.25		0.78		121.44	
JB Sig	0.00		0.68		0.00	
ARCH(4)	6.03		3.22		0.17	
ARCH Sig	0.20		0.52		1.00	
AIC	634.74		469.96		497.95	
SBC	671.26		503.31		530.02	

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Graphs of the transition functions are presented in Figures 7.1, 7.2 and 7.3. The smoothness of the HFRI 1990 to 2002 sample and HFRI 1993 to 2002 sample are similar (with $\gamma = 5.07$ and 5.02 respectively). The CSFB transition function is smoother, with $\gamma = 2.08$, which can be seen in the lower slope in the function. The division of observations between the two regimes is asymmetric reflecting the positive performance of convertible arbitrage over the sample period.

Figure 7.1 HFRI L-STAR model transition function: F[Y(t-1)] against Y(t-1)

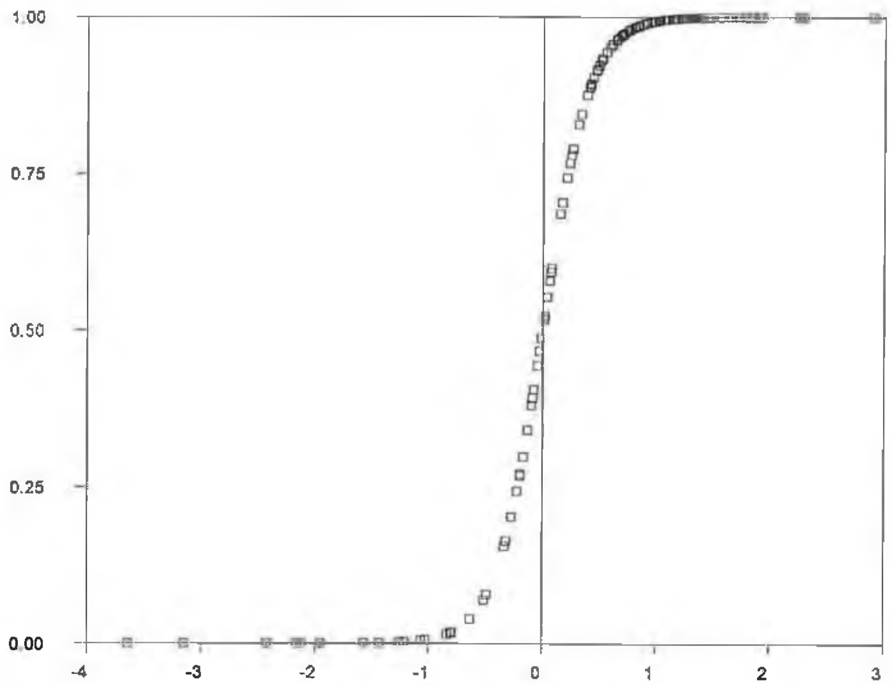


Figure 7.2 HFRI L-STAR model transition function (1993 to 2002)

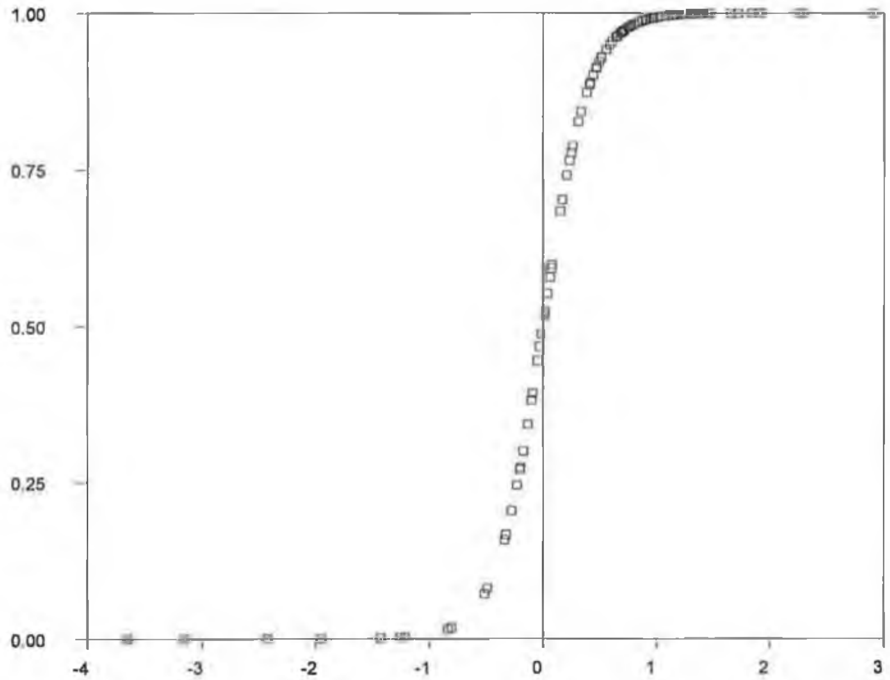
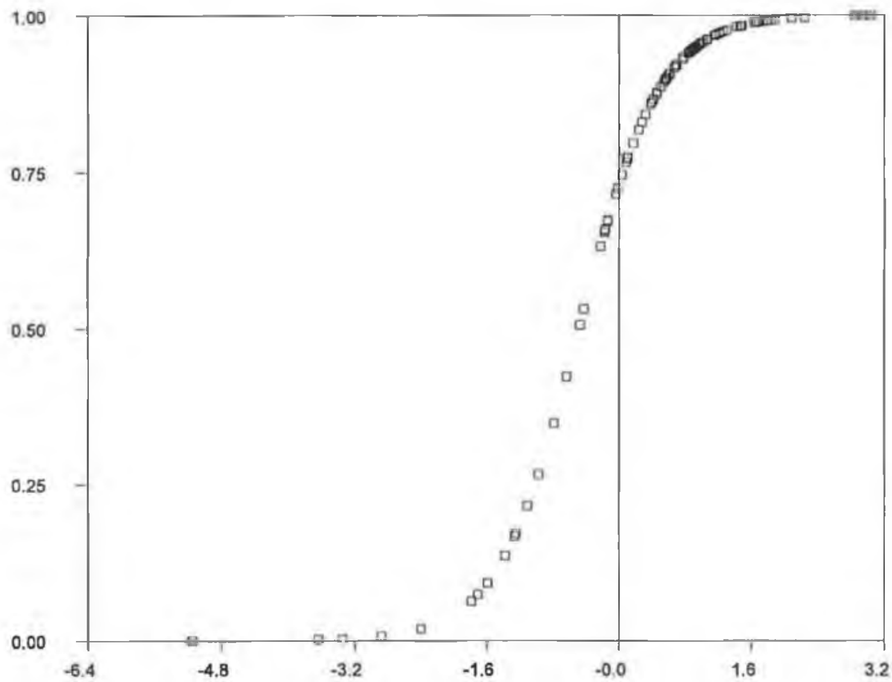


Figure 7.3 CSFB L-STAR model transition function (1993 to 2002)



7.5.2 STAR analysis of the simulated convertible arbitrage portfolio

To test the robustness of the findings for the hedge fund indices, this section models the returns of the simulated convertible arbitrage portfolio using a similar STAR analysis. The simulated convertible bond portfolio is an equally weighted portfolio of delta neutral hedged long convertible bonds and short stock positions created in Chapter 3 for evaluating convertible arbitrage risk.[67] Evidence is presented in Chapters 3 and 4 documenting the similar risk characteristics of this simulated portfolio and the hedge fund indices.

The estimation of STAR models for the simulated convertible arbitrage portfolio consists of three stages:

(a) Specification of a linear autoregressive (AR) model. Equation (7.5), the AR model for the hedge fund indices is adjusted for the simulated convertible arbitrage portfolio in (7.11). The following AR model is specified:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{7.11}$$

Where y_t is the excess return on the simulated convertible arbitrage portfolio, and x_t is the lag of the excess return on the simulated portfolio, and default and term structure risk factors (y_{t-1}, DEF_t, $TERM_t$).

[67] For details on the construction of the simulated portfolio see Chapter 3.

(b) Testing linearity, for different values of the delay parameter d, against STAR models using the linear model specified in (a) as the null. To carry out this test the auxiliary regression is estimated:

$$u_t = \beta_0 z_t + \beta_1 x_t z_t + \beta_2 x_t z_t^2 + \beta_3 x_t z_t^3 \tag{7.6}$$

Where the values of u_t are the residuals of the linear model specified in the first step. The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$. If linearity is rejected for more than one value of d then, in the absence of theory, the lag that leads to the smallest P-value is normally selected.

(c) The selection between LSTAR and ESTAR models is based on the following series of nested F tests.

$$\text{H3: } \beta_3 = 0 \tag{7.7}$$

$$\text{H2: } \beta_2 = 0 | \beta_3 = 0 \tag{7.8}$$

$$\text{H1 } \beta_1 = 0 | \beta_2 = \beta_3 = 0 \tag{7.9}$$

Accepting (7.7) and rejecting (7.8) implies selecting an ESTAR model. Accepting both (7.7) and (7.8) and rejecting (7.9) leads to an LSTAR model as well as a rejection of (7.7). The estimation of LSTAR models is then carried out by non-linear least squares. Granger and Teräsvirsta (1993) argue that strict application of this sequence of tests may lead to incorrect conclusions and suggest the computation of the P-values of the F-tests of (7.7) to (7.9) and make the choice of the STAR model on the basis of the lowest *P*-value. Consistent with the two hedge fund indices it is expected that the LSTAR model will be chosen over the ESTAR model.

Table 7.12
Results for *F*-Tests of non-linearity and tests of L-STAR against E-STAR for CSFB

This table presents the results from a series of *F*-tests carried out after estimating the following auxiliary regression.

$$u_t = \beta_0 z_t + \beta_1 z_t x_t + \beta_2 z_t x_t^2 + \beta_3 z_t x_t^3$$

Where the values of u_t are the residuals of the linear model in Table 7.4 Panel B.
The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$.
The selection between L-STAR and E-STAR models is based on the following series of nested *F* tests.

$$H_3\text{: } \beta_3 = 0$$
$$H_2\text{: } \beta_2 = 0 | \beta_3 = 0$$
$$H_1\ \beta_1 = 0 | \beta_2 = \beta_3 = 0$$

***F*-Tests Results for CBRF 1990 – 2002**

	d = 1	d = 2	d = 3	d = 4	d = 5	d = 6	d = 7	d = 8
H_0	0.0035***	0.4509	0.8889	0.0000***	0.0480**	0.0197**	0.0025***	0.0153**
H_3	0.0385**	0.8184	0.9113	0.0088***	0.1270	0.0034***	0.1362	0.4814
H_2	0.0345**	0.0698*	0.5309	0.0000***	0.7610	0.1554	0.0018***	0.0112**
H_1	0.0564*	0.8360	0.6580	0.1374	0.0164**	0.9003	0.1805	0.0719*

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

The linearity tests for the simulated convertible arbitrage portfolio for the period January 1990 to December 2002 are displayed in the first row of Table 7.12. In carrying out linearity tests the values for the delay parameter *d* over the range $1 \leq d \leq 8$ were considered. The *P*-values for the linearity test were calculated in each case. In the absence of theory the delay parameter *d* is chosen by the lowest *P*-value. Linearity is rejected at levels of *d* = 1, 4, 7 and 8, and though the lowest *P*-value is for *d* = 4, theory would suggest that $d = 1$, so this is chosen as the transition variable z_t. The results of testing for LSTAR against ESTAR are inconclusive but the *P*-values point to an LSTAR functional specification.

Table 7.13 reports results from estimating the linear AR model (7.11) and the non-linear LSTAR model (7.4).

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \tag{7.4}$$

Where $\alpha' = (\alpha_0, \alpha_y, \alpha_{DEF}, \alpha_{TERM})$, $\beta' = (\beta_0, \beta_y, \beta_{DEF}, \beta_{TERM})$, $x_t = (y_{t-1}, DEF_t, TERM_t,)$ and $f(z_t) = [1 + \exp(-\gamma(z_t - c))]^{-1}$ yielding the logistic STAR (LSTAR) model where γ is the smoothness parameter and z_t, the transition variable is y_{t-1}. Following a series of *F*-tests insignificant coefficients have been set equal to zero. The results of the simulated portfolio LSTAR model are strikingly similar to the convertible arbitrage indices LSTAR model. In the first regime, $y_{t-1} < c$, the *DEF* coefficient is 0.53 reducing to 0.18 in the alternate regime, $y_{t-1} < c$. This compares to a coefficients of 0.55 reducing to 0.05 and 0.99 reducing to 0.22 for the HFRI and CSFB indices respectively. *TERM*, the term structure risk coefficient is 0.75 in the first regime, $y_{t-1} < c$, and 0.22 in the second regime, $y_{t-1} > c$. This compares to 0.49 and 0.86 in the first regime, $y_{t-1} < c$, reducing to 0.10 and 0.23 in regime two, $y_{t-1} > c$, for the HFRI and CSFB indices respectively. This provides further evidence to support the theoretical relationship between convertible arbitrage returns and risk factors. The threshold level, *c*, is significantly negative -0.7% compared to a level insignificant from zero for the HFRI index and a threshold between

-0.7% and -1.0% for the CSFB Tremont index. Like the HFRI index, the estimated alphas are significantly negative in the $y_{t-1} < c$ regime and significantly positive in the $y_{t-1} > c$ regime. No previous study of convertible arbitrage indices has identified the strategy generating significant negative alphas.

Table 7.13
Linear AR models and non-linear LSTAR model of simulated convertible arbitrage portfolio returns

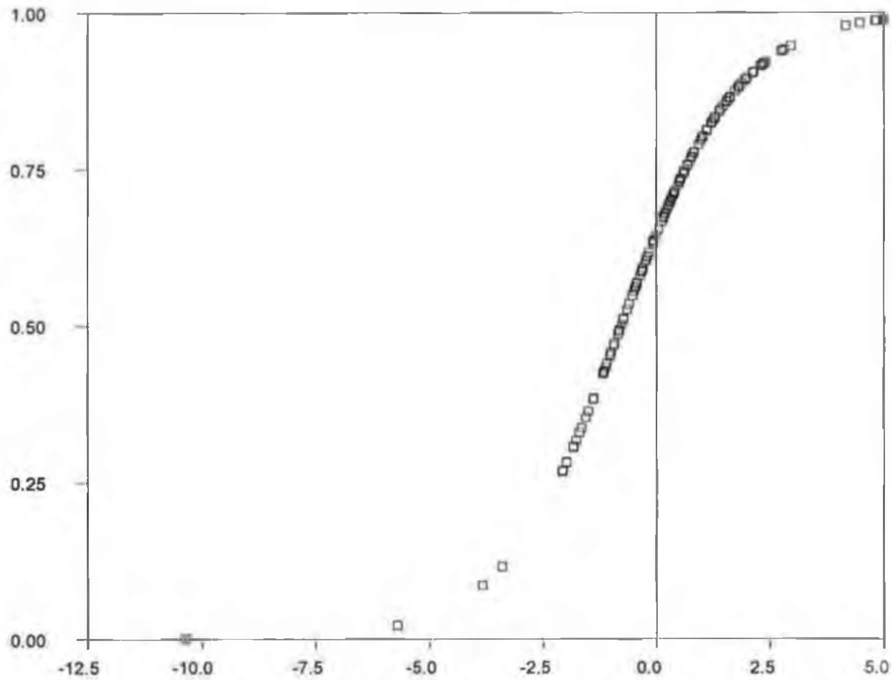
This table presents results of the linear autoregressive model of simulated convertible arbitrage portfolio returns. Panel A reports results of the linear AR model. Panel B reports results of the non-linear STAR model. σ_e is the residual standard deviation, SK is skewness, EK is kurtosis, JB is the Jacque-Bera test of normality in the residuals, JB Sig. is the *P*-Value of the Jacque-Bera statistic, ARCH(q) is the LM test of no ARCH effects up to order *q*, ARCH Sig is the *P*-Value of the LM test statistic, AIC is the Akraike Information Criteria and SBC is the Schwartz Bayesian Criterion.

	A. CBRF Linear model		B. CBRF LSTAR model	
α_0	0.12	(1.08)	-1.56	(-7.21)***
α_{yt-1}	0.08	(1.34)		
α_{DEF}	0.37	(7.84)***	0.53	(3.13)***
α_{TERM}	0.41	(6.91)***	0.75	(4.66)***
β_0			2.91	(19.51)***
β_{yt-1}			-0.35	(-4.63)***
β_{DEF}			-0.28	(-1.66)*
β_{TERM}			-0.53	(-2.25)**
c			-0.77	(-4.88)***
γ			0.77	(6.45)***
σ_{nl}/σ_{lin}			0.91	
σ_e	0.79		0.72	
SK	0.04		0.29	
EK	0.49		0.43	
JB	1.59		3.42	
JB Sig	0.45		0.18	
ARCH(4)	13.59		2.77	
ARCH Sig	0.01		0.60	
AIC	862.06		865.62	
SBC	877.28		908.22	

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

A Graph of the transition function $f(z_t)$ is presented in Figure 7.4. The smoothness coefficient, 0.77, of the simulated portfolio is smaller than the HFRI and CSFB coefficients (γ = 5.07 and 2.08 respectively), which can be seen in the lower slope in Figure 7.4.

Figure 7.4 CBRF L-STAR model transition function (1990 to 2002)



This section has provided further evidence to support the existence of two alternative convertible arbitrage risk regimes. If the one period lag of the convertible arbitrage benchmark is below the threshold level it is likely that convertible bond prices have fallen.[68] As convertible bond prices fall the arbitrageur's portfolio is more exposed to

[68] The other less likely cause of negative returns is if the portfolio is over hedged and the value of the short stock portion of the portfolio increases in excess of the increase in the value of the long bond portion.

fixed income risk characteristics, and the default and term structure risk coefficients increase, and the LSTAR model gradually moves toward the lower regime. If the one period lag of the convertible arbitrage benchmark return is above the threshold it suggests that convertible bond prices have increased and the portfolio gradually moves into the higher regime, behaving less like a fixed income instrument, with smaller coefficients on default and term structure risk factors.

7.6 Conclusion

The tests conducted in this chapter have rejected linearity for the convertible arbitrage hedge fund indices. These hedge fund indices are classified as logistic smooth transition autoregressive (LSTAR) models. The estimated LSTAR models provide a satisfactory description of the non-linearity found in convertible arbitrage hedge fund returns and have superior explanatory power relative to linear models. The estimates of the transition parameter indicate that the speed of transition is relatively slow from one regime to another but the factor loadings become relatively large as previous month's hedge fund returns become more negative.

These results support the expectation that convertible arbitrage hedge fund risk factor coefficients will vary according to previous month's hedge fund index returns. The convertible arbitrage benchmark indices represent an aggregate of hedged convertible bonds held by arbitrageurs. If the benchmark generates negative returns then aggregate hedged convertible bonds held by arbitrageurs have fallen in value. This fall in value is caused either by a decrease in the value of the short stock position in excess of the increase in the value of the long corporate bond position or, more likely, a decrease in the value of the long convertible bond position in excess of the increase in the value of the short stock position. When the one period lag of the convertible arbitrage benchmark return is below the threshold level, convertible bond prices and deltas have decreased. As convertible bond prices fall the arbitrageur's portfolio is more exposed to default and term structure risk and their coefficients increase in magnitude and significance. When the one period lag of the convertible arbitrage benchmark return is above the threshold level, convertible bond prices and deltas have increased and the portfolio behaves less like a fixed income instrument, with smaller coefficients on the default and term structure risk factors.

There are several important contributions to the understanding of convertible arbitrage and hedge fund risk and returns in this chapter. The evidence presented in this chapter supports the existence of two alternate risk regimes, a higher default and term structure risk regime if previous month's returns are below a threshold level, and a lower default and term structure risk regime if previous month's returns are above a threshold level. Previous research has identified only one risk regime for convertible arbitrage. Estimated alphas in the higher risk regime are significantly negative for the HFRI index and the simulated portfolio. Previous research has only documented significantly positive or insignificant alphas. This is an important finding as it indicates that when arbitrageurs are more exposed to default and term structure risk they generate negative alpha. Finally, the existence of two risk regimes is likely to be a contributing factor to serial correlation in hedge fund returns. Estimates of the one period lag of the hedge fund index coefficient were lower for the non-linear model than the linear model providing evidence that an assumption of linearity contributes to observed serial correlation in convertible arbitrage returns. This is a finding consistent with Getmansky, Lo and Makarov's (2004) hypothesis that serial correlation is caused in part by time varying expected returns.

7.7 Limitations of this analysis and avenues for further research

7.7.1 Could the non-linear relationship between convertible arbitrage returns and market risk factors be driven by something other than previous month's returns?

While the linear HFRI and CSFB sub-sample tests point clearly towards previous month's returns driving the non-linearity it is conceivable that the non-linearity is being driven by one or other of the other factors or by a factor which has not been specified in the model. The possibility that one of the other factors is driving the non-linearity was informally examined by a series of linear tests (which are reported in the robustness section in Section 4.5.2 of Chapter 4) which leaves the possibility that a missing variable is driving the non-linearity.

However, this should be considered unlikely. In the course of evaluating the risk factors which affected convertible arbitrage risk other factors drawn from the Arbitrage Pricing Theory literature (Currency returns, commodity returns, oil returns, momentum factor returns, size and book to market factor returns, changes in implied volatility and a variety of stock market bond market and economic factors) were initially tested and found to be insignificant in the convertible arbitrage data generating process.

Chapter 8: A review of Residual Augmented Least Squares (RALS)

8.1 Introduction

The assumption of normality in the distribution of returns is crucial for most of the econometric techniques typically used in empirical finance research such as mean variance analysis and OLS. Fama (1965) provides early evidence that the assumption of normality in stock returns may not hold. Fama's (1965) tests of the normality hypothesis on the daily stock market of Dow Jones Industrial Average stocks revealed more kurtosis than that permitted under normality. Phillips, McFarland and McMahon (1996) highlight that the distributions of financial asset returns typically exhibit heavy tails. Brook and Kat (2001) and Kat and Lu (2002) highlight the significant excess kurtosis and skewness in hedge fund trading strategies. Fama (1965), Praetz (1972), Kon (1984) and Bookstaber and McDonald (1987) amongst others provide several competing hypotheses to accurately describe the distribution of stock returns. Simkowitz and Beedles (1978) and Badrinath and Chatterjee (1988) address the issue of skewness preference and its impact on portfolio choice. Both of these studies contend that, as investors prefer positive skewness, if skewness is persistent they will tailor their portfolios accordingly. What is evident from these studies is that the returns of financial time series are often non-normally distributed, and, given the Gauss-Markov conditions will not be satisfied for these series, any explanatory variable coefficients estimated using OLS will be biased. Because least squares minimises squared deviations, it places a higher relative weight on outliers, and, in the presence of residuals that are non-normally distributed, leads to inefficient coefficient estimates.

A number of alternative robust estimation techniques have been specified to more efficiently model non-normal data. These models include M-estimators, L-estimators and R-estimators.[69] Bloomfield and Steiger (1983) demonstrate that Basset and Koenker's (1978) Least Absolute Deviations (LAD)[70] estimator, from the L-estimator class has particularly useful properties in time series regression models and LAD is often specified as an alternative to least squares when the disturbances exhibit excess kurtosis. Phillips, McFarland and McMahon (1996) and Phillips and McFarland (1997) specify FM-LAD, a non-stationary form of the LAD regression procedure, due to Phillips (1995), to model the relationship between daily forward exchange rates and future daily spot prices. Results of both studies highlight the significant improvements in efficiency from robust estimation where series are non-normally distributed.

This chapter reviews the non-normal hedge literature, provides a review of the LAD estimator and discusses in detail, a relatively new estimation technique, Residual Augmented Least Squares (RALS) developed by Im and Schmidt (1999), which explicitly allows for the excess skewness and kurtosis found in many financial time series. As negative skewness and excess kurtosis are prevalent in convertible arbitrage returns[71], which exhibit significant excess kurtosis and negative skewness, failing to control for these characteristics in an evaluation of convertible arbitrage performance will result in biased estimates of performance. As RALS explicitly allows for non-normality this estimation technique should lead to increased efficiency in estimates of

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[69] See Judge, Hill, Griffiths, Lütkepohl and Lee (1985), chapter 20 for a review of survey of *M*-estimators, *L*-estimators and *R*-estimators.
[70] The LAD estimator is also known as the L_1 estimator.
[71] Brooks and Kat (2001) and Kat and Lu (2002) document these features of convertible arbitrage returns.

hedge fund risk factors and performance. As RALS specifies skewness and kurtosis functions of the OLS residuals as regression terms, the coefficients on these terms should also serve as useful measures of skewness and kurtosis risk. The magnitude and significance of the coefficients provide evidence of the degree of skenwess and kurtosis risk being borne by a fund or hedge fund index.

Section 8.2 discusses some of the hedge fund literature which attempts to model the non-normal distribution of returns. Section 8.3 reviews the LAD estimator and the RALS estimation technique is described in Section 8.4. Section 8.5 reviews the empirical literature which has utilised the RALS technique and Section 8.6 concludes.

8.2 The non-normal distribution of hedge fund returns

Brooks and Kat (2001) and Kat and Lu (2002) discuss in detail the statistical properties of hedge fund strategy indices and hedge fund strategy portfolios respectively. Their findings indicate that the returns to several of these strategies are negatively skewed and leptokurtic. Convertible arbitrage clearly displays these characteristics with significantly negative skewness and positive kurtosis. These features of hedge fund returns are particularly important when assessing hedge fund risk. Investors have a preference for positively skewed assets so will require a risk premium for holding hedge funds which are negatively skewed. Ignoring the distribution of stock prices and estimating a linear factor model with OLS in the presence of negative skewness and excess kurtosis will understate the risk inherent in the strategy and bias estimates of performance as the Gauss-Markov conditions will not be satisfied.

Several studies attempt to deal with the non-normal distribution of hedge funds by including contingent claims as risk factors in a linear factor model specification. Agarwal and Naik (2004) and Mitchell and Pulvino (2001) incorporate short positions in put options, while Fung and Hsieh (2001) use positions in look-back straddles as risk factors. While these studies partially address the issue of non-normality it is likely that the residual distributions of these factor models are non-normal. These studies do not report statistics on the factor model residuals. In Chapters 4, 5 and 7 of this thesis results are reported from estimating a linear model of hedge fund index and individual fund returns. A simulated convertible bond arbitrage portfolio is specified as a risk factor which shares the non-normal characteristics of convertible arbitrage fund returns. Despite the inclusion of this factor the residuals of the models for the hedge fund indices remain non-normal.[72]

Recognising that linear asset pricing models will fail to capture the dynamic asset allocation and non-normality in the returns of hedge funds and this in turn will affect any estimate of performance, Kat and Miffre (2005) employ a conditional model of hedge fund returns which allows the risk coefficients and alpha to vary. Kat and Miffre (2005) assume that there is a linear relationship between the risk coefficients and a set of information variables (including the one period lag of hedge fund returns allowing for potential persistence in hedge fund returns). This type of performance evaluation is superior to other studies which employ models where the coefficients on the risk factors are fixed as it does not impose coefficient constancy and normality. The risk factors which they employ are an equity index, a bond index, a commodity index, a foreign exchange index and factor mimicking portfolios for size, book to market, and proxy risk

[72] These statistics are reported in Table 7.10.

factors for skewness and kurtosis. Kat and Miffre's (2005) skewness and kurtosis proxy risk factors are constructed as factor mimicking portfolios of stocks ranked by systematic skewness and systematic kurtosis respectively, rebalanced annually. The skewnes risk factor is the return on the high minus low systematic skewness portfolios and the kurtosis risk factor is the return on the high minus low systematic kurtosis portfolios. The authors document forty eight percent of convertible arbitrage hedge funds have significant skewness risk coefficients and forty nine percent of convertible arbitrage hedge funds have significant kurtosis risk coefficients. Their results suggest that ignoring skewness and kurtosis risks will lead to an overstatement of hedge fund performance of approximately 1% per annum.

In a similar study, Kazemi and Schneeweis (2003) have also attempted to explicitly address the dynamics in hedge fund trading strategies by employing conditional models of hedge fund performance, though they do not specify skewness and kurtosis risk factors. Kazemi and Schneeweis (2003) employ the stochastic discount factor (SDF) model which has previously been employed in the mutual fund literature.[73] The results are quite similar for the SDF model and the linear model and some evidence is provided of hedge fund abnormal performance although the study is constrained by applying one factor model to a variety of uncorrelated trading strategies. In Chapter 7 of this study a non-linear logistic smooth transition autoregressive (LSTAR) model of convertible arbitrage index returns is estimated. This model allows for two regimes depending on the return on the hedge fund index at time *t-1* relative to a threshold *c*, a regime with relatively high coefficients on default and term structure risk factors, and a regime with relatively low coefficients on default and term structure risk factors. The specification

[73] See for example Chen and Knez (1996) and Farnsworth, Ferson, Jackson and Todd (2002).

of the non-linear model eliminates the autoregressive conditional heteroscedasticity for all of the sample periods, and the non-normality in the residuals in one sample period, relative to the alternative linear models. However, the residuals from two of the three hedge fund indices' remain non-normal.

An alternative to the factor model approach to evaluate the benefit of hedge funds is to estimate a modified Value at Risk (VaR). Favre and Galeano (2002) provide evidence that the standard VaR, which uses only the second moment, under the assumption of normality, as a risk measure overstates hedge fund performance. The VaR estimates the probability of loss, ignoring the earnings opportunities associated with the risk of those losses. Signer and Favre (2002) introduce a modified VaR that includes higher moments of the distribution to more efficiently analyse the benefit of hedge funds. As hedge funds returns are generally non-normally distributed the modified VaR gives a clearer indication of the benefits of hedge funds. Alexiev (2005) also examines the importance of higher moments in fully evaluating hedge fund probability of loss. In this study empirical results from estimating loss probabilities assuming a normal distribution are compared to results using the true distribution of a sample of hedge fund returns. Unsurprisingly, given the negative skewness of the funds, risk estimations assuming a normal distribution tend to underestimate the probability of loss. Extending the work of Signer and Favre (2002), Gregariou and Gueyie (2003) compare the relative rankings of fund of hedge funds using the Sharpe ratio and a similar ratio replacing the standard deviation with the modified Value-at-Risk, which takes into account the skewness and kurtosis of the return distribution. They present evidence that due to the non-normality in hedge fund returns the Sharpe ratio is ineffective for analysing the relative performance of fund of hedge funds. Madhavi (2004) introduces the Adjusted Sharpe

Ratio where the distribution of a fund's return is adjusted to match the distribution of a normally distributed benchmark. The resulting estimated Sharpe ratio can then be compared directly with the benchmark Sharpe ratio. Madhavi (2004) provides evidence for hedge funds indices, that there is no statistically significant difference between the Adjusted Sharpe Ratios and the traditional Sharpe ratio, indicating the non-normal characteristics of the indices are unimportant in terms of risk.

In an innovative study evaluating hedge fund performance, which imposes zero restrictions on the distribution of the funds' returns, Amin and Kat (2003b) evaluate hedge funds from a contingent claims perspective. They begin by assuming an initial investment at the beginning of each month in each hedge fund and in the S&P500 to create a cumulative distribution. A non-decreasing function of the S&P500 which yields an identical payoff to the hedge fund is then estimated. Finally, a dynamic S&P500 and cash trading strategy, that generates the hedge fund payoff function is valued. The price of this function is then compared to the assumed initial investment in the hedge fund to benchmark the manager's performance. If the initial investment is less than the price then the hedge fund manager has added value. If the initial investment is greater than the calculated price of the function then the hedge fund manager has acted inefficiently. Their findings indicate that the majority of hedge funds operate inefficiently but, while Amin and Kat's (2003b) study imposes no restrictions on the distribution of hedge funds' returns, the results are not interpretable in terms of the risk premium from exposure to negative skewness and excess kurtosis.

8.3 Least Absolute Deviations (LAD)

In this section details of the LAD robust estimator are provided. The LAD estimator is from the L-estimator class and is specified where the distribution of a series may be non-normally distributed. Estimation of the LAD estimator is based on the method of regression quantiles described in Bassett and Koenker (1978). Judge, Hill, Griffiths, Lütkepohl and Lee (1988) provide an accessible review of LAD estimation. Given the following simple regression (8.1).

$$y_t = \beta' z_t + u_t \tag{8.1}$$

Where $z_t = (1, x_t')'$, x_t is a $(k-1)$ x 1 vector of time series observed at time t, while β' = is the k parameter that includes the intercept and the residuals are i.i.d with distribution symmetric around zero. The regression quantile family of estimators is based on minimizing the criterion function (8.2).

$$\min_{\beta}\left[\sum_{\{t|y_t \geq x_t'\beta\}} \theta|y_t - x_t'\beta| + \sum_{\{t|y_t < x_t'\beta\}} (1-\theta)|y_t - x_t'\beta|\right] \tag{8.2}$$

Where the θth sample regression quantiles $(0 < \theta < 1)$, and any linear function of the quantiles are the possible L-estimators. As the solution is the weighted sum of absolute values of the residuals, outliers are given relatively less importance than with least squares estimation. The LAD estimator is a particular form of the L-estimator where all the weight is placed on $\theta = 0.5$. Thus for the LAD estimator, β_L, the minimisation problem is equivalent to (8.3).

$$\min_{\beta_L}\left[\sum\left|y_t - x_t' \beta\right|\right] \quad (8.3)$$

The limiting distribution of β_L is given by (8.4).

$$\sqrt{T}[\beta_L - \beta]^d \rightarrow N\left(0,[2f(0)]^{-2}Q^{-1}\right) \quad (8.4)$$

Where Q is a positive definite matrix equal to $\text{plim}_{T\rightarrow\infty}T^{-1}X'X$, and X is the matrix of regressors. The term $[2f(0)]^{-2}$ is the asymptotic variance of the sample median from samples with distribution function F and density function f, with its value at the median given by $f(0)$. Thus the LAD estimator is more efficient than the least squares estimator for all error distributions where the median is superior to the mean as an estimate of location. This class of error distributions includes the Cauchy and the Student's t.

8.4 Residual Augmented Least Squares (RALS)

An alternative estimator to LAD is Im and Schmidt's (1999) RALS estimator which is robust to skewness and kurtosis in the distribution of the error term. This estimator is particularly practical as it provides robust coefficient estimates without imposing any restrictions on the distribution of returns, is easily estimated using two step OLS and the coefficients are interpretable as skewness and kurtosis risk premia.

Given a multivariate linear regression model

$$y_t = \beta' z_t + u_t \tag{8.5}$$

Where $z_t = (1, x_t')'$, x_t is a $(k-1)$ x 1 vector of time series observed at time t, while $\beta' = (\alpha\beta')$ where α is the intercept and β' is the $(k-1)$ x 1 vector of coefficients on x_t. Assuming the following moment conditions hold:

$$E[x'(y - x'\beta)] = 0 \tag{8.6}$$

$$E\{x \otimes [h(y - x'\beta) - K]\} = 0 \tag{8.7}$$

Where (8.6) is the least squares moment condition which asserts that x and u are uncorrelated and (8.7) refers to some additional moment conditions that some function of u is uncorrelated with x. $h(.)$ is a J x 1 vector of differentiable functions and K is a J x 1 vector of constants. Therefore, there are kJ additional moment conditions.

The inclusion of these estimators is useful in obtaining a more efficient estimator if the distribution of the error term is non-normal. Normality of the error term can be tested using the Jacque and Bera (1987) test statistic. Excess kurtosis in the residual implies that the standardized fourth central moment of the series exceeds three, so that:

$$E(u_t^4 - 3\sigma^4) = E[u_t(u_t^3 - 3\sigma^2 u_t)] \neq 0 \tag{8.8}$$

implying that $u_t^3 - 3\sigma^2 u_t$ is correlated with u_t but not with the regressors since x_t and u_t are by assumption independent. Similarly when errors are skewed the standardised third central moment is non-zero so that:

$$E(u_t^3 - \sigma^3) = E[u_t(u_t^2 - \sigma^2)] \neq 0 \tag{8.9}$$

which implies that $u_t^2 - \sigma^2$ is correlated with u_t but not with the regressors (again since x_t and u_t are by assumption independent).

Im and Schmidt (1999) suggest a two step estimator that can be simply computed from OLS applied by equation (8.5) augmented with the term (8.10).

$$\hat{w}_t = [(\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t)(\hat{u}_t^2 - \hat{\sigma}^2)]' \tag{8.10}$$

Where $\hat{u}_t$ denotes the residual and $\hat{\sigma}^2$ denotes the standard residual variance estimate obtained from OLS applied to equation (8.5). The resulting estimator is the RALS estimator of β, β^*, and Im and Schmidt (1999) derives analytically its asymptotic distribution and showed how the covariance matrix of β^* can be consistently estimated.

Im and Schmidt (1999) also provided a measure of the asymptotic efficiency gain from employing RALS as opposed to OLS through the statistic ρ^2 constructed as ρ^*/ρ where ρ^* is the residual variance from the RALS estimation and ρ is the residual variance from the OLS estimation (ρ^2 is small for large efficiency gains). This statistic shows that this gain can be substantial for a range of alternative non-normal error distributions. The quantification of the efficiency gain and the ability to achieve it using the RALS estimation technique depends on the homoskedastic assumption that the third and fourth conditional moments do not depend on the regressors.

The RALS technique is easily applied to other tests which incorporate the assumption of normality. Im (2001) suggests applying the RALS estimator to obtain a RALS unit root test obtained by an extension of the standard Dickey-Fuller test. The methodology involves estimating the auxiliary Dickey-Fuller (ADF) regression and the covariance matrix of the parameters by RALS and then constructing the test statistic in the standard way.

An additional potential extension of the RALS methodology is the interpretation of the coefficients on (8.10) as risk factor weightings. Non-normality in the return distribution can be interpreted not only as a statistical issue but also as an issue of risk. Negative skewness is an undesirable risk characteristic for investors and investors should be compensated for holding an asset that exhibits negative skewness relative to an asset that is positively skewed. It is therefore possible to interpret the coefficients on the RALS term (8.10) as skewness and kurtosis risk factor coefficients. When evaluating the risk and return of individual hedge funds there are two potential approaches to interpreting the coefficient on the RALS term (8.10) as a risk factor. Firstly, Im and Schmidt's (1999) two step estimator can be computed from OLS applied by equation (8.5) augmented with the term (8.10) for each individual hedge fund, resulting in robust estimates of performance. The significance of the coefficients on (8.10) for each fund will highlight the non-normality in that fund's return distribution. However, the magnitude of coefficients across funds is not comparable as (8.10) will be different for each fund.

The alternative approach is to compute (8.10) from the residuals of OLS estimation of (8.5) with a benchmark of the strategy as the dependent variable. (8.10) then serves as benchmark skewness and kurtosis risk factors. Specifying these benchmark skewness and kurtosis factors in a linear risk factor model of individual fund performance, estimated by OLS, will provide robust estimates of performance and comparable estimates of skewness and kurtosis risk across funds.

8.5 RALS literature

In this section several studies which have specified RALS as a robust estimator are reviewed. Taylor and Peel (1998) propose RALS estimation to test for periodically collapsing stock market bubbles and overcome the econometric problems when testing the co-integrating relationship between the log of real prices and the log of real dividends or the log real dividend-real price ratio and the real rate of return, highlighted by Evans (1991). Taylor and Peel (1998) demonstrate that the RALS co-integrating Dickey-Fuller statistic, based on the RALS estimator, is superior to the co-integrating Dickey-Fuller statistic when testing for the presence of periodically collapsing stock price bubbles and is capable of discriminating between explosive and mean-reverting departures from fundamentals. The authors apply the test to a long run series of US real stock price and dividend data rejecting the bubble hypothesis. Sarno and Taylor (1999) follow Taylor and Peel (1998) employing RALS estimation techniques to test for stock market bubbles in East Asia. Using data on China, Indonesia, Malaysia, Philippines, Singapore, South Korea, Taiwan, Thailand and Japan, with Australia as a control country they find clear evidence supporting the presence of bubbles in all countries other than Australia. The log dividend-price ratio and the *ex post* stock return is only stationary in the Australian data and after regressing the stock price series on to the dividend series no-cointegration is only rejected for Australia, providing further evidence of bubbles in all countries other than Australia. Sarno and Taylor (1999) then go on and test whether portfolio flows could have caused these bubbles. Sarno and Taylor (2003) apply a similar analysis to Latin American emerging markets, specifically Argentina, Brazil, Chile, Colombia, Mexico and Venezuela. While not testing the causes they find evidence of bubbles in each of the countries using data for the previous ten years.

Gallagher and Taylor (2000) use the RALS estimation technique as a robust test of the mean reversion hypothesis in US stock prices. The authors employ a Vector Autoregression (VAR) of real stock prices and nominal interest rates to identify the temporary and permanent component of stock prices. Gallagher and Taylor's (2000) results support the mean reversion hypothesis and they provide evidence that least squares estimation will understate the mean reverting component relative to RALS.

8.6 Conclusion

Hedge fund literature pointing to the importance of tests incorporating skewness and excess kurtosis were reviewed in this chapter. A relatively new estimation technique known as RALS developed by Im and Schmidt (1999) and extended by Im (2001) and existing literature utilising these techniques was reviewed. The next chapter presents some empirical evidence highlighting the usefulness of RALS when estimating the risk factors which affect convertible arbitrage. Evidence is also presented highlighting the skewness and kurtosis risk coefficients of hedge fund indices and individual funds.

Chapter 9: Skewness, kurtosis and the robust estimation of convertible arbitrage risk factors

9.1 Introduction

The purpose of this chapter is to provide a robust estimation of convertible arbitrage risk factors using Residual Augmented Least Squares (RALS) a recently developed estimation technique designed to exploit non-normality in a time series' distribution, a feature often found in hedge fund returns. Linear factor models of convertible arbitrage hedge fund index risk are estimated employing this robust estimation technique which explicitly allows for non-Gaussian innovations. It is then demonstrated that the estimates of risk factor model coefficients using this procedure are more efficient than coefficients estimated using OLS. Utilising these estimation techniques improves the efficiency of linear convertible arbitrage risk factor model estimates.

This chapter employs the RALS estimation technique, proposed by Im and Schmidt (1999), discussed in detail in Chapter 8, which explicitly allows for the negative skewness and excess kurtosis inherent in hedge fund returns. This estimation technique has not to date been used in the estimation of hedge fund risk factors. Third and fourth moment functions of the HFRI convertible arbitrage index residuals are then employed as proxy risk factors, for skewness and kurtosis, in a multi-factor examination of individual hedge fund returns. As negative skewness and excess kurtosis are undesirable characteristics for investors, the inclusion of these risk factors adds to the understanding of individual convertible arbitrage hedge fund performance.

This chapter expands the existing literature by providing a robust estimate of convertible arbitrage hedge fund risk factors explicitly allowing for the non-normality in hedge fund returns. Section 9.2 discusses the hedge fund index data and the convertible arbitrage risk factors. Section 9.3 provides details of the OLS and RALS estimation of the hedge fund index risk factor models. Section 9.4 provides empirical results from the estimation of individual funds risk and performance and Section 9.5 concludes.

9.2 Data

Two benchmark indices of convertible arbitrage hedge fund returns are employed: the CSFB Tremont Convertible Arbitrage Index and the HFRI Convertible Arbitrage Index. The CSFB Tremont Convertible Arbitrage Index is an asset weighted index (rebalanced quarterly) of convertible arbitrage hedge funds beginning in 1994 whereas the HFRI Convertible Arbitrage Index is equally weighted with a start date of January 1990.[74] Although the HFRI and CSFB Tremont indices now control for survivor bias HFRI did not include the returns of dead funds before January 1993.

Descriptive statistics and cross correlations for the convertible arbitrage indices and the convertible arbitrage risk factors are displayed in Table 9.1. All of the correlations cover the period January 1990 to December 2002 except for correlations with the CSFB Tremont Convertible Arbitrage Index which cover the period January 1994 to December 2002.

[74] For details on the construction of the CSFB Tremont Convertible Arbitrage Index see www.hedgeindex.com. For details on the construction of the HFRI Convertible Arbitrage Index see www.hfr.com.

Table 9.1
Descriptive statistics for the convertible bond arbitrage indices and risk factors

CSFBRF is the excess return on the CSFB Tremont Convertible Arbitrage index, HFRIRF is the excess return on the HFRI Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio.

	Mean	T-Stat	Variance	Std Error	Skewness	Kurtosis	Jarque-Bera
			Panel A: Dependent Variables				
CSFBRF	0.440	3.291	1.930	1.744	-1.76***	4.61***	151.16***
HFRIRF	0.538	6.818	0.972	0.986	-1.42***	3.28***	122.46***
			Panel B: Explanatory Returns				
DEF	0.540	3.064	9.391	2.453	-0.37*	2.59***	47.20***
TERM	0.112	0.577	5.825	2.413	-0.36*	0.22	3.65
CBRF	0.325	2.307	3.104	1.762	-1.36***	9.00***	573.96***

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Statistics are generated using RATS 5.0

Panel C: Correlations

	TERM	*DEF*	*CSFBRF*	*HFRIRF*	*CBRF*
TERM	1.00				
DEF	-0.71	1.00			
CSFBRF	0.04	0.23	1.00		
HFRIRF	0.09	0.27	0.80	1.00	
CBRF	0.01	0.39	0.32	0.48	1.00

With the exception of the *CSFBRF* correlations, coefficients greater than absolute 0.25, 0.19 and 0.17 are significant at the 1%, 5% and 10% levels respectively.
CSFBRF correlation coefficients greater than absolute 0.22, 0.17 and 0.14 are significant at the 1%, 5% and 10% levels respectively.

In Chapter 4 several alternative linear factor models of convertible arbitrage returns were specified. Findings indicate that factors proxying for term structure risk, default risk and a delta neutral hedged convertible arbitrage risk factor are the most significant factors in explaining convertible arbitrage returns. DEF_t is the default risk factor, constructed as the difference between the overall return on a portfolio of long term corporate bonds (here the return on the CGBI Index of high yield corporate bonds from DataStream is used) minus the long term government bond return at month t (here the return on the Lehman Index of long term government bonds from DataStream is used). $TERM_t$ is the factor proxy for term structure risk at time t. It is constructed as the difference between monthly long term government bond return and the short term government bond return (here the return on the Lehman Index of short term government bonds from DataStream is used). The third factor, *CBRF*, is a factor proxy for convertible bond arbitrage risk. It is constructed by combining long positions in convertible bonds with short positions in the underlying stock.[75] Hedges are then rebalanced daily. These delta neutral hedged convertible bonds are then combined to create an equally weighted convertible bond arbitrage portfolio. $CBRF_t$ is the monthly return on this portfolio in excess of the risk free rate of interest at time t. Data used to construct *CBRF* are from DataStream and Monis. Table 9.1, Panel B presents descriptive statistics of the risk factors. The two market factors *DEF* and *TERM* have low standard errors, but of the two, only *DEF* produces a mean return (0.54%) significantly different from zero at the 1% level.[76] *CBRF*'s mean return is a significant 0.33%[77] per month with a variance of 3.104. The mean return of *CBRF* is lower and the variance higher than the two convertible arbitrage hedge fund indices, *CSFBRF* and *HFRIRF*. *CBRF* is negatively skewed and has positive kurtosis as do the two hedge fund indices.

Table 9.1, Panel C presents the correlations between the two dependent variables, *CSFBRF* and *HFRIRF* and the explanatory variables. Both of the variables are highly correlated with a coefficient of 0.80. Both are positively related to *DEF* the default risk

[75] For details on the construction of CBRF see Chapters 3 and 4.
[76] In discussions in the text statistical significance indicates t-stats are significant from zero at least at the 10% level unless reported.
[77] At the 5% level.

factor and *CBRF* the factor proxy for convertible bond arbitrage risk. *CBRF* is positively correlated with *DEF* and *TERM* is negatively correlated with *DEF*.

9.3 Analysis of hedge fund indices

In this section results are presented from estimating the linear model of convertible arbitrage benchmark index risk using OLS and RALS. Given the distribution of the hedge fund indices is non–normal the OLS risk factor coefficient estimates are likely to be biased. As RALS explicitly incorporates skewness and kurtosis terms, estimation of the hedge fund indices' risk factor coefficients with RALS should lead to unbiased estimators. The coefficients on the RALS skewness and kurtosis terms should also provide evidence of the risk premium arbitrageurs are receiving for taking on skewness and kurtosis risk. Theory would suggest that arbitrageurs will need to be rewarded for holding portfolios with negatively skewed return distributions as negative skewness implies the probability of large losses is increased relative to a normal distribution. [78] Positive kurtosis indicates a relatively peaked distribution with more occurrences in the middle and at the extreme tails of the distribution. Theory would suggest that investors would view an investment with returns showing high positive kurtosis as unfavourable, indicating more frequent extreme observations.

In Table 9.2 the results of OLS estimation of the following linear multi-factor model of convertible arbitrage risk are presented.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \varepsilon_t \qquad (9.1)$$

[78] See for example Simkowitz and Beedles (1978) and Badrinath and Chatterjee (1988).

Where y_t is the excess return on the convertible arbitrage index at time t, $TERM_t$ and DEF_t are term structure risk and default risk proxy factors at month t. $CBRF_t$ is the excess return on the simulated convertible arbitrage portfolio at time t. The results indicate that convertible arbitrage is significantly exposed to default and term structure risk and the convertible arbitrage risk factor. The significantly positive Jacque and Bera (1987) test statistics indicate that the residuals are non-Gaussian. Estimates of skewness and kurtosis of the factor model residuals are both significantly different from zero with negative skewness and positive excess kurtosis for all of the hedge fund indices. The disturbance terms of the estimated models are also first order autocorrelated.

Table 9.2
Linear model estimated by OLS

This table presents the results from estimating the following linear model of convertible arbitrage returns.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \varepsilon_t$$

Where y_t is the excess return on the HFRI Convertible Arbitrage index. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio. JB Stat is the Jacque and Bera (1987) statistical test of normality of the residuals. Skewness and Kurt are estimates of the skewness and kurtosis of the factor model residuals.

α	β_{CBRF}	β_{DEF}	β_{TERM}	Q Stat	JB Stat	Skewness	Kurt	Adj. R^2
Panel A: HFRI 1990 to 2002								
0.3838	0.1709	0.1502	0.1578	69.14***	71.04***	-1.14***	2.39***	32.41%
(3.65)***	(4.44)***	(2.70)***	(3.00)***					
Panel B: HFRI 1993 to 2002								
0.3947	0.2119	0.1496	0.1679	47.73***	64.69***	-1.16***	2.75***	27.54%
(3.23)***	(2.60)***	(2.20)**	(2.95)***					
Panel C: CSFB 1994 to 2002								
0.3014	0.1715	0.1694	0.1791	106.60***	91.15***	-1.36***	3.59***	12.99%
(1.30)	(1.91)*	(2.27)**	(3.49)***					

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).

*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

Table 9.3 presents results of RALS estimation of the convertible arbitrage linear risk factor model (9.2). RALS is a two step estimator, proposed by Im and Schmidt (1999) that can be simply computed from OLS applied to equation (9.1) augmented with the terms (9.3) and (9.4).

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_w w_t + \beta_v v_t + \varepsilon_t \tag{9.2}$$

$$w_t = (\hat{u}_t^3 - 3\hat{\sigma}^2 \hat{u}_t) \tag{9.3}$$

$$v_t = (\hat{u}_t^2 - \hat{\sigma}^2) \tag{9.4}$$

Where w_t is the kurtosis function and v_t is the skewness function of the residuals from (9.1) $\hat{u}_t$ denotes the residual and $\hat{\sigma}^2$ denotes the standard residual variance estimate obtained from OLS applied to equation (9.1). There are two moment conditions necessary for RALS estimation. The first is the least squares moment condition which asserts that the explanatory variables in (9.1) and the error term from (9.1) are uncorrelated and the second refers to the additional moment conditions that a function of the error term (9.1) is uncorrelated with the explanatory variables in (9.1). Im and Schmidt (1999) also provided a measure of the asymptotic efficiency gain from employing RALS as opposed to OLS through the statistic ρ^2 constructed as ρ^*/ρ where ρ^* is the residual variance from the RALS estimation and ρ is the residual variance from the OLS estimation (ρ^2 is small for large efficiency gains).

Table 9.3
Linear model estimated by RALS

This table presents the results from estimation of the following linear model of convertible arbitrage returns using RALS

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_w w_t + \beta_v v_t + \varepsilon_t$$

Where y_t is the excess return on the HFRI Convertible Arbitrage index and the lag of y acts as a proxy for illiquidity. *TERM* and *DEF* are Fama and French's proxies for the deviation of long-term bond returns from expected returns due to shifts in interest rates and shifts in economic conditions that change the likelihood of default. *CBRF* is the excess return on the simulated convertible arbitrage portfolio. w_t is the RALS kurtosis function of the OLS residuals and v_t is the RALS skewness function of the OLS residuals. ρ^2 is the efficiency test proposed by Im and Schmidt (1999).

α	β_{CBRF}	β_{DEF}	β_{TERM}	β_W	β_V	Q Stat	Adj. R^2	ρ^2
				Panel A: HFRI 1990 to 2002				
0.3682	0.2019	0.1037	0.0843	-0.0779	-0.4992	33.30**	54.71%	0.66
(4.07)***	(6.04)***	(2.17)**	(1.66)*	(-1.16)	(-3.11)***			
				Panel B: HFRI 1993 to 2002				
0.3873	0.2220	0.1123	0.0830	-0.0513	-0.4300	32.51***	49.47%	0.69
(3.62)***	(3.98)***	(1.96)*	(1.31)	(-0.71)	(-2.44)**			
				Panel C: CSFB 1994 to 2002				
0.4216	0.1167	0.1291	0.1010	0.0266	-0.1385	108.64***	44.96%	0.62
(1.37)	(1.45)	(3.28)***	(2.28)**	(0.51)	(-0.76)			

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
*, **, *** indicate coefficient is significantly different from zero at the .10, .05 and .01 levels respectively.

The efficiency gain for the three models, as characterised by ρ^2, ranges from 0.62 to 0.69. The adjusted R^2 indicates an improvement in the goodness of fit with the inclusion of the RALS terms. The skewness coefficient, β_V, is significantly negative for the HFRI index irrespective of sample period consistent with arbitrageurs receiving a risk premium for holding skewness. This is consistent with the theoretical expectation that arbitrageurs must receive a risk premium for holding a portfolio with negative skewness in the distribution of its returns. However, the skewness coefficient, β_V, is insignificant for the CSFB Tremont index and the kurtosis coefficient is insignificant from zero for all of the samples. The coefficients on *CBRF* have increased in both magnitude and significance while the coefficients on *DEF* and *TERM* have reduced in magnitude and significance. The alphas (performance measures) generated by the RALS estimation of the linear model are higher than those from the OLS estimation of the linear model indicating that OLS estimation may in fact understate performance. However, the Q-Stats indicate that the error terms remain autocorrelated, though the statistics have decreased in magnitude.[79]

The RALS estimate of the linear factor model provides useful information on the skewness and kurtosis risks of convertible arbitrage hedge fund indices. The evidence presented supports the theoretical expectation that arbitrageurs receive a risk premium for holding a portfolio with negative skewness in its return distribution.

9.4 Empirical analysis of individual funds

In addition to hedge fund indices, it is well documented that the returns of many individual convertible arbitrage hedge funds are also characterised by negative skewness and excess kurtosis (See Kat and Lu (2001)). There are two alternative approaches to estimate the skewness and kurtosis risk of these funds. First, Im and Schmidt's (1999) two step estimator can be computed from OLS applied by equation (9.1) augmented with the terms (9.3) and (9.4) for each individual hedge fund, resulting in robust estimates of performance. However, this methodology does not provide an easy comparison between funds of skewness and kurtosis risk. The magnitude of coefficients

[79] In Chapter 4 the lag of the hedge fund index excess return was specified as an illiquidity risk factor. The hedge fund index exhibits high first order autocorrelation and specifying this factor corrects both the serial correlation and the skewness and kurtosis characteristics of the series. As the aim of this chapter is to identify the skewness and kurtosis risks of the strategy, the one period lag of the hedge fund index is therefore not specified as an explanatory variable.

across funds is not comparable as the terms (9.3) and (9.4) are functions of the OLS residuals and will be different for each fund. What are needed to evaluate the relative performance of individual funds are common risk factors. The RALS methodology produces individual skewness and kurtosis functions for each dependent variable. Rather than employing the estimation technique of Im and Schmidt (1999) for individual funds, this section utilises the skewness (9.4) and kurtosis (9.3) functions of the HFRI linear model OLS estimated residuals from (9.1) as common risk factors in the returns of individual hedge funds. These risk factors are specified in three alternative factor model specifications, a contemporaneous explanatory factor model, a model including contemporaneous and lagged observations of the explanatory variables and a model including contemporaneous and lagged observations of the explanatory variables and a one period lag of the dependent variable as a proxy illiquidity risk factor. The model incorporating lagged variables should capture some of the illiquidity in the securities held by hedge funds, a characteristic of convertible arbitrage explored in Chapters 4 and 5. Specifying the one period lag of the hedge fund excess return as a proxy illiquidity risk factor was discussed in detail in Chapter 5. Assuming the illiquidity hypothesis holds, if a hedge fund holds zero illiquid securities then hedge fund returns at time t should have no relationship with hedge fund returns at time $t-1$. If the fund holds illiquid securities then there will be a relationship between returns at time t and $t-1$, captured by a significant positive coefficient on the one period lag of the hedge fund return. The larger the lagged hedge fund return coefficient the greater the illiquidity exposure.

The individual fund data is sourced from the HFR database. The original database consists of 113 funds. However, many funds have more than one series in the database.

Often this appears to be due to a dual domicile. (E.g. Fund X *Ltd* and Fund X *LLC* with almost identical returns.) To ensure that no fund is included twice, the cross correlations between the individual funds returns are estimated. If two funds have high correlation coefficients, then the details of the funds are examined in depth. In two cases high correlation coefficients are reported due to a fund reporting twice, in USD and in EUR. In this situation the EUR series is deleted. Finally, in order to have adequate data to run the factor model tests, any fund which does not have 24 consecutive monthly returns between 1990 and 2002 is excluded. The final sample consists of fifty five hedge funds. Of these fifty five funds, twenty five are still alive at the end of December 2002 and thirty are dead. Table 9.4 reports descriptive statistics on each hedge fund. The mean number of observations is fifty seven months up to a maximum of eighty two. The mean monthly return[80] is 0.90% and the minimum monthly return by a fund over the sample period was -34%. The maximum monthly return was 23%. The mean skewness is -0.47 and the mean kurtosis is 3.48. The Ljung and Box (1978) Q-Statistic tests the joint hypothesis that the first ten lagged autocorrelations are all equal to zero. The results reject this hypothesis for twenty four of the hedge funds.

Table 9.4
Statistics on individual hedge fund returns

This table presents descriptive statistics on the fifty five hedge funds included in the sample. For each fund *N* is the number of monthly return observations, *Min* and *Max* are the minimum and maximum monthly return, *Skewness* and *Kurtosis* are the skewness and kurtosis of the hedge fund's return distribution and *Q-Stat* is the Ljung and Box (1978) Q-Statistic jointly testing the series' ten lags of autocorrelation are significantly different from zero.

	N	*Mean*	*Min*	*Max*	*Skewness*	*Kurtosis*	*Q-Stat*
HF1	69	1.01	-4.41	4.95	-0.65	3.05	6.94
HF2	69	1.04	-8.07	9.77	0.32	2.80	13.11
HF3	38	1.74	-1.57	11.21	1.92	6.66	7.68
HF4	60	1.55	-1.62	11.74	2.08	8.85	9.46

[80] Returns are logarithmic.

HF5	69	1.31	-10.27	12.08	-0.64	4.44	12.36
HF6	69	1.33	-8.99	9.31	-1.19	4.37	16.39*
HF7	58	0.98	-2.49	3.43	-0.61	1.78	8.82
HF8	82	1.28	0.00	4.54	1.12	1.96	83.37***
HF9	57	0.80	-5.70	9.03	0.01	0.02	6.66
HF10	27	1.23	-1.69	5.48	0.25	-0.02	14.13
HF11	52	0.59	-0.74	3.00	1.73	7.62	10.65
HF12	58	0.82	-2.38	3.95	0.40	1.55	25.39***
HF13	30	0.33	-0.77	0.95	-1.11	3.49	4.24
HF14	55	1.02	-0.81	2.88	0.27	0.13	26.07***
HF15	42	1.05	-0.81	3.38	0.54	0.02	28.55***
HF16	38	1.18	0.00	2.87	0.46	-0.55	16.40*
HF17	25	0.45	-0.59	1.65	0.20	-0.49	9.33
HF18	36	1.27	-2.51	7.08	0.90	2.65	11.88
HF19	69	0.92	-5.20	3.17	-2.34	5.87	37.27***
HF20	69	1.02	-4.31	3.64	-1.71	3.99	10.88
HF21	37	0.24	-34.16	3.84	-5.72	34.05	0.76
HF22	69	1.37	-2.77	5.08	0.32	0.18	21.23**
HF23	69	0.68	-1.88	2.75	-0.58	1.09	18.23*
HF24	69	0.85	-2.17	6.53	1.27	6.12	7.50
HF25	69	1.02	-4.31	3.64	-1.71	3.99	10.88
HF26	69	0.96	-4.41	4.95	-0.53	2.56	7.94
HF27	69	1.05	-2.13	3.11	-0.55	1.20	18.14*
HF28	25	0.92	-0.88	2.60	-0.10	-0.73	14.13
HF29	24	-0.40	-5.52	4.00	-0.21	-0.66	18.33**
HF30	38	1.21	-2.68	6.88	0.56	1.14	9.43
HF31	69	1.06	-8.96	5.54	-2.04	6.49	23.27***
HF32	69	0.82	-1.70	3.86	0.36	-0.07	12.58
HF33	69	0.41	-24.68	23.25	-0.17	2.22	6.66
HF34	69	1.24	-3.98	6.77	-0.14	0.50	23.27***
HF35	69	1.00	-11.88	7.14	-1.29	4.62	17.20*
HF36	69	0.69	-1.61	1.78	-1.21	3.22	57.12***
HF37	36	0.83	-1.78	2.92	-0.19	1.49	13.55
HF38	69	0.87	-4.82	4.07	-1.22	5.80	11.67
HF39	51	0.94	-2.30	3.95	0.03	1.07	14.97
HF40	51	0.92	-1.60	2.41	-0.85	1.78	17.50*
HF41	69	1.25	-9.19	4.10	-3.01	12.59	24.62***
HF42	24	1.02	-2.09	2.94	-0.82	1.63	13.19
HF43	69	0.75	-2.16	2.80	-0.86	1.54	7.28
HF44	69	1.66	-9.56	5.20	-2.86	11.47	30.42***
HF45	41	1.45	-8.13	8.30	-0.20	1.78	39.69***
HF46	69	1.03	-2.02	3.45	-0.84	1.87	8.89
HF47	69	0.95	-2.30	4.16	0.43	3.25	24.78***
HF48	69	0.98	-1.32	4.83	0.45	1.73	10.20
HF49	69	0.82	-1.08	2.22	-0.49	0.97	13.15
HF50	67	0.80	-3.29	3.37	-0.77	1.51	17.65*
HF51	57	0.93	-8.34	4.21	-2.34	10.54	14.35
HF52	52	0.94	-2.40	3.40	-0.39	-0.02	8.26
HF53	69	1.02	-3.70	6.05	-0.51	4.32	23.33***
HF54	57	0.72	-2.00	2.28	-0.84	2.89	19.30**

HF55	69	0.82	-0.98	2.01	-0.53	1.09	18.54**
Mean	57	0.96	-4.47	5.06	-0.47	3.48	
Min	24	-0.40	-34.16	0.95	-5.72	-0.73	
Max	82	1.74	0.00	23.25	2.08	34.05	

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Statistics are generated using RATS 5.0

Table 9.5 provides descriptive characteristics of the default (*DEF*), term structure (*TERM*), convertible bond arbitrage (*CBRF*), skewness (*SKEW*) and kurtosis (*KURT*) risk factors. *KURT* is the kurtosis function (9.3) of the residuals from (9.1), estimated for the HFRI convertible arbitrage index, and *SKEW* is the skewness function (9.4) of the residuals from (9.1), estimated for the HFRI convertible arbitrage index. The correlation coefficient for *SKEW* and *KURT* is significantly negative at -0.86. *SKEW*, the skewness risk factor is also significantly negatively correlated with *DEF*, the default risk factor at the 5% level.

Table 9.5
Descriptive statistics of the individual fund risk factors

This table presents descriptive statistics and cross correlations for the common risk factors in convertible arbitrage. Where *DEF* is the default risk factor, *TERM* is the term structure risk factor, *CBRF* is the convertible bond arbitrage risk factor, *KURT* is the factor mimicking kurtosis risk and *SKEW* is the factor mimicking skewness risk.

	Mean %	Variance	Min	Max
DEF	0.54	9.39	-10.59	9.48
TERM	0.11	5.82	-6.56	6.81
CBRF	0.33	3.10	-10.36	4.99
KURT	-0.57	8.19	-26.70	1.19
SKEW	-0.00	1.76	-0.64	9.62

	DEF	*TERM*	*CBRF*	*KURT*	*SKEW*
DEF	1.00				
TERM	-0.71	1.00			
CBRF	0.39	0.01	1.00		
KURT	0.14	-0.02	0.07	1.00	
SKEW	-0.19	0.03	-0.06	-0.86	1.00

Coefficients greater than 0.25, 0.19 and 0.17 are significant at the 1%, 5% and 10% levels respectively.
Statistics are generated using RATS 5.0

Table 9.6 presents results from estimating the following factor model on individual convertible arbitrage hedge funds.

$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + \varepsilon_t \quad (9.5)$$

Where $KURT_t$ is a common risk factor mimicking kurtosis at time t and $SKEW_t$ is a common risk factor mimicking skewness, both characteristics of convertible arbitrage returns not captured in the linear model of performance evaluation in Chapter 5.

Table 9.6
Individual fund factor model using the HFRI RALS residual functions as a factor

This table presents results from estimating the factor model on individual fund returns
$$y_t = \alpha + \beta_{CBRF} CBRF_t + \beta_{DEF} DEF_t + \beta_{TERM} TERM_t + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + \varepsilon_t$$
Where y_t is the excess return on the fund, *DEF* is the default risk factor, *TERM* is the term structure risk factor, *CBRF* is the convertible bond arbitrage risk factor and *KURT* and *SKEW* are the factors mimicking kurtosis and skewness risk.

Fund	$r_i - r_f$	α	β_{DEF}	β_{TERM}	β_{CBRF}	β_{KURT}	β_{SKEW}	Adj. R^2	N
1	0.65	0.6308	-0.0270	-0.0894	0.1069	0.0308	-0.1473	-3.1%	69
		(3.26)***	(-0.35)	(-0.88)	(0.76)	(0.23)	(-0.50)		
2	0.69	-0.0635	-0.1045	-0.4861	0.6510	-0.6360	-1.3384	19.8%	69
		(-0.15)	(-0.51)	(-2.11)**	(2.52)**	(-2.89)***	(-2.78)***		
3	1.38	1.3028	-0.2559	-0.2920	-0.1136	-0.7968	-0.9919	4.9%	38
		(3.27)***	(-2.17)**	(-1.56)	(-0.22)	(-3.04)***	(-1.41)		
4	1.19	1.1537	-0.2922	-0.3166	0.0664	-0.2751	-0.9287	11.3%	60
		(3.99)***	(-4.13)***	(-2.92)***	(0.22)	(-2.31)**	(-3.26)***		
5	0.95	0.6380	-0.4140	-0.4064	0.2926	-0.4994	-1.3674	5.9%	69
		(1.11)	(-1.53)	(-1.72)*	(1.34)	(-1.47)	(-2.18)**		
6	0.97	0.7933	-0.3758	-0.3728	0.3571	-0.2775	-0.9212	2.2%	69
		(1.80)*	(-2.04)**	(-1.77)*	(1.84)*	(-0.97)	(-1.51)		
7	0.62	0.5069	-0.1564	-0.1282	0.3955	-0.2362	-0.4790	15.1%	58
		(3.19)***	(-3.48)***	(-1.85)*	(2.65)***	(-2.96)***	(-2.64)***		
8	0.92	0.7823	0.0215	0.0396	-0.0125	-0.1191	-0.3190	0.9%	82
		(5.60)***	(0.43)	(0.74)	(-0.18)	(-1.88)*	(-2.33)**		
9	0.44	-0.4732	0.7769	0.4048	-0.1403	-0.1203	-0.6283	21.4%	57
		(-1.28)	(4.92)***	(2.35)**	(-0.87)	(-0.77)	(-1.55)		

10	0.87	1.0688	0.0337	-0.1541	0.2075	-0.7101	0.2616	8.3%	27
		(3.25)***	(0.29)	(-1.62)	(0.89)	(-2.18)**	(0.51)		
11	0.23	0.2554	-0.0075	-0.0049	0.0102	-0.0420	-0.1213	-7.7%	52
		(3.53)***	(-0.28)	(-0.19)	(0.16)	(-0.34)	(-1.39)		
12	0.46	0.4663	-0.0434	-0.0541	0.1039	0.0305	0.1784	-5.2%	58
		(2.37)**	(-0.75)	(-0.78)	(0.64)	(0.33)	(1.11)		
13	-0.03	0.0227	-0.0488	-0.0626	0.1279	-0.1447	-0.0276	22.4%	30
		(0.49)	(-1.77)*	(-1.87)*	(2.31)**	(-2.44)**	(-0.39)		
14	0.66	0.6834	-0.0164	-0.0277	0.0672	-0.0117	-0.1536	-2.0%	55
		(5.32)***	(-0.51)	(-0.62)	(0.88)	(-0.26)	(-1.26)		
15	0.69	0.7137	-0.0043	-0.0503	0.1981	-0.4397	0.3901	10.9%	42
		(3.52)***	(-0.06)	(-0.73)	(1.41)	(-1.83)*	(1.31)		
16	0.82	0.8349	0.0214	0.0276	0.1379	-0.2705	0.3376	2.8%	38
		(6.10)***	(0.39)	(0.35)	(1.29)	(-2.44)**	(1.52)		
17	0.09	0.1850	-0.0207	-0.0082	0.1044	0.0256	-0.1014	-21.1%	25
		(1.41)	(-0.43)	(-0.13)	(0.94)	(0.17)	(-0.53)		
18	0.91	0.8931	-0.1828	-0.4055	0.2210	-0.5775	-0.5123	8.3%	36
		(3.95)***	(-1.74)*	(-3.19)***	(1.04)	(-1.70)*	(-1.27)		
19	0.56	0.3650	-0.2278	-0.1512	0.1401	-0.4818	-1.3647	30.7%	69
		(1.43)	(-2.17)**	(-1.42)	(1.49)	(-3.71)***	(-5.25)***		
20	0.66	0.3706	-0.1527	-0.1486	0.1632	-0.3988	-0.8705	11.3%	69
		(1.15)	(-1.20)	(-1.30)	(1.37)	(-2.26)**	(-2.17)**		
21	-0.12	-0.8756	-0.3862	0.5953	0.2368	-2.4773	-0.8100	18.9%	37
		(-0.69)	(-0.97)	(1.84)*	(0.44)	(-1.83)*	(-0.63)		
22	1.11	0.9950	-0.1172	-0.0520	-0.1058	-0.2041	-0.6829	0.4%	69
		(4.03)***	(-0.71)	(-0.43)	(-0.72)	(-2.23)**	(-2.94)***		
23	0.38	0.3230	-0.1620	-0.0510	0.1413	-0.0260	-0.2026	10.5%	69
		(2.25)**	(-1.50)	(-0.57)	(1.72)*	(-0.44)	(-1.56)		
24	0.38	0.2041	0.2340	0.2928	0.0249	0.0044	-0.1042	6.4%	69
		(1.16)	(1.23)	(1.74)*	(0.20)	(0.05)	(-0.52)		
25	0.66	0.3706	-0.1527	-0.1486	0.1632	-0.3988	-0.8705	11.3%	69
		(1.15)	(-1.20)	(-1.30)	(1.37)	(-2.26)**	(-2.17)**		
26	0.60	0.5934	-0.0683	-0.1180	0.1072	0.0493	-0.1116	-4.2%	69
		(2.99)***	(-0.77)	(-1.05)	(0.70)	(0.35)	(-0.36)		
27	0.69	0.5082	-0.0091	-0.0673	0.1626	-0.1050	-0.3260	5.7%	69
		(3.23)***	(-0.09)	(-0.67)	(1.79)*	(-1.84)*	(-2.23)**		
28	0.56	0.5826	0.0672	0.1007	0.2399	-0.2027	-0.0192	18.6%	25
		(3.62)***	(0.86)	(1.41)	(1.58)	(-1.09)	(-0.06)		
29	-0.76	-0.6623	-0.0894	-0.4504	0.1963	-0.2046	-0.5562	-2.0%	24
		(-1.28)	(-0.78)	(-1.84)*	(0.49)	(-0.30)	(-0.91)		
30	0.85	0.5671	-0.2141	-0.2135	0.7159	-1.1031	-0.0941	20.7%	38
		(1.96)*	(-1.67)*	(-1.18)	(2.30)**	(-2.90)***	(-0.19)		
31	0.70	0.3123	-0.3511	-0.3318	0.3132	-0.5832	-1.6595	21.5%	69

		(0.78)	(-2.63)***	(-2.33)**	(1.32)	(-2.48)**	(-3.07)***		
32	0.33	0.1935	-0.0490	-0.0547	-0.0087	-0.3270	-0.8848	5.3%	69
		(0.97)	(-0.26)	(-0.39)	(-0.08)	(-2.90)***	(-3.20)***		
33	0.05	-1.2382	0.0974	0.3391	1.4888	-0.7168	-1.4568	4.3%	69
		(-0.99)	(0.18)	(0.54)	(1.79)*	(-1.36)	(-1.09)		
34	0.67	0.2159	0.2281	0.0390	0.1102	-0.3295	-1.2086	15.8%	69
		(0.70)	(1.71)*	(0.28)	(0.60)	(-2.97)***	(-4.57)***		
35	0.64	0.2414	-0.2909	-0.3265	0.4896	-0.2960	-1.3411	7.6%	69
		(0.41)	(-0.68)	(-0.97)	(2.06)**	(-0.77)	(-1.94)*		
36	0.13	0.3043	0.0357	0.0753	-0.0334	0.0366	-0.0691	20.6%	69
		(2.67)***	(1.01)	(2.23)**	(-0.75)	(0.86)	(-0.87)		
37	0.47	0.5759	0.0056	0.0012	-0.0097	0.3080	0.0605	-10.2%	36
		(2.59)***	(0.13)	(0.02)	(-0.07)	(1.68)*	(0.19)		
38	0.52	0.2791	-0.1306	-0.0942	0.2941	-0.1960	-0.5712	8.6%	69
		(1.02)	(-1.63)	(-1.10)	(2.09)**	(-1.29)	(-1.98)**		
39	0.58	0.4155	-0.1417	-0.1793	0.5256	-0.4984	-0.1717	27.7%	51
		(3.20)***	(-3.36)***	(-2.35)**	(4.09)***	(-3.28)***	(-1.04)		
40	0.52	0.2904	0.0640	-0.0138	0.0236	-0.2521	-0.5739	27.7%	51
		(1.82)*	(1.02)	(-0.24)	(0.46)	(-1.68)*	(-4.54)***		
41	0.89	0.5384	-0.4671	-0.4020	0.2971	-0.5945	-1.6948	36.8%	69
		(1.22)	(-3.83)***	(-3.29)***	(1.47)	(-1.98)**	(-2.64)***		
42	0.66	0.8846	0.0566	0.0949	0.0041	0.3405	0.6936	-10.1%	24
		(3.20)***	(0.86)	(1.14)	(0.02)	(1.34)	(1.58)		
43	0.39	0.3986	-0.0142	-0.0717	-0.0040	-0.0486	0.0165	-4.8%	69
		(3.19)***	(-0.29)	(-1.13)	(-0.03)	(-0.54)	(0.11)		
44	1.30	0.8649	-0.5007	-0.3955	0.5795	-0.6590	-1.8082	35.5%	69
		(1.67)*	(-3.14)***	(-2.70)***	(2.60)***	(-1.98)**	(-2.43)**		
45	1.09	1.2635	0.0248	-0.2655	-0.0948	-0.8432	0.6727	-3.3%	41
		(1.70)*	(0.12)	(-1.34)	(-0.22)	(-1.08)	(0.74)		
46	0.67	0.6417	0.0174	0.0054	-0.1345	-0.0155	0.0057	-5.9%	69
		(4.24)***	(0.26)	(0.08)	(-0.99)	(-0.14)	(0.03)		
47	0.36	0.4045	0.0077	0.0542	-0.0303	-0.2154	-0.6841	15.9%	69
		(2.74)***	(0.11)	(0.85)	(-0.43)	(-3.14)***	(-4.21)***		
48	0.62	0.4255	-0.0874	-0.0464	0.1964	-0.1711	-0.4465	4.4%	69
		(2.53)**	(-1.12)	(-0.53)	(1.62)	(-1.52)	(-1.88)*		
49	0.46	0.3899	-0.1519	-0.1531	0.0949	-0.0997	-0.3580	20.3%	69
		(3.27)***	(-3.02)***	(-2.77)***	(1.62)	(-1.59)	(-2.93)***		
50	0.44	0.3099	-0.2321	-0.3036	0.3932	-0.2742	-0.6572	25.2%	67
		(1.95)*	(-4.13)***	(-3.84)***	(3.28)***	(-2.40)**	(-2.87)***		
51	0.57	0.4005	-0.1115	-0.1585	0.2263	-0.5768	-0.9962	12.6%	57
		(1.55)	(-0.94)	(-1.70)*	(1.15)	(-1.94)*	(-1.54)		
52	0.58	0.5379	-0.0939	-0.2210	0.0411	-0.3967	-0.2924	2.8%	52
		(2.18)**	(-1.23)	(-2.71)***	(0.21)	(-1.28)	(-1.16)		

53	0.66	0.5638	0.0148	0.0871	-0.0531	-0.1457	-0.4439	0.5%	69
		(2.85)***	(0.14)	(0.63)	(-0.31)	(-1.64)	(-2.11)**		
54	0.36	0.3428	-0.1033	-0.0891	0.3251	0.0088	-0.0719	11.0%	57
		(3.36)***	(-2.92)***	(-1.88)*	(3.38)***	(0.14)	(-0.46)		
55	0.46	0.3338	-0.0013	-0.0348	0.0913	-0.0639	-0.1941	6.1%	69
		(3.72)***	(-0.02)	(-0.60)	(1.74)*	(-1.98)**	(-2.34)**		
Mean		0.43	-0.08	-0.10	0.18	-0.31	-0.49	9.1%	
P- Value		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		

t-statistics in parenthesis are heteroskedasticity and autocorrelation-consistent, due to Newey and West (1987).
***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

β_{KURT}, the kurtosis coefficient is significantly different from zero for twenty nine of the hedge funds. One of the coefficients is positive with twenty eight negative coefficients. The mean coefficient is -0.31. β_{SKEW}, the skewness coefficient is significantly different from zero for twenty four of the hedge funds. Thirty five of the hedge funds display non-normal characteristics, having at least one significant skewness or kurtosis coefficient. These findings are consistent with Kat and Miffre (2005) who document fifty percent of convertible arbitrage hedge funds exhibiting significant skewness and kurtosis risk coefficients. All of the significant coefficients are negative with a mean coefficient of -0.49 remarkably consistent with the HFRI index (coefficients ranging from -0.43 to -0.49). The default risk coefficients, β_{DEF}, are significantly different from zero for seventeen of the hedge funds and the term structure risk, β_{TERM}, and convertible bond arbitrage risk coefficients, β_{CBRF}, are significantly different from zero for twenty one and fifteen hedge funds respectively. The mean estimate of alpha for the hedge funds is 0.43 but given a mean adjusted R^2 of the model of 9.1% few conclusions can be drawn on performance.[81]

[81] All of the mean coefficients are statistically significant from zero at the 1% level.

In Chapter 5 evidence was presented, consistent with the findings of Asness Krail and Liew (2001) that, due to the illiquidity in the securities held by convertible arbitrage hedge funds, the specification of lagged and contemporaneous risk factors more fully captures the risk characteristics of these funds. Table 9.7 presents results from estimating the following model of individual fund performance measurement (derived from the non-synchronous trading literature).

$$y_t = \alpha + \beta_0' \, DEF + \beta_1' TERM + \beta_2' CBRF + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + u_t \quad (9.4)$$

This is the factor model from Chapter 5 augmented with the skewness and kurtosis common risk factors $KURT_t$ and $SKEW_t$. $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$, and $KURT_t$ is equal to $(\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t)$ and $SKEW_t$ is equal to $(\hat{u}_t^2 - \hat{\sigma}^2)$ and $\hat{u}_t$ denotes the residual and $\hat{\sigma}^2$ denotes the standard residual variance estimate obtained from OLS applied to equation (9.1) on the HFRI index.

Table 9.7
Results of estimating non-synchronous regressions of individual fund risk factors

This table presents the results of estimating the excess returns of individual hedge funds on the following model of hedge fund returns.

$$y_t = \alpha + \beta_0' \, DEF + \beta_1' TERM + \beta_2' CBRF + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + u_t$$

Where $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$, *KURT* is the kurtosis risk factor and *SKEW* is the skewness risk factor and the β coefficient is the sum of the contemporaneous β and lagged β s. Numbers in parenthesis are *P*-Values from the joint test of $\beta_{jt} = \beta_{jt-1} = \beta_{jt-2} = 0$ for *DEF*, *TERM* and *CBRF* and $\beta = 0$ for *KURT* and *SKEW*.

Fund	$r_i - r_f$	α	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	β_{KURT}	β_{SKEW}	Adj R^2	Q Stat (10)
1	0.65	0.57	0.09	0.01	0.42	0.15	0.17	9.1%	0.57
		(0.00)	(0.83)	(0.97)	(0.00)	(0.30)	(0.56)		(0.00)
2	0.69	-0.17	-0.18	-0.57	1.10	-0.55	-1.21	20.9%	-0.17
		(0.64)	(0.27)	(0.05)	(0.02)	(0.06)	(0.06)		(0.64)
3	1.38	1.00	-0.77	-0.89	1.59	-0.70	-1.12	27.2%	15.23

		(0.02)	(0.05)	(0.05)	(0.00)	(0.03)	(0.05)		(0.02)
4	1.19	1.05	-0.54	-0.69	1.45	-0.13	-0.54	31.4%	21.16
		(0.00)	(0.01)	(0.02)	(0.00)	(0.27)	(0.02)		(0.00)
5	0.95	0.21	0.95	0.74	0.96	0.09	-0.05	51.2%	33.25
		(0.61)	(0.00)	(0.00)	(0.02)	(0.64)	(0.87)		(0.00)
6	0.97	0.45	0.53	0.38	1.11	0.06	-0.06	28.0%	19.19
		(0.19)	(0.33)	(0.35)	(0.17)	(0.80)	(0.90)		(0.00)
7	0.62	0.54	0.15	0.27	0.51	-0.14	-0.30	32.9%	26.42
		(0.00)	(0.00)	(0.00)	(0.05)	(0.01)	(0.02)		(0.00)
8	0.92	0.77	-0.02	0.15	0.00	-0.15	-0.41	5.6%	18.78
		(0.00)	(0.82)	(0.57)	(0.82)	(0.02)	(0.01)		(0.00)
9	0.44	0.02	0.27	0.59	0.56	0.03	0.01	44.3%	20.61
		(0.95)	(0.08)	(0.01)	(0.00)	(0.87)	(0.98)		(0.00)
10	0.87	1.08	0.40	0.39	0.00	-0.09	0.12	6.9%	15.01
		(0.00)	(0.22)	(0.36)	(0.70)	(0.80)	(0.83)		(0.02)
11	0.23	0.26	0.02	0.01	-0.03	-0.07	-0.07	-12.7%	21.69
		(0.00)	(0.44)	(0.96)	(0.86)	(0.56)	(0.42)		(0.00)
12	0.46	0.40	-0.05	0.22	0.48	-0.01	0.07	-5.1%	19.05
		(0.02)	(0.98)	(0.06)	(0.18)	(0.95)	(0.65)		(0.00)
13	-0.03	-0.12	-0.10	0.00	0.47	-0.03	-0.09	46.2%	19.87
		(0.01)	(0.00)	(0.00)	(0.00)	(0.56)	(0.10)		(0.00)
14	0.66	0.64	-0.02	0.10	0.45	0.00	-0.15	4.6%	18.91
		(0.00)	(0.91)	(0.56)	(0.02)	(0.92)	(0.15)		(0.00)
15	0.69	0.67	-0.11	-0.14	0.20	-0.56	0.33	0.1%	17.76
		(0.00)	(0.20)	(0.13)	(0.00)	(0.05)	(0.20)		(0.01)
16	0.82	0.66	-0.14	0.02	0.71	-0.29	0.13	13.5%	17.10
		(0.00)	(0.06)	(0.12)	(0.00)	(0.04)	(0.53)		(0.01)
17	0.09	0.07	-0.21	-0.21	0.33	-0.07	-0.08	-8.7%	18.59
		(0.53)	(0.00)	(0.00)	(0.00)	(0.54)	(0.67)		(0.00)
18	0.91	0.95	0.15	0.15	-0.07	-0.21	-0.69	24.0%	13.39
		(0.00)	(0.01)	(0.00)	(0.55)	(0.49)	(0.06)		(0.04)
19	0.56	-0.07	0.40	0.48	0.09	-0.39	-1.10	57.4%	8.95
		(0.71)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)		(0.18)
20	0.66	0.22	0.15	0.16	0.10	-0.37	-0.78	14.7%	10.40
		(0.50)	(0.22)	(0.05)	(0.07)	(0.00)	(0.02)		(0.11)
21	-0.12	-0.83	0.05	1.17	0.33	-2.32	-0.53	32.5%	16.61
		(0.40)	(0.01)	(0.06)	(0.57)	(0.05)	(0.48)		(0.01)
22	1.11	0.98	-0.03	0.28	-0.15	-0.13	-0.48	7.7%	16.49
		(0.00)	(0.05)	(0.05)	(0.29)	(0.16)	(0.06)		(0.01)
23	0.38	-0.18	0.51	0.54	0.03	0.02	0.04	23.3%	22.14
		(0.32)	(0.00)	(0.00)	(0.26)	(0.66)	(0.73)		(0.00)
24	0.38	-0.15	0.69	0.78	-0.17	0.00	0.09	24.7%	19.38
		(0.50)	(0.01)	(0.01)	(0.33)	(1.00)	(0.63)		(0.00)

25	0.66	0.22	0.15	0.16	0.10	-0.37	-0.78	14.7%	18.29
		(0.50)	(0.22)	(0.05)	(0.07)	(0.00)	(0.02)		(0.01)
26	0.60	0.53	0.09	0.07	0.36	0.17	0.20	6.6%	8.89
		(0.00)	(0.55)	(0.74)	(0.01)	(0.28)	(0.51)		(0.18)
27	0.69	0.17	0.69	0.54	0.02	-0.02	-0.02	38.7%	12.74
		(0.22)	(0.00)	(0.00)	(0.41)	(0.69)	(0.92)		(0.05)
28	0.56	0.48	0.06	0.19	0.47	-0.18	-0.10	32.3%	21.10
		(0.00)	(0.22)	(0.02)	(0.00)	(0.26)	(0.73)		(0.00)
29	-0.76	0.06	0.53	-0.88	-1.57	0.41	0.13	70.9%	22.12
		(0.85)	(0.00)	(0.00)	(0.00)	(0.11)	(0.67)		(0.00)
30	0.85	0.64	-0.06	-0.15	0.93	-0.72	0.03	50.5%	17.84
		(0.03)	(0.04)	(0.09)	(0.00)	(0.04)	(0.95)		(0.01)
31	0.70	0.29	-0.53	-0.82	0.86	-0.47	-1.36	22.2%	13.97
		(0.42)	(0.09)	(0.18)	(0.12)	(0.08)	(0.03)		(0.03)
32	0.33	-0.21	0.15	0.11	0.35	-0.30	-0.65	11.1%	17.67
		(0.44)	(0.39)	(0.30)	(0.03)	(0.00)	(0.01)		(0.01)
33	0.05	-2.10	-0.66	-0.80	4.43	-0.46	-0.59	8.8%	16.57
		(0.10)	(0.56)	(0.28)	(0.02)	(0.46)	(0.70)		(0.01)
34	0.67	-0.56	0.45	0.18	0.79	-0.31	-0.96	34.5%	39.05
		(0.07)	(0.00)	(0.12)	(0.01)	(0.00)	(0.00)		(0.00)
35	0.64	-0.39	0.92	0.44	1.04	0.27	0.20	40.0%	9.16
		(0.47)	(0.00)	(0.00)	(0.07)	(0.48)	(0.70)		(0.16)
36	0.13	0.26	0.11	0.27	-0.13	0.07	0.04	32.9%	13.53
		(0.01)	(0.02)	(0.01)	(0.13)	(0.12)	(0.70)		(0.04)
37	0.47	0.36	-0.16	0.13	0.18	0.20	-0.30	15.1%	28.32
		(0.03)	(0.13)	(0.31)	(0.00)	(0.16)	(0.28)		(0.00)
38	0.52	0.11	0.35	0.24	0.49	-0.02	-0.14	37.0%	17.63
		(0.65)	(0.00)	(0.01)	(0.03)	(0.90)	(0.55)		(0.01)
39	0.58	0.39	0.02	0.07	0.82	-0.20	-0.17	49.9%	5.14
		(0.01)	(0.01)	(0.00)	(0.00)	(0.25)	(0.09)		(0.53)
40	0.52	0.15	0.17	0.11	0.15	-0.24	-0.29	57.3%	3.81
		(0.16)	(0.00)	(0.06)	(0.40)	(0.02)	(0.00)		(0.70)
41	0.89	0.34	-0.26	-0.31	0.57	-0.59	-1.65	40.2%	37.97
		(0.43)	(0.00)	(0.01)	(0.20)	(0.03)	(0.01)		(0.00)
42	0.66	0.63	-0.17	0.12	0.47	0.40	0.61	-1.4%	36.40
		(0.00)	(0.08)	(0.39)	(0.00)	(0.08)	(0.14)		(0.00)
43	0.39	0.38	0.13	0.09	0.10	0.00	0.10	-4.0%	8.79
		(0.00)	(0.48)	(0.50)	(0.04)	(0.96)	(0.54)		(0.19)
44	1.30	0.62	-0.29	-0.31	0.89	-0.59	-1.61	40.4%	21.15
		(0.23)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)		(0.00)
45	1.09	1.20	-0.19	-0.50	-0.15	-1.06	0.60	-19.7%	60.18
		(0.16)	(0.68)	(0.40)	(0.85)	(0.17)	(0.64)		(0.00)
46	0.67	0.56	0.16	0.10	0.01	0.01	0.08	-5.2%	20.35

		(0.00)	(0.70)	(0.60)	(0.20)	(0.90)	(0.67)		(0.00)
47	0.36	0.31	0.11	0.31	-0.08	-0.19	-0.52	25.4%	21.03
		(0.07)	(0.32)	(0.05)	(0.50)	(0.00)	(0.00)		(0.00)
48	0.62	0.27	0.18	0.21	0.57	-0.05	-0.17	29.1%	28.44
		(0.01)	(0.00)	(0.01)	(0.05)	(0.52)	(0.27)		(0.00)
49	0.46	0.23	0.08	0.07	0.16	-0.04	-0.19	47.9%	38.53
		(0.00)	(0.00)	(0.00)	(0.07)	(0.40)	(0.04)		(0.00)
50	0.44	0.26	-0.06	-0.07	0.60	-0.19	-0.50	41.1%	12.32
		(0.03)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)		(0.06)
51	0.57	0.46	-0.02	-0.13	-0.42	-0.61	-1.05	11.9%	13.73
		(0.11)	(0.17)	(0.32)	(0.07)	(0.05)	(0.12)		(0.03)
52	0.58	0.55	0.09	0.05	0.11	-0.41	-0.14	9.3%	12.31
		(0.01)	(0.21)	(0.10)	(0.27)	(0.05)	(0.52)		(0.06)
53	0.66	0.25	0.60	0.57	-0.27	-0.10	-0.29	12.0%	23.29
		(0.21)	(0.02)	(0.08)	(0.02)	(0.21)	(0.22)		(0.00)
54	0.36	0.34	0.01	0.14	0.47	0.04	-0.03	15.1%	42.09
		(0.00)	(0.03)	(0.03)	(0.00)	(0.51)	(0.80)		(0.00)
55	0.46	0.15	0.39	0.30	0.01	-0.02	-0.02	36.4%	16.79
		(0.07)	(0.00)	(0.00)	(0.43)	(0.60)	(0.82)		(0.01)
Mean		0.29	0.26	0.08	0.41	-0.21	-0.30	23.3%	
P-Value		(0.00	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)		

The coefficient of the kurtosis risk factor is significantly different from zero for twenty two hedge funds with a mean coefficient of -0.21. The skewness risk factor is significantly different from zero for twenty of the hedge funds with a mean coefficient of -0.30. Both of these results are consistent with the expectation that arbitrageurs are rewarded for holding portfolios exhibiting skewness and kurtosis in their return distribution. The default risk, term structure risk and convertible bond arbitrage risk coefficients are significantly different from zero for between thirty three and thirty five hedge funds with mean coefficients of 0.26, 0.08 and 0.41 respectively. The explanatory power of the model is higher than the contemporaneous model with a mean adjusted R^2 of 23.3%. The alphas for the fifty five funds are significantly different from zero (minimum of -2.3% and maximum of 0.9% per month) with a mean alpha coefficient of

29 basis points per month or 3.5% per annum. This compares to the mean alpha of 34 basis points per month for the non-synchronous model which omitted skewness and kurtosis risk factors reported in Chapter 5.[82] This is equivalent to 15% of the abnormal performance estimate from the model omitting skewness and kurtosis risk. This evidence suggests that convertible arbitrageurs are being rewarded with a risk premium of approximately five basis points per month, or sixty basis points per annum, for bearing skewness and kurtosis risk. This is a finding consistent with Kat and Miffre (2005) who estimate that failure to specify kurtosis and skewness risk factors will lead to an upward bias in hedge fund performance estimates of 1%.

Finally, this analysis is repeated for a non-synchronous model augmented with skewness and kurtosis risk factors and the one period lag of the hedge fund excess return, as a proxy for illiquidity. Table 9.8 presents results from estimating the following model (9.4) of individual fund performance measurement.

$$y_t = \alpha + \beta_0' \, DEF + \beta_1' TERM + \beta_2' CBRF + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + \beta_Y y_{t-1} + u_t \quad (9.4)$$

Where y_{t-1}, the illiquidity risk factor proxy is the excess return on the individual hedge fund at time $t-1$.

[82] All of the mean coefficients are statistically significant from zero at the 1% level, with the exception of *DEF*, which is significant at the 15% level.

Table 9.8

Results of estimating non-synchronous regressions of individual fund risk factors augmented with an illiquidity risk factor proxy

This table presents the results of estimating the excess returns of individual hedge funds on the following model of hedge fund returns.

$$y_t = \alpha + \beta_0' DEF + \beta_1' TERM + \beta_2' CBRF + \beta_{KURT} KURT_t + \beta_{SKEW} SKEW_t + \beta_Y y_{t-1} + u_t$$

Where $DEF = (DEF_t, DEF_{t-1}, DEF_{t-2})$, $TERM = (TERM_t, TERM_{t-1}, TERM_{t-2})$, $CBRF = (CBRF_t, CBRF_{t-1}$ and $CBRF_{t-2})$, *KURT* is the kurtosis risk factor and *SKEW* is the skewness risk factor and the β coefficient is the sum of the contemporaneous β and lagged β s. Numbers in parenthesis are *P*-Values from the joint test of $\beta_{jt} = \beta_{jt-1} = \beta_{jt-2} = 0$ for *DEF*, *TERM* and *CBRF* and $\beta = 0$ for *KURT*, *SKEW* and y_{t-1}.

Fund	$r_i - r_f$	α	$\beta_{DEF(t\ to\ t-2)}$	$\beta_{TERM(t\ to\ t-2)}$	$\beta_{CBRF(t\ to\ t-2)}$	β_Y	β_{KURT}	β_{SKEW}	Adj. R^2	Q Stat (10)
1	0.65	0.55	0.09	0.04	0.39	0.15	0.16	0.07	7.9%	10.99
		(0.00)	(0.79)	(0.94)	(0.00)	(0.32)	(0.59)	(0.43)		(0.09)
2	0.69	-0.41	0.04	-0.28	0.90	-0.57	-1.01	0.27	24.5%	6.57
		(0.27)	(0.71)	(0.15)	(0.03)	(0.07)	(0.12)	(0.01)		(0.36)
3	1.38	0.78	-0.77	-0.90	1.59	-0.73	-1.11	0.17	25.1%	6.90
		(0.09)	(0.09)	(0.08)	(0.00)	(0.02)	(0.03)	(0.22)		(0.33)
4	1.19	0.87	-0.49	-0.63	1.40	-0.14	-0.49	0.16	31.4%	9.05
		(0.00)	(0.06)	(0.08)	(0.00)	(0.24)	(0.04)	(0.31)		(0.17)
5	0.95	0.09	0.98	0.82	0.79	0.01	-0.01	0.17	51.7%	16.15
		(0.81)	(0.00)	(0.01)	(0.03)	(0.95)	(0.98)	(0.33)		(0.01)
6	0.97	0.26	0.62	0.59	0.91	-0.02	-0.11	0.25	33.4%	6.98
		(0.45)	(0.14)	(0.13)	(0.18)	(0.92)	(0.84)	(0.04)		(0.32)
7	0.62	0.42	0.18	0.32	0.44	-0.14	-0.31	0.25	42.2%	12.54
		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.07)		(0.05)
8	0.92	0.22	0.01	0.12	0.00	-0.07	-0.12	0.69	50.6%	25.38
		(0.04)	(0.58)	(0.19)	(0.33)	(0.04)	(0.10)	(0.00)		(0.00)
9	0.44	-0.11	0.45	0.81	0.47	-0.03	-0.13	-0.19	45.1%	14.28
		(0.79)	(0.01)	(0.00)	(0.00)	(0.85)	(0.79)	(0.20)		(0.03)
10	0.87	0.79	0.40	0.51	-0.26	-0.06	-0.18	0.29	-1.6%	11.14
		(0.01)	(0.11)	(0.44)	(0.78)	(0.82)	(0.76)	(0.09)		(0.08)
11	0.23	0.28	-0.03	-0.07	-0.05	-0.34	0.16	-0.04	0.3%	15.90
		(0.00)	(0.44)	(0.70)	(0.96)	(0.01)	(0.07)	(0.74)		(0.01)
12	0.46	0.23	-0.06	0.19	0.43	-0.05	-0.05	0.39	10.1%	13.29
		(0.06)	(0.61)	(0.04)	(0.06)	(0.50)	(0.69)	(0.00)		(0.04)
13	-0.03	-0.10	-0.08	0.03	0.43	0.02	-0.10	0.03	48.8%	14.15
		(0.03)	(0.00)	(0.00)	(0.00)	(0.70)	(0.04)	(0.92)		(0.03)
14	0.66	0.37	-0.03	0.10	0.33	0.02	-0.12	0.43	19.5%	14.77
		(0.00)	(0.84)	(0.48)	(0.05)	(0.71)	(0.22)	(0.00)		(0.02)

15	0.69	0.34	-0.09	-0.04	0.03	-0.44	0.00	0.46	18.2%	12.68
		(0.12)	(0.06)	(0.09)	(0.03)	(0.07)	(0.99)	(0.00)		(0.05)
16	0.82	0.14	-0.06	0.18	0.38	-0.32	-0.12	0.65	43.6%	13.96
		(0.25)	(0.00)	(0.02)	(0.00)	(0.00)	(0.54)	(0.00)		(0.03)
17	0.09	0.07	-0.23	-0.22	0.38	-0.03	0.13	0.21	-4.6%	14.39
		(0.48)	(0.00)	(0.00)	(0.00)	(0.81)	(0.37)	(0.04)		(0.03)
18	0.91	0.89	0.11	0.06	-0.09	-0.33	-0.65	0.09	20.3%	10.25
		(0.00)	(0.01)	(0.00)	(0.75)	(0.31)	(0.09)	(0.46)		(0.11)
19	0.56	-0.20	0.43	0.47	0.15	-0.24	-0.69	0.32	64.0%	7.19
		(0.11)	(0.00)	(0.00)	(0.26)	(0.02)	(0.01)	(0.02)		(0.30)
20	0.66	0.20	0.16	0.16	0.10	-0.26	-0.57	0.17	14.8%	7.90
		(0.50)	(0.10)	(0.02)	(0.18)	(0.17)	(0.14)	(0.45)		(0.25)
21	-0.12	-0.90	0.10	1.30	0.46	-2.09	-0.53	0.05	29.3%	17.18
		(0.37)	(0.02)	(0.06)	(0.61)	(0.09)	(0.47)	(0.42)		(0.01)
22	1.11	0.55	0.15	0.38	-0.14	-0.07	-0.29	0.32	17.3%	14.23
		(0.05)	(0.23)	(0.10)	(0.22)	(0.40)	(0.20)	(0.00)		(0.03)
23	0.38	-0.18	0.49	0.50	0.02	0.03	0.07	0.15	24.5%	21.00
		(0.32)	(0.00)	(0.00)	(0.17)	(0.58)	(0.58)	(0.15)		(0.00)
24	0.38	-0.14	0.68	0.77	-0.18	0.01	0.11	0.04	22.6%	18.78
		(0.52)	(0.02)	(0.01)	(0.42)	(0.93)	(0.59)	(0.72)		(0.00)
25	0.66	0.20	0.16	0.16	0.10	-0.26	-0.57	0.17	14.8%	16.61
		(0.50)	(0.10)	(0.02)	(0.18)	(0.17)	(0.14)	(0.45)		(0.01)
26	0.60	0.49	0.09	0.08	0.32	0.17	0.20	0.12	6.3%	10.29
		(0.00)	(0.46)	(0.60)	(0.02)	(0.28)	(0.50)	(0.22)		(0.11)
27	0.69	0.15	0.67	0.50	0.01	0.03	0.14	0.13	42.2%	10.94
		(0.31)	(0.00)	(0.00)	(0.32)	(0.49)	(0.35)	(0.35)		(0.09)
28	0.56	0.34	0.00	0.18	0.43	-0.20	0.10	0.31	40.7%	10.87
		(0.01)	(0.00)	(0.00)	(0.00)	(0.25)	(0.72)	(0.05)		(0.09)
29	-0.76	0.16	0.16	-0.93	-1.03	0.43	0.94	0.50	78.6%	10.65
		(0.35)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)		(0.10)
30	0.85	0.22	-0.18	-0.10	0.89	-0.72	-0.33	0.39	54.5%	18.58
		(0.34)	(0.00)	(0.03)	(0.00)	(0.01)	(0.47)	(0.00)		(0.00)
31	0.70	0.20	-0.49	-0.75	0.80	-0.41	-1.19	0.21	24.6%	8.90
		(0.52)	(0.10)	(0.21)	(0.08)	(0.07)	(0.02)	(0.05)		(0.18)
32	0.33	-0.20	0.21	0.15	0.35	-0.32	-0.73	-0.14	10.9%	13.76
		(0.46)	(0.39)	(0.29)	(0.02)	(0.00)	(0.00)	(0.39)		(0.03)
33	0.05	-2.13	-0.45	-0.64	4.22	-0.36	-0.23	0.17	9.6%	11.09
		(0.09)	(0.35)	(0.17)	(0.02)	(0.54)	(0.87)	(0.26)		(0.09)
34	0.67	-0.58	0.33	0.09	0.84	-0.26	-0.77	0.22	36.3%	23.33
		(0.03)	(0.00)	(0.12)	(0.01)	(0.00)	(0.00)	(0.01)		(0.00)
35	0.64	-0.34	0.88	0.42	1.06	0.31	0.27	0.01	39.1%	7.52
		(0.54)	(0.00)	(0.00)	(0.08)	(0.41)	(0.62)	(0.90)		(0.28)
36	0.13	0.23	0.08	0.19	-0.10	0.08	0.05	0.26	35.2%	12.30

		(0.00)	(0.03)	(0.04)	(0.18)	(0.08)	(0.60)	(0.00)		(0.06)
37	0.47	0.21 (0.01)	-0.05 (0.21)	0.20 (0.15)	-0.09 (0.00)	0.16 (0.21)	-0.36 (0.14)	0.44 (0.00)	30.9%	30.05 (0.00)
38	0.52	0.06 (0.77)	0.32 (0.00)	0.22 (0.00)	0.53 (0.04)	-0.01 (0.96)	-0.03 (0.88)	0.21 (0.06)	42.4%	13.81 (0.03)
39	0.58	0.34 (0.00)	0.02 (0.00)	0.09 (0.00)	0.66 (0.00)	-0.19 (0.21)	-0.18 (0.08)	0.17 (0.25)	49.3%	3.08 (0.80)
40	0.52	0.18 (0.15)	0.19 (0.00)	0.11 (0.09)	0.16 (0.44)	-0.27 (0.00)	-0.35 (0.00)	-0.13 (0.37)	56.8%	3.02 (0.81)
41	0.89	0.12 (0.69)	-0.13 (0.00)	-0.15 (0.00)	0.51 (0.07)	-0.43 (0.05)	-1.14 (0.02)	0.37 (0.03)	49.3%	5.87 (0.44)
42	0.66	0.57 (0.04)	-0.11 (0.05)	0.21 (0.09)	0.38 (0.00)	0.16 (0.67)	0.53 (0.22)	0.18 (0.27)	2.7%	10.88 (0.09)
43	0.39	0.47 (0.00)	0.10 (0.59)	0.04 (0.26)	0.09 (0.05)	-0.02 (0.85)	0.01 (0.95)	-0.19 (0.04)	-2.7%	11.48 (0.07)
44	1.30	0.36 (0.36)	-0.08 (0.01)	-0.13 (0.00)	0.62 (0.04)	-0.40 (0.11)	-1.11 (0.06)	0.32 (0.04)	46.3%	9.48 (0.15)
45	1.09	0.45 (0.50)	-0.28 (0.58)	-0.09 (0.48)	0.17 (0.97)	-0.30 (0.54)	-0.19 (0.87)	0.48 (0.01)	-1.8%	22.60 (0.00)
46	0.67	0.71 (0.00)	0.12 (0.75)	0.07 (0.56)	0.00 (0.09)	-0.05 (0.69)	-0.03 (0.89)	-0.26 (0.00)	1.0%	26.29 (0.00)
47	0.36	0.21 (0.16)	0.09 (0.32)	0.26 (0.08)	-0.04 (0.54)	-0.13 (0.02)	-0.36 (0.01)	0.28 (0.04)	29.8%	28.73 (0.00)
48	0.62	0.26 (0.01)	0.19 (0.00)	0.24 (0.01)	0.53 (0.06)	-0.07 (0.29)	-0.21 (0.15)	0.06 (0.65)	29.9%	46.01 (0.00)
49	0.46	0.17 (0.01)	0.08 (0.00)	0.07 (0.00)	0.16 (0.04)	0.00 (0.91)	-0.10 (0.14)	0.24 (0.01)	50.4%	53.04 (0.00)
50	0.44	0.22 (0.03)	-0.03 (0.00)	0.02 (0.00)	0.55 (0.00)	-0.21 (0.00)	-0.54 (0.00)	0.13 (0.37)	43.6%	11.24 (0.08)
51	0.57	0.45 (0.11)	-0.02 (0.19)	-0.13 (0.38)	-0.44 (0.06)	-0.61 (0.05)	-1.06 (0.11)	0.08 (0.43)	11.1%	7.10 (0.31)
52	0.58	0.37 (0.03)	0.01 (0.16)	0.03 (0.20)	0.13 (0.38)	-0.64 (0.03)	-0.05 (0.81)	0.24 (0.07)	12.1%	8.40 (0.21)
53	0.66	0.16 (0.32)	0.59 (0.01)	0.58 (0.09)	-0.28 (0.09)	-0.06 (0.48)	-0.17 (0.46)	0.23 (0.03)	15.0%	19.92 (0.00)
54	0.36	0.26 (0.00)	0.03 (0.03)	0.15 (0.01)	0.33 (0.00)	0.05 (0.51)	0.01 (0.94)	0.32 (0.00)	19.9%	37.60 (0.00)
55	0.46	0.13 (0.14)	0.38 (0.00)	0.28 (0.00)	0.00 (0.33)	0.02 (0.54)	0.08 (0.38)	0.13 (0.35)	40.9%	15.22 (0.02)
Mean **P-Value**		0.17 (0.01)	0.11 (0.02)	0.12 (0.03)	0.38 (0.00)	0.20 (0.00)	-0.19 (0.00)	-0.24 (0.00)	28.3%	

The mean coefficients on *DEF* (0.11), *TERM* (0.12), *CBRF* (0.38), and y_{t-1} (0.20) are all significantly positive. The mean coefficients on *KURT* and *SKEW*, the kurtosis (-0.19) and skewness (-0.24) risk factors remain significantly negative. The mean estimated alpha coefficient is 0.17% per month, significant at the 1% level. This compares to an estimated alpha of 0.20% per month for the same model omitting skewness and kurtosis risk factors estimated in Chapter 5. Again, these results indicate that 15% of the estimated abnormal performance from a model omitting higher moment risk factors is attributable to skewness and kurtosis risk.

9.5 Conclusion

The contribution of the empirical research in this chapter is the estimation of convertible arbitrage risk factors using RALS, an estimation technique explicitly incorporating non-normality in a time series' return distribution, a feature of convertible arbitrage hedge fund returns. An additional contribution is the specification and estimation of skewness and kurtosis risk factors which are highly significant explanatory variables in the returns of individual hedge funds.

Evidence is presented demonstrating RALS estimation of the hedge fund index risk factor models improves efficiency relative to OLS. This is expected, considering the non-normality documented in the return distribution of these hedge fund indices. Evidence also presented in this chapter indicates that skewness is a significant risk factor in the returns of both convertible arbitrage hedge funds and hedge fund indices. Consistent with theoretical expectations arbitrageurs are rewarded with a risk premium for holding portfolios with negative skewness in the return distribution. This risk premium is estimated to be sixty basis points per annum. Kurtosis is also a significant factor in the returns of convertible arbitrage hedge funds but is not significant for the indices. Individual convertible arbitrage hedge funds are rewarded for holding portfolio with significant excess kurtosis in the distribution of returns. These findings are consistent with previous research by Kat and Miffre (2005) who highlight the risk premium received by convertible arbitrage hedge funds for bearing skewness and kurtosis risks.

Chapter 10: Conclusions

10.1 Introduction

This chapter presents an overview, a summary of contributions and the conclusions of this thesis. The aim of this thesis is to examine the risk and return characteristics of convertible arbitrage and provide estimates of historical convertible arbitrage hedge fund performance. Analysing the risk and return characteristics assists in the definition and estimation of models of convertible arbitrage performance measurement. The estimation of these convertible arbitrage performance measurement models then provides historical estimates of the performance of convertible arbitrage hedge funds.

The thesis began with a review of the literature related to convertible arbitrage and hedge fund performance measurement. This review highlighted several key issues and research questions to be addressed in the later empirical analyses. Previous research highlights the difficulty in assessing convertible arbitrage hedge fund performance due to, (1) biases in hedge fund data, (2) the difficulty in isolating robust convertible arbitrage risk factors, (3) the serial correlation inherent in convertible arbitrage hedge fund returns, (4) the potential for non-linearity in the relationship between the returns of hedge funds and risk factors, and (5) the non-normal distribution of hedge fund returns.

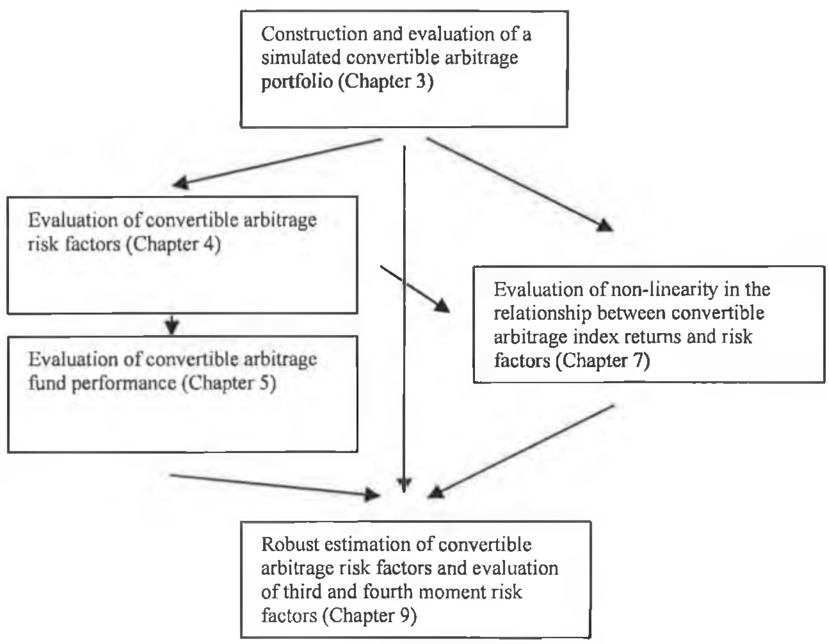
To overcome the biases in hedge fund data a simulated convertible arbitrage portfolio is specified. This portfolio shares the risk characteristics of convertible arbitrage hedge funds and serves as a useful performance benchmark. When specified as a benchmark factor the portfolio also helps account for the non-normality in convertible arbitrage hedge fund returns as it shares the non-normal distribution of returns. This passive portfolio combined with default and term structure risk factors explain much of the risk in convertible arbitrage hedge fund indices. To address the issue of serial correlation a lag of the hedge fund return is specified. The coefficient on this term is also interpretable as an illiquidity risk factor. If hedge fund returns at time t are related to returns are time $t-1$ this suggests the fund is exposed to illiquidity risk. Illiquidity risk is also controlled by specifying a model including lags of the risk factors to fully capture the risk exposure of individual hedge funds. Non-linearity in the relationship between convertible arbitrage returns and risk factors is addressed by specifying a non-linear model which captures the theoretical relationship between convertible arbitrage returns and default and term structure risk factors. Finally, the issue of non-normality in the returns of hedge funds is addressed by specifying an estimation technique which incorporates higher moments and also specifying skewness and kurtosis risk factors in a linear analysis of individual fund performance.

The remainder of this chapter is organised as follows. Section 10.2 summarises the principle innovations and contributions of this thesis. Avenues for future research are presented in Section 10.3 while Section 10.4 offers some concluding thoughts on the nature of convertible arbitrage risk and return.

10.2 Summary of contributions

This thesis has made several original contributions to the academic literature on dynamic trading strategies and these are summarised in this section under the following sub-headings, 10.2.1 construction and evaluation of a simulated convertible arbitrage portfolio, 10.2.2 evaluation of convertible arbitrage risk factors, 10.2.3 evaluation of individual fund performance, 10.2.4 evaluation of non-linearity in the relationship between convertible arbitrage index returns and risk factors and 10.2.5 robust estimation of convertible arbitrage risk factors and evaluation of third and fourth moment risk factors and the estimation of individual fund performance.

Figure 10.1
Summary of the overall research design



Before reviewing the important findings of the empirical research it is worth revisiting the overall research design and how the individual empirical chapters fit together. Figure 10.1 summarises the overall research design. The first empirical chapter, Chapter 3 focuses on construction and evaluation of a historical simulated convertible bond arbitrager portfolio. This chapter serves as an introduction to convertible bond arbitrage, and demonstrates how the strategy works in its simplest form, the delta neutral hedge. The resulting time series from 1990 to 2002 also serves as a useful benchmark risk factor in the following empirical chapters. As this convertible bond arbitrage risk factor is non-normally distributed it also helps account for the non-normality in the returns of convertible arbitrage hedge funds. The second empirical chapter, Chapter 4, focuses on the identification and estimation of risk factors and their relationship with convertible arbitrage hedge fund indices' returns and the returns of the simulated portfolio. This multi-factor analysis of hedge fund indices provides evidence of the risk factors affecting the convertible arbitrage strategy. By defining a set of asset classes that match an investment strategies' aims and returns, individual fund's exposures to variations in the returns of the asset classes can be identified. This multi-factor specification serves as a model for assessing the performance of individual hedge funds in Chapter 5. The returns of individual hedge funds are evaluated, using a multi-factor methodology, relative to a passive investment in the asset mixes. Chapter 7 provides evidence of non-linearity in the relationship between convertible arbitrage indices and risk factors. Being long a convertible bond and short an underlying stock, funds are hedged against equity market risk but are left exposed to a degree of downside default and term structure risk. This asymmetric exposure leads to non-linearity in the relationship between returns and risk factors. The final empirical chapter, Chapter 9 focuses on the additional risks in convertible arbitrage returns, skewness and kurtosis, overlooked in a mean variance analysis. In this chapter the linear factor model of convertible arbitrage risk is estimated using RALS, an estimation technique explicitly incorporating higher moments. Skewness and kurtosis functions of the estimated hedge fund index residuals are then specified as proxy risk factors for skewness and kurtosis risk.

10.2.1 Construction and evaluation of a simulated convertible arbitrage portfolio

This is the first study to construct a simulated convertible arbitrage portfolio by combining convertible bonds with rebalancing delta neutral hedges in the underlying stocks in a manner consistent with arbitrageurs. This simulated portfolio adds to the understanding of convertible arbitrage risks and serves as a useful benchmark of hedge fund performance. In this analysis long positions in convertible bonds are combined with short positions in the common stock of the issuer to create individual delta neutral hedged convertible bonds in a manner consistent with an arbitrageur capturing income. These individual positions are then dynamically hedged on a daily basis to capture volatility and maintain a delta neutral hedge. Positions are then combined into two convertible bond arbitrage portfolios and it is demonstrated that the monthly returns of the convertible bond arbitrage portfolio are positively correlated with two indices of convertible arbitrage hedge funds.

Across the entire sample period the two portfolios have market betas of between 0.048 and 0.061. However, it is also demonstrated that the relationship between daily convertible bond arbitrage returns and a traditional buy and hold equity portfolio is non-linear. In normal market conditions, when the equity risk premium is within one standard deviation of its mean the two portfolios have market betas of between 0.07 and 0.10. When the sample is limited to extreme negative equity market returns (at least two standard deviations below the mean) these betas increase to 0.13 and 0.24 for the equal weighted portfolio and the market capitalization weighted portfolio respectively. This indicates that on the average eight days per annum of extreme negative equity market returns, convertible arbitrage will exhibit a large increase in market risk.[83]

Perhaps most interesting is the finding that in extreme positive equity markets an equal weighted convertible bond arbitrage portfolio will exhibit a negative relationship with a traditional buy and hold portfolio. This is due to the drop in implied volatility associated with such market conditions and is an important factor for any investor considering the addition of a convertible bond arbitrage portfolio or fund to a traditional long only equity portfolio.

This simulated portfolio serves as a benchmark risk factor for assessing convertible arbitrage hedge fund performance in later empirical analyses. This is an approach which has not previously been employed in the literature on convertible arbitrage.

10.2.2 Evaluation of convertible arbitrage risk factors

This chapter contributes through the definition and specification of a range of risk factors drawn from the asset pricing literature which explain a large proportion of the returns in convertible arbitrage hedge fund indices. Default and term structure risk factors are highly significant in explaining the returns of convertible arbitrage indices' returns. The inclusion of a one period lag of convertible arbitrage index excess returns correcting for serial correlation, but also interpretable as a proxy for illiquidity risk, improves the explanatory power of these models. A univariate analysis of the convertible arbitrage index data generating process is also provided which provides statistical evidence to support the inclusion of the one period lag of

[83] Consistent with Agarwal and Naik (2004).

the hedge fund index returns in the model. The alpha or perceived out-performance generated by the convertible arbitrage indices is much smaller relative to a model omitting the lag of hedge fund index returns and is significant only for the HFRI index for a time period biased upward by the exclusion of dead funds. This is an innovative and original approach to estimating the risk of convertible arbitrage indices.

A convertible arbitrage factor is also specified which is important in explaining convertible arbitrage returns. This factor is constructed by combining long positions in convertible bonds with short positions in the underlying stocks into a portfolio and using the excess returns from this portfolio as an explanatory variable. This factor, which has not previously been specified in the literature, is highly significant in explaining convertible arbitrage index returns and combined with a lag of hedge fund returns and factors mimicking default and term structure risk, this four factor model should serve as an efficient model for examining individual convertible arbitrage hedge fund performance. These risk factors are remarkably consistent in explaining hedge fund index returns across time and sub-samples ranked by risk factors.

10.2.3 Evaluation of individual fund performance

Evidence from examining individual hedge funds provides additional evidence to support the default risk factor, term structure risk factor and the convertible bond risk factor being significant in hedge fund returns, particularly if both lagged and contemporaneous observations of the risk factors are specified. This is a finding which supports the evidence of Asness, Krail and Liew (2001) that to properly estimate the risks faced by hedge funds a model which includes lags of the explanatory variables should be specified. This type of model has not previously been specified for examining the performance of convertible arbitrage hedge funds. When the non-synchronous hedge fund performance model is estimated, omitting an explicit illiquidity factor, results indicate that convertible arbitrage hedge funds generate a statistically significant alpha of 0.34% per month or 4.1% per annum. However, illiquidity in the securities held by convertible arbitrage hedge funds also appears to be a key risk factor. Here y_{t-1}, the one period lag of the hedge fund or portfolio of hedge fund's return is employed as a proxy risk factor for illiquidity. Including this lag also corrects for much of the serial correlation in hedge fund returns. When this illiquidity factor is specified in a four factor model the mean estimate of abnormal performance is lower (0.20% per month) though remains statistically significant from zero. These estimates of performance are lower than those reported in other linear studies incorporating convertible arbitrage.[84] Evidence is also presented on persistence in convertible arbitrage hedge fund performance.

10.2.4 Evaluation of non-linearity in the relationship between convertible arbitrage index returns and risk factors

There are several important contributions to the understanding of convertible arbitrage and hedge fund risk and returns in this analysis. The evidence presented supports the existence of two alternate risk regimes, a higher default and term structure risk regime if previous month's returns are below a threshold level, and a lower default and term structure risk regime if previous month's returns are above a threshold level. Previous research has identified only one risk regime for convertible

[84] Capocci and Hübner (2004) report estimates of abnormal performance of 0.42% per month.

arbitrage.[85] Estimated alphas in the higher risk regime are significantly negative for the HFRI index and the simulated portfolio. Previous research has only documented significantly positive or insignificant alphas. This is an important finding as it indicates that when arbitrageurs are more exposed to default and term structure risk they generate negative alpha. Finally, the existence of two risk regimes is likely to be a contributing factor to serial correlation in hedge fund returns.

The tests conducted in this analysis reject linearity for the convertible arbitrage hedge fund indices. These hedge fund indices are classified as Logistic Smooth Transition Autoregressive (LSTAR) models. This is the first time the STAR models have been specified in the hedge fund performance literature. The estimated LSTAR models provide a satisfactory description of the non-linearity found in convertible arbitrage hedge fund returns and have superior explanatory power relative to linear models. The estimates of the transition parameter indicate that the speed of transition is relatively slow from one regime to another but the factor loadings become relatively large as previous month's hedge fund returns become more negative. These results support the expectation that convertible arbitrage hedge fund risk factor coefficients will vary according to previous month's hedge fund index returns. The convertible arbitrage benchmark indices represent an aggregate of hedged convertible bonds held by arbitrageurs. If the benchmark generates negative returns then aggregate hedged convertible bonds held by arbitrageurs have fallen in value. This fall in value is caused either by a decrease in the value of the short stock position in excess of the increase in the value of the long corporate bond position or, more likely, a decrease in the value of the long convertible bond position in excess of the increase in the value of the short stock position. When the one period lag of the

[85] Kat and Miffre (2005) and Agarwal and Naik (2004) recognise that the relationship between convertible arbitrage returns and risk factors may be non-linear.

convertible arbitrage benchmark return is below the threshold level, convertible bond prices and deltas have decreased. As convertible bond prices fall the arbitrageur's portfolio is more exposed to default and term structure risk and their coefficients increase in magnitude and significance. When the one period lag of the convertible arbitrage benchmark return is above the threshold level, convertible bond prices and deltas have increased and the portfolio behaves less like a fixed income instrument, with smaller coefficients on the default and term structure risk factors.

10.2.5 Robust estimation of convertible arbitrage risk factors and evaluation of third and fourth moment risk factors and the estimation of individual fund performance

The contribution to the understanding of non-normality in hedge fund return is the estimation of convertible arbitrage risk factors using RALS, an estimation technique explicitly incorporating non-normality in a time series' return distribution, a feature of convertible arbitrage hedge fund returns. An additional contribution is the specification and estimation of skewness and kurtosis risk factors derived from hedge fund data which are highly significant explanatory variables in the returns of individual hedge funds.

Evidence is presented demonstrating RALS estimation of the hedge fund index risk factor models improves efficiency relative to OLS. This is expected, considering the non-normality documented in the return distribution of these hedge fund indices. Evidence also presented in this chapter indicates that skewness is a significant risk factor in the returns of both convertible arbitrage hedge funds and hedge fund indices. Consistent with theoretical expectations arbitrageurs are rewarded with a risk premium for holding portfolios with negative skewness in the return distribution. Kurtosis is also a significant factor in the returns of convertible arbitrage hedge funds but is not significant for the indices. Results indicate that individual convertible arbitrage hedge funds are rewarded, for holding portfolios with negative skewness and excess kurtosis in the distribution of returns, approximately 0.60% per month.

10.3 Avenues for future research

This thesis contains many innovative empirical tests and results. Some of these tests have not previously been considered in the hedge fund literature. There are also some issues raised in this thesis which require further research. This section suggests future avenues for research which were inspired by the current work. They are listed under the following sub-headings: Factor analysis of other individual strategies; Non-linear analysis of other hedge fund trading strategies; RALS type analysis of other trading strategies; and, The source of serial correlation in hedge fund returns?

10.3.1 Factor analysis of other individual strategies

Generally, academic studies of hedge fund performance specify one set of market factors for a variety of trading strategies. As the trading strategies employed by hedge funds are heterogeneous it is highly unlikely that one set of common market factors will capture the very different risks in the different strategies.[86] If all of the correct factors were specified this factor model is likely to be over-parameterized.

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[86] These common factor models tend to perform particularly badly when addressing arbitrage style trading strategies where the majority of market risk is hedged.

More useful results will surely be derived by examining strategies in isolation and deriving a set of factors for each strategy. Particular attention should be focused on special situations, distressed securities and fixed income arbitrage as they display all of the statistical attributes, serial correlation, negative skewness and kurtosis that make analysis more difficult. Only through correct identification and specification of risk factors for each strategy can efficient estimates of performance of individual hedge funds be made.

10.3.2 Non-linear analysis of other hedge fund trading strategies

The dynamic and often opportunistic nature of hedge fund trading strategies is likely to lead to non-linearity in the relationship between strategy returns and risk factors. There is a wide variety of non-linear functional specifications, some of which are discussed in Chapter 6. Future research on hedge funds specifying these models is likely to yield interesting results and add to the understanding of hedge fund risk and return.

The smooth transition autoregressive (STAR) family of models seems particularly well specified in dealing with the non-linearity in hedge fund returns. Because there are many arbitrageurs engaged in a strategy and they will each have a portfolio of positions, it seems unlikely that they will all act simultaneously. It is therefore also unlikely that the change in risk factor weighting for a portfolio of hedge funds will be sudden. Because the STAR family of models allows for a smooth transition between regimes, further work incorporating these models in studies of other hedge fund trading strategies is likely to lead to interesting results.

10.3.3 RALS type analysis of other trading strategies

As discussed in Chapter 1, many hedge fund trading strategy returns are negatively skewed and leptokurtic. In Table 1.1 special situations, distressed securities and fixed income arbitrage have the highest kurtosis and these three strategies along with convertible arbitrage exhibit the largest negative skewness. As RALS explicitly incorporates higher moments it is a particularly suitable technique for estimating hedge fund risk factor models. It is also likely that third and fourth moment functions of the strategy hedge fund indices will serve as useful benchmarks for individual hedge fund skewness and kurtosis risk.

Other non-normal estimation techniques such as Least Absolute Deviations (LAD) discussed in Chapter 8, Mean Absolute Deviations (MAD) and extensions of these models including the Fully Modified – Least Absolute Deviations (FM-LAD) statistical approach (Phillips, 1995), should yield additional insights on the importance of higher moments in the risk and return of hedge funds and provide further robustness of the performance estimates reported in the literature on hedge funds.

10.3.4 The source of serial correlation in convertible arbitrage return?

Although not a primary focus of this thesis, as serial correlation is such an unusual characteristic in monthly time series it deserves further investigation. Getmansky, Lo and Makarov (2004) provide a comprehensive set of explanations of its source. However, they do not empirically test the hypotheses. In Chapter 7 of this thesis, evidence is presented supporting variation in convertible arbitrage risk factor weightings. This non-linearity will contribute to serial correlation. Other potential contributors are illiquidity, smoothing, time varying leverage and the high water mark in hedge fund fees. In Chapters 4 and 5 of this thesis the lag of the hedge fund return was specified as an illiquidity risk factor. More research is needed to generate a more efficient proxy for illiquidity risk. When data becomes available on convertible bond trading volume, an illiquidity factor mimicking portfolio, similar to Eckbo and Norli's (2005) turnover factor for stocks, should produce interesting results. Isolating the source of serial correlation in hedge fund returns is of importance when evaluating hedge fund risk and more clarity is needed to decide conclusively that serial correlation in hedge fund returns is a function of risk.

10.4 Conclusion

Evidence presented in this study provides useful guidance for practitioners and investors in the alternative investment universe. A simulated convertible arbitrage portfolio, such as that created in Chapter 3 serves as a useful benchmark of hedge fund performance. However, the individual hedge fund returns used to evaluate performance contain interesting features that add to the complication of their analysis. They are generally autocorrelated, due in part to illiquidity of the securities held by the funds, which unless controlled for leads to overestimation of performance. When a risk factor mimicking illiquidity in the securities held by these funds is combined with factors mimicking default risk, term structure risk and the convertible bond arbitrage risk factor in a linear factor model, estimates of performance are lower than previous estimates. In Chapter 4 evidence is presented that these four factors explain a large proportion of the risk in convertible arbitrage hedge funds' returns. Evidence is also presented in Chapter 5 on individual hedge fund exposure to these risk factors, supporting the inclusion of default risk, term structure risk and the convertible bond arbitrage risk factor in any examination of convertible arbitrage performance.

However, there is also evidence to suggest that the functional relationship between convertible bond arbitrage returns and risk factors is non-linear. Evidence presented in Chapter 7 supports the theoretical non-linear relationship between convertible arbitrage and risk factors. There appears to be two regimes, a high fixed income risk regime when previous month's returns were negative and a lower fixed income risk regime when previous month's returns were positive. This non-linearity may also contribute to the serial correlation in convertible arbitrage hedge fund returns.

The empirical tests in Chapters 3, 4 and 5 are estimated using OLS ignoring the negative skewness and kurtosis inherent in convertible arbitrage returns. Chapter 9 overcomes this bias for the linear models with RALS estimation, a technique which incorporates higher moments. Skewness and kurtosis functions of the residuals from OLS estimation of hedge fund index risk also serve as highly significant skewness and kurtosis risk factors in the returns of convertible arbitrage hedge funds. The specification of these factors reduces estimates of abnormal performance by approximately 0.60% per annum.

These empirical analyses have been designed and conducted with the intention that they can add some clarity to the assessment of hedge fund performance. These strategies have received huge attention in recent times as they are purported to generate excessive risk adjusted returns. The estimates of abnormal performance reported for convertible arbitrage hedge funds in this thesis are 0.34% per month for the non-synchronous model incorporating lags of the risk factors, 0.20% per month for the non-synchronous model augmented with the lag of the hedge fund return and 0.29% per month for the non-synchronous model augmented with skewness and kurtosis proxy risk factors. Annualised, the estimates of historical convertible arbitrage hedge fund abnormal performance is in a range of 2.4% to 4.2% per annum. These estimates of performance are smaller than those reported in previous research.[87] In addition, the hedge fund data used in this study is likely to contain survivor bias. Fung and Hsieh (2000b) and Liang (2000) estimate that this feature of hedge fund returns may upward bias estimates of performance by approximately 2% per annum.

[87] For example, Capocci and Hübner (2004) estimate that convertible arbitrage hedge funds generate annualised abnormal returns of 5.2% per annum.

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