MACROECONOMIC DRIVERS OF NON-DIRECTIONAL HEDGE FUND PERFORMANCE

by

David D. Lee & Jeremy Ma

PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF BUSINESS ADMINISTRATION

In the Faculty of Business Administration

Global Asset and Wealth Management

© David D. Lee and Jeremy Ma 2007

SIMON FRASER UNIVERSITY

Spring 2007

All rights reserved. This work may not be reproduced in whole or in part, by photocopy or other means, without permission of David D. Lee and Jeremy Ma
APPROVAL

Name: David D. Lee / Jeremy Ma

Degree: Master of Business Administration

Title of Project: Macroeconomic Drivers of Non-directional Hedge Fund Performance

Supervisory Committee:

Dr. Peter Klein
Senior Supervisor
Professor, Faculty of Business Administration

Dr. Christophe Perignon
Second Reader
Professor, Faculty of Business Administration

Date Approved: December 19, 2006
DECLARATION OF
PARTIAL COPYRIGHT LICENCE

The author, whose copyright is declared on the title page of this work, has granted to Simon Fraser University the right to lend this thesis, project or extended essay to users of the Simon Fraser University Library, and to make partial or single copies only for such users or in response to a request from the library of any other university, or other educational institution, on its own behalf or for one of its users.

The author has further granted permission to Simon Fraser University to keep or make a digital copy for use in its circulating collection (currently available to the public at the “Institutional Repository” link of the SFU Library website <www.lib.sfu.ca> at: <http://ir.lib.sfu.ca> and, without changing the content, to translate the thesis/project or extended essays, if technically possible, to any medium or format for the purpose of preservation of the digital work.

The author has further agreed that permission for multiple copying of this work for scholarly purposes may be granted by either the author or the Dean of Graduate Studies.

It is understood that copying or publication of this work for financial gain shall not be allowed without the author’s written permission.

Permission for public performance, or limited permission for private scholarly use, of any multimedia materials forming part of this work, may have been granted by the author. This information may be found on the separately catalogued multimedia material and in the signed Partial Copyright Licence.

The original Partial Copyright Licence attesting to these terms, and signed by this author, may be found in the original bound copy of this work, retained in the Simon Fraser University Archive.

Simon Fraser University Library
Burnaby, BC, Canada.

Revised: Fall 2006
ABSTRACT

With more than one hundred macroeconomic variables, we study the nature of hedge fund indices of different strategies. We categorize hedge fund strategies into directional and non-directional groups. We run multifactor regressions in order to find out whether hedge fund indices of different strategies are exposed to the direction of the market and which macroeconomic variables drive performance of non-directional hedge fund strategies such as fixed income arbitrage, convertible bond arbitrage, equity market neutral, and merger arbitrage. We conclude that non-directional indices are not significantly exposed to equity market except for merger arbitrage, meaning they are relatively well hedged against equity market as generally understood. Furthermore, we suggest important macroeconomic factors for non-directional strategies and rationales behind these factors.
ACKNOWLEDGEMENTS

We would like to deeply thank various people who provided us with useful and helpful assistance during last several months in which this endeavour lasted. Without their care and consideration, this thesis would likely not have matured.

First of all, we thank our thesis supervisor Dr. Peter Klein. With his enthusiasm, inspiration and great efforts to explain things clearly and simply, he helped to make statistical analysis fun for us. Throughout our thesis-writing period, he provided encouragement, sound advice, good teaching, good company, and lots of good ideas. We would have been lost without him.

In addition, we acknowledge our econometric professor, Dr. Andrey Pavlov and capital market professor, Dr. Rob Grauer. Without their intellectual inspiration, we could not finish this thesis. Todd Brulhart provided us with an early critique of our work. We also thank all people who discussed this project with us.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approval</td>
<td>ii</td>
</tr>
<tr>
<td>Abstract</td>
<td>iii</td>
</tr>
<tr>
<td>Acknowledgements</td>
<td>iv</td>
</tr>
<tr>
<td>List of Figures</td>
<td>vi</td>
</tr>
<tr>
<td>List of Tables</td>
<td>vii</td>
</tr>
<tr>
<td>1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>2 Literature review</td>
<td>4</td>
</tr>
<tr>
<td>2.1 Market exposures of hedge funds strategies</td>
<td>6</td>
</tr>
<tr>
<td>2.2 Factors for different hedge fund styles</td>
<td>7</td>
</tr>
<tr>
<td>2.3 Macroeconomic drivers of non-directional strategies</td>
<td>7</td>
</tr>
<tr>
<td>3 Data</td>
<td>12</td>
</tr>
<tr>
<td>3.1 Dependent Variables</td>
<td>12</td>
</tr>
<tr>
<td>3.2 Independent Variables</td>
<td>16</td>
</tr>
<tr>
<td>3.2.1 Market Indices</td>
<td>16</td>
</tr>
<tr>
<td>3.2.2 Economic Variables</td>
<td>16</td>
</tr>
<tr>
<td>3.2.3 Volatility Indices</td>
<td>16</td>
</tr>
<tr>
<td>3.2.4 Yield Spreads</td>
<td>17</td>
</tr>
<tr>
<td>3.2.5 Style Factors</td>
<td>18</td>
</tr>
<tr>
<td>4 Methodology</td>
<td>21</td>
</tr>
<tr>
<td>4.1 Multi-factor Regression Model</td>
<td>21</td>
</tr>
<tr>
<td>4.2 Stepwise and All-subset Regressions</td>
<td>21</td>
</tr>
<tr>
<td>4.2.1 Forward entry stepwise</td>
<td>22</td>
</tr>
<tr>
<td>4.2.2 Backward removal stepwise</td>
<td>22</td>
</tr>
<tr>
<td>4.2.3 All-possible-subset regression</td>
<td>23</td>
</tr>
<tr>
<td>4.3 Rolling regressions with a window of 60 months</td>
<td>23</td>
</tr>
<tr>
<td>5 Results</td>
<td>24</td>
</tr>
<tr>
<td>5.1 How much is each strategy exposed to the direction of market?</td>
<td>24</td>
</tr>
<tr>
<td>5.2 Which macro economic factors drive the return of each non-directional strategy?</td>
<td>25</td>
</tr>
<tr>
<td>5.2.1 Regression for full period</td>
<td>25</td>
</tr>
<tr>
<td>5.2.2 Rolling regression</td>
<td>29</td>
</tr>
<tr>
<td>6 Conclusion</td>
<td>39</td>
</tr>
<tr>
<td>Appendix</td>
<td>41</td>
</tr>
<tr>
<td>Matlab Code</td>
<td>41</td>
</tr>
<tr>
<td>References</td>
<td>51</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 1  Classifying Hedge Fund Strategies .......................................................... 2
Figure 2  Consistency of Factor Loadings: Fixed Income Arbitrage .......................... 33
Figure 3  Consistency of Factor Loadings: Convertible Arbitrage .............................. 34
Figure 4  Consistency of Factor Loadings: Equity Market Neutral ............................. 35
Figure 5  Consistency of Factor Loadings: Merger Arbitrage .................................... 36
LIST OF TABLES

Table 1  Descriptive Statistics for the CSFB/Tremont Hedge Fund Indices, 1994 – 2006........14
Table 2  Definition of Yield Spreads and Their Symbols in the Regression..........................17
Table 3  Summary of Independent Variables.........................................................................19
Table 4  Correlations of 21 Important Variables out of Total 38 Independent Variables.......20
Table 5  Market Exposures of Hedge Fund Strategies..........................................................24
Table 6  Stepwise Regression Results for CSFB/Tremont Hedge Fund Index from January 1998 to May 2006 ..................................................................................27
Table 7  Rolling Regression Results for CSFB/Tremont Hedge Fund Index with 60 month window size..........................................................................................31
1 INTRODUCTION

Since Alfred Jones established the first hedge fund in 1949, hedge funds have gained public attention and showed spectacular growth. Global hedge fund assets grow from $39 billion in 1990 to $1.2 trillion in 2006, equivalent to an average annual growth rate of 22.3%. Despite its increasing popularity, little is known about the risks and returns involved in hedge fund strategies. This is in large part because many hedge fund managers are not required to fully disclose their performance and strategies.

Early academic studies on hedge funds have been focused on hedge fund performance persistence and the degree of market exposures of different hedge fund strategies. Not many academics have analyzed the performance drivers of hedge fund strategies until recently.

Hedge fund strategies can be classified in a variety of ways, including investing processes or strategies, asset classes, geographical locations, industry sectors, or return drivers. To date, no standard classification system of hedge fund strategies has developed yet in the industry. Many hedge fund index providers have their own classifications and definitions for hedge fund strategies, but there are generally three broad categories based on investment characteristics: relative value, event driven, and opportunistic groups. Depending on the degree of market exposure, these strategies can be further classified into directional and non-directional strategies.

According to Alternative Investment Management Association (AIMA), relative value strategies include convertible arbitrage, fixed income arbitrage and equity market neutral, and event driven strategies include merger arbitrage and distressed securities. Opportunistic strategies include equity hedge (long/short equity), global macro, managed futures and emerging markets. Figure 1 provides the summary of AIMA framework to classify hedge fund strategies.
Of several hedge fund index providers, we obtain and use hedge fund index data, one composite, four non-directional and five directional indices, from Credit Suisse First Boston/Tremont (CSFB/Tremont). In pursuing our research, we focus on non-directional strategies. The four non-directional strategies are convertible arbitrage, fixed income arbitrage, equity market neutral, and merger arbitrage. We study more than 100 macroeconomic variables, and explain performance of non-directional indices with macroeconomic factors, using multifactor regressions.

We seek to answer the question of whether non-directional strategies are actually “hedged” against market risks and how comparable they are with composite and directional strategies. We further research in order to find our specific macroeconomic variables that drive non-directional
hedge fund performance, employing stepwise regressions for both the full period and rolling
periods with a window size of 60 months.

The rest of the paper is organized as follows. Section 2 provides the literature review of
previous hedge fund studies. Section 3 describes the basic statistics of the hedge fund indices and
macroeconomic variables we used. Section 4 explains the multifactor model and regression
methodology. Section 5 displays the results and discussion of the results. Section 6 summarizes
the paper.
2 LITERATURE REVIEW

Sharpe (1992) suggests an asset class factor model in order to determine risk exposures of mutual funds. He establishes a multifactor model with an assumption that factor returns are the only sources of correlation and non-factor returns (residual components) are not correlated each other. In order to evaluate his asset class factor model, he employs R-square as a main measure of fitness of the regression model.

He develops a twelve asset class model. Asset classes are represented by low cost index funds, including 3 month US T-bills, intermediate-term government bonds, long term government bonds, corporate bonds, mortgage-related securities, large cap value and growth stocks, medium and small cap stocks, non-US bonds, European stocks and Japanese stocks. He performs multifactor regressions with monthly returns of Trustees’ Commingled US Portfolio (an open-end mutual fund offered by the Vanguard Group) between January 1985 and December 1989. He finds R-squares to be over 90% on all his regressions.

He suggests betas of each asset class represent the degree of exposure to that asset class. He further analyzes mutual fund styles, categorizing mutual funds into utility stock funds, growth and income equity funds, small stock funds, balanced funds, high-quality bond funds and convertible bond funds.

Inspired by Sharpe’s ideas, Fung and Hsieh (1997) apply the asset class factor model to hedge funds in order to find out factor exposures of hedge fund returns. They employ a multifactor model and run Sharpe’s style regression for 3,327 open-ended mutual funds in the Morningstar database through December 1995. They find that 47% of mutual funds have R-squares higher than 75% and 90% of mutual funds have R-squares higher than 50%. They
suggest that the high level of correlation between mutual fund returns and asset classes indicates that mutual fund styles are generally buy-and-hold strategies with various asset classes. They further investigate on hedge funds. They run Sharpe's style regression on 409 hedge funds and find that 48% of hedge funds have R-Squares lower than 25% and 25% of hedge funds are negatively correlated with the standard asset classes. They suggest three dynamic trading strategies that are employed by hedge fund managers, such as systems/trend following, systems/opportunistic, and global macro styles. They then conclude that hedge funds are dynamically different than mutual funds because of these option-like dynamic trading strategies.

Liang (1999) analyzes annual risks and returns of different hedge fund strategies from 1990 to 1999. Over the sample period he studied, hedge funds have 14.2% annual rate of return, trailing S&P 500 annual rate of return by 4.6%. Liang believes the higher return of S&P 500 is associated with higher degree of risk. To be more fairly compared the risk and return trade-off, Liang applies the Sharpe ratio. The Sharpe ratios are 0.27 for S&P 500 and 0.41 for all hedge funds respectively. Hence on a risk-adjusted basis, hedge funds outperform S&P 500.

Nevertheless, Liang claims that hedge fund historical returns are subjected to survivorship bias. On average, 8.54% of hedge funds disappear every year due to poor performance. Those terminating funds, along with their performance data, are usually excluded from hedge fund data base. As a result, hedge fund returns are upward biased due to the disappearance of poor performing funds. To estimate the magnitude of survivorship bias, Liang calculates the return difference between the survived funds and all funds from 1994 to 1999. He finds out that the bias is as high as 2.43% per year.

Liang further investigates hedge fund performance in the year 1998 since hedge funds are heavily affected by the global financial turmoil in 1998. The total number of dead funds in 1998 is the highest and that of newborn funds is the lowest during the period of 1994 to 1998. He also argues that hedge funds rarely change their fee structures and that the funds performing poorly in the current and the previous years tend to drop incentive fees.
2.1 Market exposures of hedge funds strategies

Ennis and Sebastian (2003) question how market-neutral a diversified hedge fund investment actually is. They examine Hedge Fund Research (HFR) fund of fund and composite indices to calculate the percentage exposures to market factors. They propose that fund of fund and composite indices are best indicators of hedge fund performance because they are the most diversified hedge fund indices. Using monthly returns between January 1994 and December 2002, they regress these fund of fund index against seven market factors including US T-bill, US large cap stocks (S&P 500), US small cap stocks (Wilshire 4500), non-US equities (MSCI EAFE), emerging markets (MSCI Emerging Markets), duration (5 years US T-bond index), and credit (Salomon Brothers US High-Yield index).

They argue that truly market neutral index would show 100% exposure on T-bill and zero on all other factors. So, based on their finding that the fund of fund index is 56% market neutral and 44% persistent on long or short positions of market factors, they conclude that fund of fund index is not completely market neutral as hedge fund claim.

Patton (2005) suggests that the market neutrality of hedge funds has two components: breadth and depth. The breadth component reflects the number of market risks to which a fund is neutral, and the depth component reflects the completeness of the neutrality of the fund to market risks. Focusing on neutrality depth, he proposes five different neutrality tests: correlation, mean, variance, tail and complete neutrality.

Patton uses 1,691 hedge funds that are categorized as market neutral style to apply their five neutrality tests. He finds that 29.2% of these market neutral funds fail the neutrality test, but that such failure rate is far less than other styles, including fund of funds 49.7%, equity hedge 53.9%, event driven 61.1%, and equity non-hedge 85.7%. Patton concludes that significant exposures of market neutral funds to market risks are less than the proportion of significant exposures of other hedge fund styles.
2.2 Factors for different hedge fund styles

Fung and Hsieh (2002b) study on risk factors in fixed-income hedge fund styles. In order to extract common sources of risks for fixed-income hedge funds, they investigate 16 funds in fixed-income convertible bond group, 16 funds in fixed-income high-yield group, 29 funds in fixed-income mortgage backed group, 43 funds in fixed-income arbitrage group, and 41 hedge funds in fixed-income diversified group. Based on their results, they suggest that fixed-income hedge funds tend to be exposed to “credit spread” as a common asset base style factor.

Stanley Block (2004) examines various forms of merger arbitrage for both cash and stock transactions. He concludes that the merger arbitrage fund can earn a strong return by taking a long position in the target firm and a short position in acquiring firm. However, he further suggests that the likelihood of successful deal closing and time period for consummation should be carefully considered before investing.

2.3 Macroeconomic drivers of non-directional strategies

Brealery and Kaplanis (2001) obtain data of individual hedge funds from TASS management. They provide summary of mean annualized standard deviation and mean correlation between fund returns within the same category. They find that non-directional and fixed income categories are among the least risky strategy types based on the standard deviations of returns.

They then perform multifactor regression in order to observe loadings of hedge fund returns on various factors. They assume that coefficients of risk factors are constant over time and use OLS to estimate the regressions for each fund. They choose risk factors in four broad groups: equity, fixed income, currency, and commodity. They provide their regression results with each significant factor loading and adjusted R-square. They suggest that the factor loadings fit broadly with prior studies: emerging market funds are almost all significantly positive on
regional emerging market indices, and event driven are significantly and negatively affected by changes in equity market volatility.

They estimate the trade-off between employing a larger number of observations rather than more recent data. They perform rolling regressions and find that squared forecast errors reach a minimum with about 36 months of observations. Beyond 36 months, the advantage of adding more observations is generally outweighed by the disadvantage of using more dated information. However, there is relatively little benefit from shortening the interval since the ratio of noise to signal increases sharply for small numbers of observations.

Fung and Hsieh (2002a) perform multifactor regressions of monthly returns of sixteen HFR indices and nine CS/Tremont indices against three asset classes. They find that nine out of sixteen HFR indices and four out of nine CSFB/Tremont indices have significant market exposures. They conclude that directional hedge fund strategies can be modelled with long-only asset-based style factors.

Agarwal and Naik (2004) characterize risk exposures of hedge fund strategies employing a two-step approach. They estimate the factor loadings of hedge funds using the returns on standard asset classes and construct replicating portfolios that best fit for in-sample testing. They then study how well these replicating portfolios explain out-of-sample performance. They find that hedge fund returns resemble the performance of put-writing returns. They also conclude that more hedge funds are correlated positively to down-markets.

Jaeger and Wagner (2005) points out the problems with hedge fund indices, such as survivorship, backfilling, selection and autocorrelation. They compare cumulative performance for HFR investable indices versus noninvestable counterparts and also suggest that theoretical and practical problems that are related to hedge fund index do not disappear when the index is designed to be investable.

They perform regression of hedge fund returns on systematic risk factors, using Hedge Fund Research (HFR) strategy sector indices between January 1994 and December 2004. Equity
hedge (long/short equity), short selling, and event driven show the highest adjusted R-squares of 88.5%, 81.2%, and 79.3% respectively. Non-directional strategy sectors provide relatively low adjusted R-squares, generally less than 50%. They find autoregressive term AR(1) is significant in five out of 11 strategy sectors and suggest that there is persistent price lags in valuation of hedge funds based on AR(1) term.

They also perform rolling regressions with a 60-month time window as a test for model stability. They plot the obtained factor sensitivities over time in a rolling regression and find a generally high degree of stability of the factors.

They further show that rolling alphas of long/short equity continued to decrease since January 2000 and suggest that average alpha extracted by hedge fund managers is destined to decline. They also calculate that the capacity of hedge fund industry is $1,833 billion based on the required rate of return to hedge fund investors and the pure alpha available to hedge funds.

Das, Kish, and Muething (2005) are of opinion that hedge funds are also influenced by macroeconomic variables because some hedge funds and mutual funds trade the same types of asset classes. They perform OLS regressions and conclude based on the results of their macroeconomic model that default premium and term-premium are two important macroeconomic factors to explain hedge fund performance.

Kooli (2005) extends previous works of Capoccie and Hubner (2004) and Liang (1999) by using different approaches to measure hedge fund performance and also different statistical tests.

He employs four models to examine abnormal performances of hedge fund indices. In market model, he apply traditional CAPM model to hedge fund indices, and in market model with GARCH estimation, he measure the performance of hedge funds with CAPM with GARCH (1, 1) errors. In Fama and French three-factor model, he extend the CAPM regression by taking the size and the book-to-market ratio of into account, and in multifactor model, he additionally considers
momentum factors (PR1 YR), aggregate US bond index (LBUSBI), emerging market bond index (JPMEMBI), and commodity index (GSCI).

He summarizes descriptive statistics of ten CSFB/Tremont hedge fund indices between 1994 and 2004, and provides performance measurement using four models, employing calendar time approach, which, in other words, performs regressions based on the time period since formation. With market model, he finds that all hedge fund indices outperform the market and alphas are significant at the 1% confidence level. In addition, he estimates abnormal performance using the GARCH extension, for robustness check, and finds that hedge fund indices significantly outperform the market.

With Fama-French three-factor model, he finds that SMB and HML factors are significantly positive, and suggests that hedge fund managers prefer smaller stocks and those with high book-to-market ratios. He also provides that hedge funds performances show alphas that are significant after 12 months since inception, and concludes that hedge funds outperform the market.

With multifactor model, he finds alphas, factor loadings, adjusted R square for different hedge fund indices, and concludes that more hedge fund indices show significant alphas when fewer independent factors are taken into account, and fewer indices show significant alphas when more independent factors are considered.

Stephen Foerster (2006) examines equity market neutral hedge fund performance. He investigates asset-based style factors, including earnings-price (EP), price-to-book (PB), price momentum (PRM), and size (MKT), and macroeconomic variables, including the yield curve (YLD), a default premium (PREM), an inflation change measure (INFCH) and a measure of market volatility (VIX).

After examining the index of equity market neutral hedge fund returns in excess of 3 month T-bill returns (EMNE) against market index excess returns, the author provides a significant positive alpha (0.43% monthly) and a significant low positive beta (0.07).
Furthermore, he suggests that those style factors and macroeconomic variables can explain much of the excess returns of both directional and non-directional hedge fund portfolios. Multifactor models including four style factors and a few significant economic variables suggest insignificant alphas for all hedge fund strategies except for event driven risk-arbitrage.

He concludes that equity market neutral hedge fund performance are negatively related to the shape of the yield curve and positively related to market volatility.
3 DATA

3.1 Dependent Variables

Hedge funds are not required to disclose their results, and hence capturing performance characteristics of hedge funds is not straightforward. Hedge fund database vendors collect data from industry and provide indices for different hedge fund strategies. However, such indices have been subject to criticism that hedge fund performances are biased upward due to the errors inherent in collecting and processing data.

Malkiel and Saha (2005) suggest that hedge fund returns are characterized by undesirably high kurtosis and negative skewness and that the hypothesis of normality is rejected for all the hedge fund categories except managed futures and global macro. They also provide that several biases can exist in the published hedge fund indices. Backfill bias occurs when hedge fund managers begin to report their results at a later date after inception. Since managers report their results if their performance is favourable, the index is biased upward with this back-filling. Authors suggest that the backfilled returns are more than 500 bps higher than the contemporaneously reported returns.

Survivorship bias occurs when an index provider does not include the returns from hedge funds that reported in the past but are not in existence any more or stop reporting their results. Authors estimate that there is 442 bps difference between the average return of the surviving funds of 13.74% for the 1996-2003 period and that for all funds of 9.32%.

Jaeger and Wagner (2005) elaborate on the selection bias. Selection bias occurs because an index provider covers only small portion of the hedge funds and rely on hedge funds’ voluntary reporting of their performance. Since hedge fund managers are not required to make
public disclosure of their performance, this self-selection bias leads to significant distortions in the construction of the index, pushing hedge fund returns upward.

However, because there is no better source for hedge fund performance, we need to use hedge fund indices in spite of the shortcomings described above. Of several hedge fund index providers, we use hedge fund index data from Credit Suisse First Boston/Tremont (CSFB/Tremont) because it is one of the most comprehensive hedge fund index vendors that covers all varieties of hedge fund strategies.

We obtain CSFB/Tremont hedge fund indices to calculate the historical excess monthly returns for the four non-directional strategies we studied. The CSFB/Tremont hedge fund indices are publicly available at www.hedgeindex.com. The constituent funds in CSFB/Tremont indices must have a minimum of US $50 million assets under management, a minimum one-year track record, and current audited financial statements. The indices are calculated on an asset-weighted basis and are rebalanced monthly. To minimize survivorship bias, constituent funds are not removed from the indices until they are fully liquidated or fail to meet the financial reporting requirements.

We retrieve ten out of 13 CSFB/Tremont indices: composite, four non-directional and five directional indices for our research. Table 1 shows the descriptive statistics of monthly performances of different hedge fund strategies. Generally speaking, the standard deviations for non-directional strategies are smaller than those of directional strategies. This is why non-directional hedge funds are sometimes referred to as low-volatility hedge funds. CSFB/Tremont Composite index is more highly correlated with directional indices than to non-directional indices. Correlations among directional indices are higher than those among non-directional indices. Managed future, a directional strategy, has none or low correlation with all other strategies. On the other hand, dedicated short strategy is the only strategy negatively correlated with any other strategies (except with managed future).
For the use of regressions described later in this paper, we calculate excess returns of these ten indices against yields of 3-month US treasury bills.

Table 1  Descriptive Statistics for the CSFB/Tremont Hedge Fund Indices, January 1994 – May 2006

The indices used are CDFB/Tremont hedge fund indices, monthly data from January 1994 to May 2006. The upper portion of the table displays the descriptive statistic for composite index (COMP), fixed income arbitrage (FINA), convertible arbitrage (CONA), equity market neutral (EMNU), merger arbitrage (MRGA), distressed securities/high yield (DSHB), emerging market (EMRG), long/short equity (LSEQ), global macro (GLMA), and managed futures (MNGF). The lower portion of the table provides the correlation analysis for each strategy.

Negative signs indicated as parenthesis on this table.

<table>
<thead>
<tr>
<th></th>
<th>COMP</th>
<th>FINA</th>
<th>CONA</th>
<th>DSHB</th>
<th>EMRG</th>
<th>EMNU</th>
<th>MRGA</th>
<th>GLMA</th>
<th>LSEQ</th>
<th>MNGF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0089</td>
<td>0.0053</td>
<td>0.0072</td>
<td>(0.0006)</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0063</td>
<td>0.0013</td>
<td>0.0018</td>
<td>0.059</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.023</td>
<td>0.011</td>
<td>0.014</td>
<td>0.050</td>
<td>0.047</td>
<td>0.008</td>
<td>0.012</td>
<td>0.032</td>
<td>0.030</td>
<td>0.095</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.101</td>
<td>(3.046)</td>
<td>(1.319)</td>
<td>0.835</td>
<td>(0.581)</td>
<td>0.302</td>
<td>(1.250)</td>
<td>0.017</td>
<td>0.208</td>
<td>0.039</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>COMP</th>
<th>FINA</th>
<th>CONA</th>
<th>DSHB</th>
<th>EMRG</th>
<th>EMNU</th>
<th>MRGA</th>
<th>GLMA</th>
<th>LSEQ</th>
<th>MNGF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: CSFB/Tremont Hedge Fund Indices</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
CSFB/Tremont provides the definition for each hedge fund strategy. Here we quote from CSFB/Tremont website www.hedgeindex.com the definitions of four non-directional strategies that are frequently used in our study:

**Convertible Arbitrage**

Convertible Arbitrage managers seek to profit from investments in convertible securities employing both single security and portfolio hedging strategies. Managers typically build long positions of convertible and other equity hybrid securities and then hedge the equity component of the long securities positions by shorting the underlying stock or options of that company. Interest rate, volatility and credit hedges may also be employed. Hedge ratios need to be adjusted as markets move and positions are typically designed with the objective of creating profit opportunities irrespective of market moves.

**Equity Market Neutral**

Equity Market Neutral managers seek to profit from exploiting pricing relationships between different equities or related securities while typically hedging exposure to overall equity market moves. There are a number of sub-sectors including statistical arbitrage, quantitative long/short, fundamental long/short and index arbitrage. Managers often apply leverage to enhance returns.

**Merger Arbitrage (Risk Arbitrage)**

Specialists invest simultaneously in long and short positions in both companies involved in a merger or acquisition. Risk arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquiring company. The principal risk is deal risk, should the deal fail to close.

**Fixed Income Arbitrage**

Fixed Income Arbitrage managers seek to profit from relationships between different fixed income securities; leveraging long and short positions in securities that are related either mathematically or economically. Many managers trade globally with a goal of generating steady returns with low volatility. The sector includes yield curve relative value trading involving interest rate swaps, government securities and futures; volatility trading involving options; and mortgage-backed securities arbitrage (the mortgage-backed market is primarily US-based, over-the-counter, and particularly complex).
3.2 Independent Variables

Our independent variables can be categorized into five groups: stock market indices, economic variables, volatility measures, yield spreads, and style factors. Table 3 summarize the independent variables used in the regression process.

3.2.1 Market Indices

Market indices, such as S&P 500 (SP) and Merrill Lynch Global 300 Convertible Securities (CON), are collected from Bloomberg and Yahoo Finance. Excess returns of market indices are calculated against 3-month US Treasury Bills on a monthly basis. We employ return differences between Russell 2000 and Russell 1000, which is the similar factor as Fama-French small cap effect (SM), and return differences between S&P 500/Citigroup Value and S&P 500/Citigroup Growth, which is similar as Fama-French value effect (VG).

3.2.2 Economic Variables

Most US economic variables, such as 10 year T-Bond (10Y) and US Treasury Inflation Protected Securities (TIPS) are collected from FRED® (Federal Reserve Economic Data), which is maintained by Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/). The inflation year over year (CPI) is calculated based on historical Consumer Price Index (CPI) data set and the yield-term spread (YS) is calculated as 10 year T-Bond yield minus 3 month T-Bill yield. The US leading indicator (US Lead), Goldman Sachs Commodity Total Return (COM), and US Trade Weighted Broad Currency Index (US$) are downloaded from Bloomberg.

3.2.3 Volatility Indices

Three volatility indices are in our independent variables pool: Merrill Lynch MOVE (MV), Merrill Lynch MOVE3 (MV3), and Chicago Board Option Exchange Volatility Index (VIX). Merrill Lynch MOVE and MOVE3 are yield curve weighted indices of the normalized
implied volatilities of 1 month and 3 month Treasury options respectively. VIX is a popular measure of the implied volatility of S&P 500 index options. Merrill Lynch MOVE and MOVE3 are retrieved from Bloomberg and VIX from Yahoo Finance.

3.2.4 Credit Spreads

Yield spreads are important factors in fixed income strategies and convertible arbitrage strategies. We collected and calculated 13 yield spreads of fixed income securities with different credit ratings, issuers, and structures. Most of the fixed income instrument we collected has mid-long maturity. Hence, the yield spreads are calculated against 10 year US treasury. In the case of Libor and Eurodollar, the spreads are calculated against 3 month US treasury. The sources of our data are Merrill Lynch Global Index system, FRED and Bloomberg. The following table summarizes the definition of our 13 yield spreads.

Table 2 Definition of Yield Spreads and Their Symbols in the Regression

The yield spreads are calculated for the sample period of January 1998 to May 2006. We have chosen this sample period to accommodate different inception date of our variables. The monthly change of a yield spread is calculated as (current yield spread - last month yield spread) / last month yield spread.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF</td>
<td>Monthly change of default premium (Moody's Baa - Moody's Aaa)</td>
</tr>
<tr>
<td>GC</td>
<td>Monthly change of (Merrill Lynch Global Broad Market Corp. – US 10 year treasury)</td>
</tr>
<tr>
<td>GH</td>
<td>Monthly change of (Merrill Lynch Global High Yield – 10 year treasury)</td>
</tr>
<tr>
<td>10Y Strip</td>
<td>Monthly change of (US 10 year strip bond – US 10 year treasury)</td>
</tr>
<tr>
<td>SWAP</td>
<td>Monthly change of (SWAP rate – 10 year treasury)</td>
</tr>
<tr>
<td>MBS</td>
<td>Monthly change of (Merrill Lynch MBS Master – 10 year treasury)</td>
</tr>
<tr>
<td>CMBS3A</td>
<td>Monthly change of (Morgan Stanley CMBS AAA Conduit – 10 year treasury)</td>
</tr>
<tr>
<td>CMBS3B</td>
<td>Monthly change of (Morgan Stanley CMBS BBB Conduit – 10 year treasury)</td>
</tr>
<tr>
<td>CMO</td>
<td>Monthly change of (Merrill Lynch CMO – 10 year treasury)</td>
</tr>
<tr>
<td>ABS</td>
<td>Monthly change of (Merrill Lynch ABS – 10 year treasury)</td>
</tr>
</tbody>
</table>
3.2.5 Style Factors

We employ five style factors: JP Morgan CarryMax index (CARRY), SWAP spread arbitrage index (SW), Swiss Partner Future index (SF), and Chicago Buy Write Index (CBW).

CarryMAX is a market neutral fixed income strategy developed by JPMorgan Fixed Income Research. CarryMAX updates one of the oldest investment strategies, which is called the Carry Trade, in order to exploit a persistent mis-pricing in interest rate markets for generating a consistent return. CarryMAX selects from a universe of nine developed interest-rate swap markets - US, Japan, Euro Area, Denmark, Sweden, Canada, Australia, and Switzerland. The strategy first ranks the markets with the highest carry in 10 year swaps, where carry is defined as the yield differential of the 10 year swap rate over the Cash or LIBOR rate. Then, it trades based on the two-pair strategy, buying two 10 year swaps with the highest carry and selling two 10 year swaps with the lowest carry.

SWAP spread arbitrage (SW) is inspired by Duarte, Longstaff, and Yu (2006). They identify SWAP spread arbitrage as a very popular trading strategy employed by many hedge fund managers. Duarte, Longstaff, and Yu describe the swap spread arbitrage strategy as follows:

The swap spread arbitrage strategy has two legs. First, an arbitrageur enters into a par swap and receives a fixed coupon rate (CMS) and pays the floating Libor rate (L). Second, the arbitrageur shorts a par Treasury bond with the same maturity as the swap and invests the proceeds in a margin account earning the repo rate (r). The cash flows from the second leg consist of paying the fixed coupon rate of the Treasury bond (CMT) and receiving the repo rate from the margin account. Combining the cash flows from the two legs shows that the arbitrageur receives a fixed annuity of \( SS = CMS - CMT \) and pays the floating spread \( St = L - r \). The cash flows from the reverse strategy are just the opposite of these cash flows. There are no initial or terminal principal cash flows in this strategy. ... What makes the strategy attractive to hedge funds is that the floating spread \( St \) has historically been very stable over time, averaging 26.8 basis points with a standard deviation of only 13.3 basis points during the past 16 years. Thus, the expected average
value of the floating spread over, say, a five-year horizon may have a standard deviation of only a few basis points (and, in fact, is often viewed as essentially constant by market participants).

In our analysis, SWAP spread arbitrage index is constructed as (10 year SWAP rate – 10 month t-bill) – (3 month Libor – 3 month Repo rate).

Swiss Partners Group Futures Index (SF) is a simple trend-following model on 25 liquid futures. The Chicago Buy Write (CBW) is an index defined by the Chicago Board of Trade for a simple “buy write” strategy on the S&P 500. We retrieved all the yields and index returns from Bloomberg.

### Table 3 Summary of Independent Variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Market Indices</td>
<td>Excess return of S&amp;P 500 Excess return of Merrill Lynch Global 300 Convertible Index</td>
</tr>
<tr>
<td>Economic Variables</td>
<td>10-year Treasury Yieldspread (10 year treasury – 3 month treasury)</td>
</tr>
<tr>
<td></td>
<td>Inflation year over year change TIPS – 10 year treasury US leading indicator</td>
</tr>
<tr>
<td></td>
<td>Goldman Sachs Commodity Index US Trade Weighted Currency Exchange Rate</td>
</tr>
<tr>
<td>Volatility Measures</td>
<td>MOVE MOVE3 VIX</td>
</tr>
<tr>
<td>Yield Spreads</td>
<td>Default premium (Moody’s Baa – Moody’s Aaa)</td>
</tr>
<tr>
<td></td>
<td>Merrill Lynch Global Broad Market Corp. – US 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Lynch Global High Yield – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>US 10 year strip bond – US 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>SWAP rate – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Lynch MBS master – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Stanley CMBS AAA Conduit – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Stanley CMBS BBB Conduit – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Lynch ABS – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>Merrill Lynch Municipal – 10 year treasury</td>
</tr>
<tr>
<td></td>
<td>3 month Libor – 3 month treasury</td>
</tr>
<tr>
<td></td>
<td>3 month Eurodollar yield – 3 month treasury</td>
</tr>
<tr>
<td>Style Factors</td>
<td>JP Morgan Carry Max</td>
</tr>
<tr>
<td></td>
<td>SWAP spread arbitrage</td>
</tr>
<tr>
<td></td>
<td>Swiss Partner Future</td>
</tr>
<tr>
<td></td>
<td>Chicago Buy Write index</td>
</tr>
</tbody>
</table>

*Note: All variables are calculated as monthly percentage changes unless mentioned otherwise.*
Table 4 Correlation Table of Independent Variables

Correlation is analyzed for 38 independent variables for the sample period between January 1998 and May 2006. Correlations of 21 independent variables that we believe relatively more important are displayed on this table.

Negative correlation is indicated with parenthesis.

<table>
<thead>
<tr>
<th></th>
<th>SP</th>
<th>CON</th>
<th>SM</th>
<th>VG</th>
<th>10Y</th>
<th>YS</th>
<th>CPI*</th>
<th>MV</th>
<th>MV3</th>
<th>VIX</th>
<th>DEF</th>
<th>GH</th>
<th>10Y STRIP</th>
<th>MBS</th>
<th>CMBS 3B</th>
<th>CMO</th>
<th>EURO</th>
<th>CARRY</th>
<th>CBW</th>
<th>CCM</th>
<th>USS</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CON</td>
<td>0.732</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SM</td>
<td>0.018</td>
<td>0.225</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VG</td>
<td>0.461</td>
<td>0.482</td>
<td>0.001</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10Y</td>
<td>0.064</td>
<td>0.086</td>
<td>0.023</td>
<td>0.107</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>YS</td>
<td>0.024</td>
<td>0.075</td>
<td>0.110</td>
<td>0.012</td>
<td>0.498</td>
<td>0.100</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI*</td>
<td>0.060</td>
<td>0.061</td>
<td>0.117</td>
<td>0.000</td>
<td>0.071</td>
<td>0.399</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MV</td>
<td>0.269</td>
<td>0.204</td>
<td>0.012</td>
<td>0.122</td>
<td>0.008</td>
<td>0.030</td>
<td>0.079</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MV3</td>
<td>0.300</td>
<td>0.228</td>
<td>0.019</td>
<td>0.134</td>
<td>0.055</td>
<td>0.012</td>
<td>0.031</td>
<td>0.099</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td>0.705</td>
<td>0.320</td>
<td>0.201</td>
<td>0.340</td>
<td>0.042</td>
<td>0.123</td>
<td>0.100</td>
<td>0.399</td>
<td>0.399</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEF</td>
<td>0.187</td>
<td>0.277</td>
<td>0.000</td>
<td>0.230</td>
<td>0.011</td>
<td>0.004</td>
<td>0.109</td>
<td>0.044</td>
<td>0.101</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GH</td>
<td>0.492</td>
<td>0.428</td>
<td>0.321</td>
<td>0.140</td>
<td>0.132</td>
<td>0.248</td>
<td>0.031</td>
<td>0.300</td>
<td>0.314</td>
<td>0.476</td>
<td>0.314</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10Y STRIP</td>
<td>0.004</td>
<td>0.086</td>
<td>0.150</td>
<td>0.020</td>
<td>0.031</td>
<td>0.100</td>
<td>0.057</td>
<td>0.241</td>
<td>0.245</td>
<td>0.006</td>
<td>0.171</td>
<td>0.133</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MBS</td>
<td>0.016</td>
<td>0.022</td>
<td>0.109</td>
<td>0.011</td>
<td>0.121</td>
<td>0.061</td>
<td>0.031</td>
<td>0.537</td>
<td>0.322</td>
<td>0.013</td>
<td>0.098</td>
<td>0.022</td>
<td>0.174</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMBS 3B</td>
<td>0.059</td>
<td>0.064</td>
<td>0.179</td>
<td>0.263</td>
<td>0.077</td>
<td>0.128</td>
<td>0.322</td>
<td>0.233</td>
<td>0.294</td>
<td>0.114</td>
<td>0.176</td>
<td>0.410</td>
<td>0.045</td>
<td>0.145</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMO</td>
<td>0.273</td>
<td>0.151</td>
<td>0.569</td>
<td>0.057</td>
<td>0.068</td>
<td>0.168</td>
<td>0.007</td>
<td>0.014</td>
<td>0.086</td>
<td>0.200</td>
<td>0.961</td>
<td>0.935</td>
<td>0.023</td>
<td>0.396</td>
<td>0.998</td>
<td>0.119</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EURO</td>
<td>0.676</td>
<td>0.110</td>
<td>0.123</td>
<td>0.192</td>
<td>0.561</td>
<td>0.594</td>
<td>0.106</td>
<td>0.000</td>
<td>0.014</td>
<td>0.072</td>
<td>0.396</td>
<td>0.184</td>
<td>0.039</td>
<td>0.051</td>
<td>0.241</td>
<td>0.055</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CARRY</td>
<td>0.239</td>
<td>0.077</td>
<td>0.162</td>
<td>0.170</td>
<td>0.094</td>
<td>0.320</td>
<td>0.198</td>
<td>0.136</td>
<td>0.145</td>
<td>0.509</td>
<td>0.076</td>
<td>0.132</td>
<td>0.025</td>
<td>0.236</td>
<td>0.217</td>
<td>0.067</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBW</td>
<td>0.877</td>
<td>0.632</td>
<td>0.253</td>
<td>0.341</td>
<td>0.011</td>
<td>0.126</td>
<td>0.375</td>
<td>0.266</td>
<td>0.260</td>
<td>0.027</td>
<td>0.061</td>
<td>0.420</td>
<td>0.036</td>
<td>0.071</td>
<td>0.313</td>
<td>0.145</td>
<td>0.024</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COM</td>
<td>0.004</td>
<td>0.188</td>
<td>0.116</td>
<td>0.007</td>
<td>0.003</td>
<td>0.065</td>
<td>0.240</td>
<td>0.023</td>
<td>0.023</td>
<td>0.086</td>
<td>0.017</td>
<td>0.010</td>
<td>0.040</td>
<td>0.083</td>
<td>0.026</td>
<td>0.073</td>
<td>0.024</td>
<td>0.137</td>
<td>0.109</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>USS</td>
<td>0.200</td>
<td>0.429</td>
<td>0.118</td>
<td>0.012</td>
<td>0.066</td>
<td>0.182</td>
<td>0.062</td>
<td>0.062</td>
<td>0.067</td>
<td>0.111</td>
<td>0.133</td>
<td>0.055</td>
<td>0.003</td>
<td>0.109</td>
<td>0.065</td>
<td>0.099</td>
<td>0.042</td>
<td>0.124</td>
<td>0.036</td>
<td>1.000</td>
<td></td>
</tr>
</tbody>
</table>

Note: unless otherwise specified, all the variables are monthly percentage changes value. CPI is the inflation change year over year.
4 METHODOLOGY

4.1 Multi-factor Regression Model

We use a multi-factor model as follows,

\[ R = \alpha + \sum_{i=1}^{k} \beta_i F_i + \epsilon \]

where

- \( R \): return of hedge fund index in excess of risk free rate (3 month US T-bill)
- \( \alpha \): intercept of the regression
- \( \beta_i \): coefficient of factor \( i \)
- \( F_i \): return of factor \( i \) in excess of risk free rate or spread between level factors
- \( \epsilon \): error component

We assume initially that the coefficients in this model are constant over time and we employ OLS to estimate the regressions for each index for different strategies. For each index, we apply 38 variables that we identify most relevant to hedge fund performance from 136 total variables. To estimate the average exposure of funds to each index, we perform regression of the excess returns on the relevant 38 factors.

4.2 Stepwise and All-subset Regressions

As Agarwal and Naik (2004) discuss, considering the large number of variables it is a challenging task to identify the dominant risk factors. Hedge fund researchers address this problem by using a stepwise regression, which involves adding and deleting variables sequentially using econometrics statistics such as P-value or F-statistic.
Following hedge fund researchers such as Liang (1999), Fung and Hsieh (2000), Agarwal and Naik (2004), we employ stepwise multiple regression techniques for most regressions. However, we regress based on all-subset methodology when independent variables are less than 20.

4.2.1 Forward entry stepwise

After initial model is built, additional entries of remaining variables are tested and each entry statistics is computed. The variable with the most significant value exceeding the critical value is entered into the model, and next stepping continues.

4.2.2 Backward removal stepwise

After initial model is built, the removal statistic is computed for each effect eligible to be removed from the model. If no effect has a value on the removal statistic which is less than the critical value for removal from the model, then stepping is terminated, otherwise the effect with the smallest value on the removal statistic is removed from the model.

Burki and Larque (2001) discuss that the main advantage of backward stepwise is that it is more capable of picking up two variables that jointly explain a large part of the dependent variables but do not explain much when taken separately.
4.2.3 All-possible-subset regression

All-possible-subset regression is the most accurate in finding out the best regression model. However, due to the exponential increase of the all-possible subsets according to the increase of number of independent variables, this regression method will be used in limited cases where there are less than 15 independent variables.

4.3 Rolling regressions with a window of 60 months

In addition to full period regressions, we perform rolling regressions with different windows sizes, in order to capture the dynamic changes of the hedge fund strategies. After we employ different sizes of window, such as 36, 48, 60 months, we analyze the results based on 60 month window size.

Over our sample periods in this paper, from January 1998 to May 2006, we perform 42 rolling regressions for four non-directional strategies. We compare factor loadings of these rolling regressions with those of the full regression, by examining frequency of appearance as a significant factor in the light of each full regression.
5 RESULTS

5.1 How much is each strategy exposed to the direction of market?

Inspired by Stephen Foerster (2006), we begin with a simple CAPM regression of excess returns of hedge funds against both excess returns of S&P 500 and MSCI All Country World. Table 5 provides the intercepts and betas of each strategy.

Table 5 Market Exposures of Hedge Fund Strategies

The betas are calculated by one-factor OLS regression for the sample period of January 1998 to May 2006.

Negative signs are indicated with parenthesis.

Insignificant betas are indicated with bold numbers.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>S&amp;P 500</th>
<th>MSCI All Country</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept</td>
<td>Beta</td>
</tr>
<tr>
<td>Composite (COMP)</td>
<td>0.004</td>
<td>0.293</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Fixed Income Arbitrage (FINA)</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.756)</td>
</tr>
<tr>
<td>Convertible Arbitrage (CONA)</td>
<td>0.004</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Equity Market Neutral (EQMU)</td>
<td>0.005</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Merger Arbitrage (MRGA)</td>
<td>0.003</td>
<td>0.126</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Dedicated Short Bias (DSHB)</td>
<td>0.000</td>
<td>-0.904</td>
</tr>
<tr>
<td></td>
<td>(0.914)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Emerging Market (EMGdM)</td>
<td>0.003</td>
<td>0.546</td>
</tr>
<tr>
<td></td>
<td>(0.451)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Long/Short Equity (LSEQ)</td>
<td>0.005</td>
<td>0.416</td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Global Macro (GLMA)</td>
<td>0.007</td>
<td>0.176</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Managed Futures (MNGF)</td>
<td>0.003</td>
<td>-0.119</td>
</tr>
<tr>
<td></td>
<td>(0.253)</td>
<td>(0.079)</td>
</tr>
</tbody>
</table>

Source: CSFB/Tremont Hedge Indices, processed with Minitab
Of non-directional strategies, the betas of fixed income arbitrage and convertible arbitrage are low and insignificant. Thus, this first regression result confirms that these two strategies are non-directional against the equity market. The beta of equity market neutral strategy is low (0.072) and significantly positive. This result suggests that equity market neutral strategy is not market neutral but shows very little market exposure. However, the beta of merger arbitrage strategy, which is typically regarded as non-directional, is relatively high (0.126) and significant. This result strongly indicates that merger arbitrage strategy is not non-directional against equity market.

Directional strategies have significant high betas except for one strategy, managed futures strategy which has an insignificant negative beta. Dedicated short bias strategy shows a significant negative beta, reflecting the characteristics of its shorting strategy. Emerging market, long/short equity and global macro strategies have significant positive betas, reflecting their strategic nature geared to equity markets.

Regressions with S&P 500 and MSCI All Country World index provide very similar results.

5.2 Which macro economic factors drive the return of each non-directional strategy?

5.2.1 Regression for full period

We perform regression hedge fund composite, four non-directional, and five directional hedge fund strategy indices against 38 macroeconomic variables using stepwise regression with monthly data points from January 1998 to May 2006. Table 6 summarizes regression results, suggesting that each hedge fund strategy has different sets of factors. Panel A provides significant factors for non-directional strategies. Factors, such as 10 year US treasury, monthly change of
MOVE3, and monthly change of global high yield spread, appear frequently in our regression results. The adjusted R-squares range from 0.33 to 0.60, with equity market neutral being the lowest and merger arbitrage being the highest.

Fixed income arbitrage strategy has negative factor loading with high yield bond spread, commercial mortgage backed securities spread, and Eurodollar spread. This result is consistent with the fact that fixed income arbitrage funds tend to be sensitive with change in yield spreads. Fixed income arbitrage strategy is also sensitive to volatility measures such as monthly changes in MOVE3 and VIX, which are significantly different from zero.

Convertible arbitrage strategy shares similar set of key factors as fixed income arbitrage. Convertible arbitrage index is sensitive to various yield spreads and volatility measures. The negative loadings of high yield bond spread and commercial mortgage backed securities indicate that the returns increase as the spreads against 3 months treasury narrow. The only different factor between fixed income arbitrage and convertible arbitrage is the inflation change year over year (CPI). Convertible arbitrage has a high factor loading of 0.5 with inflation change year over year (CPI).

Equity market neutral has different set of risk factors than fixed income and convertible arbitrage. Unlike these two strategies, equity market neutral is not sensitive to change in yield spreads (no loading on high yield bond, commercial mortgage, etc) but sensitive to securities risks, such as excess return of convertible bond (CON) and small cap effect (SM). Equity market neutral is sensitive to volatility measure, but the relationship is non-linear (VIXCM^2) rather than linear in the case of fixed income arbitrage and convertible arbitrage. Interestingly, equity market neutral has a negative loading with US trade-weighed exchange rate (US$), implying that depreciation of US currency has a positive effect on the return of equity market neutral.
Table 6: Stepwise Regression Results for CSFB Tremont Hedge Fund Indices from January 1998 to May 2006

<table>
<thead>
<tr>
<th>Panel</th>
<th>Four Non-directional Strategy Hedge Fund Indices</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td>CSFB/Tremont Fixed Income Arbitrage (FINA), CSFB/Tremont Convertible Arbitrage (CONA), CSFB/Tremont Equity Market Neutral (EQMN), and CSFB/Tremont Merger Arbitrage (MRGA), monthly data from January 1998 to May 2006, measured as returns in excess of 3 month t-bill returns. The monthly return of convertible securities (CON) is calculated as excess return against 3-month t-bill. The small cap effect (SM) is the return difference between Russell 2000 and Russell 1000. The 10 year treasury yield change month over month (10Y) is also calculated and the inflation change (CPI) is the change in the year-over-year consumer price index. MOVE3 (MV3) is yield curve weighted index of the normalized implied volatility of 3 month Treasury option while VIX is the CBOE VIX implied volatility for S&amp;P 500. VIX change (VIXCM) is the monthly percentage change in VIX. The monthly change in global credit spread (GH) is the monthly change in yield spread between Merrill Lynch Global High Yield Bond and 10-year treasury. The monthly change in CMBS3B spread is the monthly change in yield spread between Morgan Stanley CMBS Conduit BBB and 10 year treasury. The monthly change in Eurodollar deposit (EURO) is the monthly change in yield spread between 3 month Eurodollar and 3-month treasury rate. The US Trade Weighted Broad Currency is the weighted US dollar exchange rate against its trade partners.</td>
</tr>
<tr>
<td><strong>NOTE:</strong></td>
<td>VIX is the level value; VIXCM is the monthly change of VIX; VIXCM2 is the square of VIXCM. Other variables in this table are monthly percentage change values.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>FINA</th>
<th>CONA</th>
<th>EQMN</th>
<th>MRGA</th>
<th>R-bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>FINA</td>
<td>0.29</td>
<td>0.29</td>
<td>0.34</td>
<td>0.34</td>
<td>0.29</td>
</tr>
<tr>
<td>CONA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>EQMN</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>MRGA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>R-bar</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>FINA</th>
<th>CONA</th>
<th>EQMN</th>
<th>MRGA</th>
<th>R-bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>FINA</td>
<td>0.29</td>
<td>0.29</td>
<td>0.34</td>
<td>0.34</td>
<td>0.29</td>
</tr>
<tr>
<td>CONA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>EQMN</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>MRGA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>R-bar</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>FINA</th>
<th>CONA</th>
<th>EQMN</th>
<th>MRGA</th>
<th>R-bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>FINA</td>
<td>0.29</td>
<td>0.29</td>
<td>0.34</td>
<td>0.34</td>
<td>0.29</td>
</tr>
<tr>
<td>CONA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>EQMN</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>MRGA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>R-bar</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>FINA</th>
<th>CONA</th>
<th>EQMN</th>
<th>MRGA</th>
<th>R-bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>FINA</td>
<td>0.29</td>
<td>0.29</td>
<td>0.34</td>
<td>0.34</td>
<td>0.29</td>
</tr>
<tr>
<td>CONA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>EQMN</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>MRGA</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>R-bar</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
</tr>
</tbody>
</table>
Table 7: Stepwise Regression Results for CSFB/Tremont Hedge Fund Index from January 1998 to May 2006 - Continued

**Panel B: Composite Index and Five Directional Hedge Fund Strategy Indices**

The dependent variables are CSFB/Tremont Hedge Fund Index (COMP), CSFB/Tremont Distressed (DSHB), CSFB/Tremont Emerging Market (EMRG), CSFB/Tremont Long/Short Equity (LSEQ), CSFB/Tremont Global Macro (GLMA), and CSFB/Tremont Managed Future (MGFT), monthly data from January 1998 to May 2006, measured as returns in excess of 3-month t-bill returns. The monthly return of S&P 500 (SP) and convertible securities (CON) are calculated as excess returns against 3-month t-bill. The small cap effect (SM) is the return difference between Russell 2000 and Russell 1000 while the value effect is the return difference between S&P 500/Citigroup Value and S&P 500/Citigroup Growth. The 10 year treasury yield change (10Y) is also calculated and the inflation change (CPI), the yield spread (YS) is the yield difference between 10 year treasury and 3 month treasury, and the month change in TIPS yield spread (TIPS) is the monthly change in yield spread between 10 year treasury and 3 month treasury.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>COMP</td>
<td>0.12</td>
<td>0.05</td>
<td>2.47</td>
<td>0.015</td>
</tr>
<tr>
<td>DSHB</td>
<td>-0.04</td>
<td>0.03</td>
<td>-1.43</td>
<td>0.17</td>
</tr>
<tr>
<td>EMRG</td>
<td>0.06</td>
<td>0.03</td>
<td>1.83</td>
<td>0.07</td>
</tr>
<tr>
<td>LSEQ</td>
<td>0.03</td>
<td>0.02</td>
<td>1.51</td>
<td>0.13</td>
</tr>
<tr>
<td>GLMA</td>
<td>0.02</td>
<td>0.01</td>
<td>1.96</td>
<td>0.05</td>
</tr>
<tr>
<td>MGFT</td>
<td>-0.01</td>
<td>0.00</td>
<td>-3.23</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Note: All the variables in this table are monthly percentage change values.
Merger arbitrage strategy has the highest adjusted R-square in the four non-directional strategies we examined as it is more affected by market factors. Merger arbitrage is vulnerable to market risk (excess return of S&P 500), the small cap effect (the return difference between Russell 2000 and Russell 1000), and the value effect (the return difference between S&P 500/Citigroup Value and S&P500/Citigroup Growth). These three factors are very similar to Fama-French three factors and hence we expect that merger arbitrage is sensible to Fama-French three factors as well.

Panel B summarizes the results for the composite index and directional hedge fund strategies. Factor loadings are scattered among different strategies as no single factor dominates. R-squares range from 0.29 to 0.82. We do not provide detailed explanation with these strategies since they are self-explanatory under the explanations of non-directional strategies above.

5.2.2 Rolling regression

We further perform rolling-window stepwise regressions in order to capture the dynamics of hedge fund strategies. Table 7 summarize the results of rolling regression for four non-directional strategies with 42 rolling windows of 60-month window size from January 1998 to May 2006. Table 7 Panel A to D combine the results of the rolling window regression and the full-period regression. The frequency of appearance in the rolling window regression and the loadings for the key factors for the full-period regression is reported. For instance, in Panel A, CMBS3B shows up 23 times out of 42 total numbers of rolling window regression and has a coefficient of -0.06 for the full-period regression. Notice that some factors appearing frequently in the rolling window regression, such as US trade-weighted currency exchange (US$), do not show up in the full-period regression. On the other hand, factors, such as monthly change in MOVE3 (MV3) and monthly change in global high yield bond spreads (GH), do not appear once in rolling window regressions but in the full-period regression.
Figure 2 to 5 provide graphical presentation of changes of factor loadings of each strategy. In these figures, Y-axis shows factor loadings and X-axis shows the starting point of each 5-year rolling window. Given a specific point on the X-axis, one can identify the significant factors for the associated 5-year rolling window regression. For instance, in the first rolling regression, four factors – VIX square, monthly change in VIX, value minus growth, and CMBS3B spread – appear as important attributes in explaining monthly excess returns of fixed income arbitrage index for the period of 60 months starting in January 1998 and ending January 2002. As shown in the y-axis, the loadings are 0 for VIX, 0.035 for monthly change in VIX, -0.06 for value minus growth, and -0.097 for CMBS3B spread.
Table 8 Rolling Regression Results for CSFB/Tremont Hedge Fund Index with 60 month window size

**Panel A: Fixed Income Arbitrage**

<table>
<thead>
<tr>
<th>Factor</th>
<th>VG</th>
<th>10Y</th>
<th>TIPS</th>
<th>MV</th>
<th>MV2</th>
<th>MV3</th>
<th>MV2^2</th>
<th>VIX</th>
<th>VIXCM</th>
<th>VXCM^2</th>
<th>DEF</th>
<th>GH</th>
<th>STR</th>
<th>SWAP</th>
<th>MBIS</th>
<th>CMBS 36s</th>
<th>LB</th>
<th>EURLQ</th>
<th>CSW</th>
<th>US$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>6</td>
<td>10</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>7</td>
<td>3</td>
<td>9</td>
<td>0</td>
<td>7</td>
<td>10</td>
<td>23</td>
<td>1</td>
<td>12</td>
<td>3</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Loading for full regression</td>
<td>0.29</td>
<td>-0.02</td>
<td>0.02</td>
<td>-0.03</td>
<td>-0.06</td>
<td>-0.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.018)</td>
<td>(0.000)</td>
<td>(0.005)</td>
<td>(0.000)</td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel B: Convertible Arbitrage**

<table>
<thead>
<tr>
<th>Factor</th>
<th>SP</th>
<th>CON</th>
<th>10Y</th>
<th>YS</th>
<th>CPI</th>
<th>MV3</th>
<th>VIX</th>
<th>VIXP</th>
<th>VXCMF</th>
<th>GH</th>
<th>CMBS3A</th>
<th>CMBS3B</th>
<th>EURLQ</th>
<th>SF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>4</td>
<td>15</td>
<td>0</td>
<td>10</td>
<td>20</td>
<td>6</td>
<td>10</td>
<td>6</td>
<td>2</td>
<td>16</td>
<td>11</td>
<td>10</td>
<td>2</td>
<td>12</td>
</tr>
<tr>
<td>Loading for full regression</td>
<td>0.34</td>
<td>0.50</td>
<td>-0.03</td>
<td>0.00</td>
<td>-0.06</td>
<td>-0.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel C: Equity Market Neutral**

<table>
<thead>
<tr>
<th>Factor</th>
<th>SP</th>
<th>CON</th>
<th>SM</th>
<th>10Y</th>
<th>TIPS</th>
<th>CPI</th>
<th>MV3</th>
<th>VIXCMF</th>
<th>GC</th>
<th>GH</th>
<th>SWAP</th>
<th>CMBS3A</th>
<th>CMBO</th>
<th>ABS</th>
<th>EURLQ</th>
<th>CARRY</th>
<th>SW</th>
<th>SF</th>
<th>US$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>5</td>
<td>26</td>
<td>14</td>
<td>3</td>
<td>15</td>
<td>2</td>
<td>5</td>
<td>7</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>12</td>
<td>1</td>
<td>7</td>
<td>7</td>
<td>1</td>
<td>32</td>
</tr>
<tr>
<td>Loading for full regression</td>
<td>0.076</td>
<td>-0.03</td>
<td>-0.26</td>
<td>-0.02</td>
<td>-0.17</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.032)</td>
<td>(0.000)</td>
<td>(0.019)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 7 Rolling Regression Results for CSFB/Tremont Hedge Fund Index with 60 month window size – Continued

Panel D: Merger Arbitrage

<table>
<thead>
<tr>
<th>SP</th>
<th>CON</th>
<th>SM</th>
<th>VG</th>
<th>10Y</th>
<th>YS</th>
<th>TPS</th>
<th>CPI</th>
<th>US Load</th>
<th>MV3</th>
<th>VIX</th>
<th>VIX2</th>
<th>VIXC</th>
<th>DEF</th>
<th>GC</th>
<th>GH</th>
<th>CNBS</th>
<th>3B</th>
<th>EURO</th>
<th>CARRY</th>
<th>SW</th>
<th>CBW</th>
<th>US$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>1</td>
<td>7</td>
<td>42</td>
<td>8</td>
<td>3</td>
<td>24</td>
<td>1</td>
<td>7</td>
<td>9</td>
<td>4</td>
<td>3</td>
<td>25</td>
<td>6</td>
<td>6</td>
<td>8</td>
<td>4</td>
<td>7</td>
<td>7</td>
<td>2</td>
<td>7</td>
<td>30</td>
<td>8</td>
</tr>
<tr>
<td>Loading for full regression</td>
<td>0.15</td>
<td>(0.03)</td>
<td>0.14</td>
<td>(0.000)</td>
<td>0.09</td>
<td>(0.003)</td>
<td>0.38</td>
<td>(0.001)</td>
<td>-0.007</td>
<td>(0.000)</td>
<td>-0.17</td>
<td>(0.046)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 2: Consistency of Factor Loadings: Fixed Income Arbitrage
Figure 3  Consistency of Factor Loadings: Convertible Arbitrage
Figure 5 Consistency of Factor Loadings: Merger Arbitrage
Table 7 Panel A and Figure 2 suggest the results of rolling regression for CSFB/Tremont Fixed Income Arbitrage Index. None of the independent factors consistently appears throughout the 42 rolling regressions. Even the two most prominent independent factors, such as spread of commercial mortgage backed securities (CMBS3B) and US trade-weighted currency exchange (US$), only appear 50% of the time. CMBS3B spread is a consistently significant factor from the rolling window starting January 1998 to that starting October 1999, and US trade-weighted currency exchange shows up from the rolling window starting October 1999 to that starting June 2001.

Most academics believe that fixed income arbitrage strategies are typically exposed to three risks: interest rate risk, credit risks, and volatility risks. Our results suggest that fixed income arbitrage managers might also take currency risk and risks associated with mortgage backed securities. Also notice that Eurodollar spread has big negative loadings since September 2000. As indicated in an article from Barron’s (2001), the large negative loading of Eurodollar spread against 3 month treasury was due to the revived interests in Treasury/Eurodollar (TED) spread trading in 2001 when Federal Reserve initiated the interest rate cutting cycle. Some big hedge funds and institutional managers have taken big positions in Eurodollar future market to bet short-term interest rate movements.

Table 7 Panel B and Figure 3 show the results of the rolling regressions for CSFB/Tremont Convertible Arbitrage Index. Similar to fixed income arbitrage strategies, convertible arbitrage strategies are also sensitive to various yield spreads and volatility measures. In addition, convertible arbitrage strategies are exposed to inflation (CPI), which is one of the most important macroeconomic factor, and excess return of convertible securities (CON). These two factors appear more than 15 times out of the 42 rolling regressions. This result suggests that convertible arbitrage strategies are not immune from economic factors such as inflation and convertible securities market performance, as many academics and practitioners suggest.
Table 7 Panel C and Figure 4 provide the results of the rolling regressions for CSFB Equity Market Neutral Index. The two most prominent factors in this group of hedge fund strategies are excess return of convertible securities (CON) and US trade-weighted currency exchange rate (US$). Interestingly, US$ trade-weighted currency exchange rate has negative loading, suggesting that equity market neutral strategies would perform better when US dollar depreciates. This currency effect has shown some consistency for the sample period we studied. It appears 32 times out of 42 total rolling window regressions.

Table 7 Panel D and Figure 5 present the results of the rolling regressions of CSFB/Tremont Merger Arbitrage. This category produces the most consistent results. Adjusted R-square for each rolling window regression is usually greater than 0.6. Two independent variables are consistently significant over the 42 rolling windows: small cap effect (SM) and Chicago Buy Write (CBW) index. The positive influence of small cap effect reflects the tendency that big companies buy out small companies in most events of mergers and acquisitions.

The positive loading of Chicago Buy Write comes from the option-like payout profile of merger arbitrage, pointed out by Jaeger and Wagner (2005). Merger arbitrage strategies display rather high correlations to the equity markets when the equity market declines and comparably low correlation when stocks go up or sideways. This quasi-correlation characteristic is similar to the return profile of writing options, which is reflected in the significance of Chicago Buy Write index in our rolling window regressions.

Our rolling window regression analysis fails to find an independent factor that is statistically significant at 5% confidence level consistently during rolling window periods. The only independent factor appears 90% of time in the entire rolling window regression is the small cap effect in CSFB/Tremont Merger Arbitrage. Some independent variables appearing to be important for some periods disappear for other periods. We are not surprised to see this kind of result as we believe hedge fund strategies are dynamic and it is difficult to capture such dynamics with a static model.
6 CONCLUSION

We examine hedge fund indices in order to answer two questions. One is how much hedge fund indices are exposed to the equity market. Our regression against S&P 500 and MSCI All Country World provides that fixed income arbitrage and convertible arbitrage have insignificant beta for the equity market and that equity market neutral has significant but very low beta. Therefore, three out of four non-directional indices are lowly exposed to the equity market. However, merger arbitrage which is generally considered as a non-directional strategy has a significant and relatively high beta, suggesting that this strategy is not non-directional.

Composite and most directional indices have significant betas except for managed future, which is generally consistent with our expectation considering the nature of directional hedge fund strategies.

We investigate various macroeconomic variables in order to reveal the drivers of non-directional hedge fund performance based on both full period OLS and rolling window regressions. Fixed income arbitrage strategy is relatively well explained with adjusted R-square of 0.53, but rolling regressions reveal that such factors are not consistent in explaining the returns of indices. It is suggested from this research that arbitrage strategies are also exposed to currency risk and risks associated with mortgage backed securities, in addition to typically risks such as interest rate risk, credit risks, and volatility risks.

Convertible arbitrage strategy is also relatively well explained with adjusted R-square of 0.47. However, this research suggests that convertible arbitrage strategies are not immune from economic factors such as inflation and excess returns of convertible securities.
Equity market neutral strategy is hard to explain by OLS regression, with adjusted R-square of 0.33. While rolling regressions do not disclose distinctive consistency except for US trade-weighted currency exchange rate.

Merger arbitrage strategy is well explained, with adjusted R-square of 0.60. Small cap effects and Chicago Buy Write index appear to be significant in almost all rolling window periods. Chicago Buy Write index reflects the option-like return profile of merger arbitrage, and small cap effect reflects the tendency that big companies buy out small companies in most events of mergers and acquisitions.
APPENDIX

MatLab Code

clear; % display off; % format bank;

% Loading 'data_n.xls'
% Independent Variable: Hedge_Index, Hedge_Index_Header
% Load variables (A: Date, B-EC: Data)
excel_file = 'data_fixed.xls';
excel_sheet = 'data';
excel_range = 'B1:AL3';
[raw_data, raw_header] = xlsread(excel_file, excel_sheet, excel_range);
excel_range = 'A52:A152';
[raw_data, raw_date] = xlsread(excel_file, excel_sheet, excel_range);
excel_range = 'B52:AL152';
raw_data = xlsread(excel_file, excel_sheet, excel_range);
% Load indices (A: Date, B-0: Data)
excel_sheet = 'indices';
excel_range = 'B1:O3';

[raw_index_data raw_index_header] = xlsread(excel_file, excel_sheet, excel_range);
excel_range = 'B52:O152';
raw_index_data = xlsread(excel_file, excel_sheet, excel_range);
clear Hedge_Index_Master
clear Hedge_Index_Header

clear Hedge_Variables_Master
clear Hedge_Variables_Header

clear Hedge_Variables_Master_Rolling

clear ar_results

clear ar_results_full

% Construct: Hedge_Variables_Master, Hedge_Variables_Header
%----------------------------------------------------------
rolling_start = raw_data(1,1);
ar_num_column = size(raw_data);
num_column = ar_num_column(1,2);
num_row = ar_num_column(1,1);

num_variables = 0;
for i = 1:num_column;
    if strcmp('v', raw_header(1,i)) == 1
        num_variables = num_variables + 1;
        Hedge_Variables_Master(:, num_variables) = raw_data(:, i);
        Hedge_Variables_Header(1, num_variables) = raw_header(3, i);
    end
end

% Construct: Hedge_Index_Master, Hedge_Index_Header
%----------------------------------------------------------
ar_num_index_column = size(raw_index_data);
num_index_column = ar_num_index_column(1,2);
num_index_row = ar_num_index_column(1,1);

num_index = 0;
for i = 1:num_index_column;
    if strcmp('v', raw_index_header(1,i)) == 1
        num_index = num_index + 1;
    end
end
Hedge\_Index(:, num\_index) = raw\_index\_data(:,i);
Hedge\_Index\_Header(1, num\_index) = raw\_index\_header(3,i);
end
end

\%
% Regression: Stepwise - Forward Selection
%-----------------------------------------------

% Specify Number of Indices
count\_row\_full = -3;
% count\_cusum = -5;
for j = 1:1:num\_index
  count\_row = -3;
  %-----------------------------------------------
  % Rolling regression --> Specify size of window
  %-----------------------------------------------
  interval = 60;
  num\_rolling = num\_row - interval + 1;
  % num\_rolling = 3
  clear Hedge\_Variables\_Master\_Rolling
  clear B
  clear SE
  clear PVAL
  clear INMODEL
  clear STATS
  clear Hedge\_Variables
  clear Hedge\_Variables\_Full
  clear ar\_results
  clear ar\_results\_print
  for i = 1:1:num\_rolling
    % I. Rolling Windows - Setting up the size 60 months
    Period\_Start = i;
    Period\_End = i + interval - 1;
    % New Coding
    Hedge\_Variables\_Master\_Rolling(:, :) =
    Hedge\_Variables\_Master(Period\_Start:Period\_End, :);
% I. Rolling Windows - Remove NaN cells
Hedge_Variables_Master_Rolling(:, 1) = Hedge_Variables_Master(Period_Start:Period_End, 1);
for i = 2:1:cols
    row_nan = 0;
    for k = Period_Start:1:Period_End
        if isnan(Hedge_Variables_Master(k, i))
            row_nan = row_nan + 1;
        end
    end
    if row_nan == 0
        Hedge_Variables_Master_Rolling(:, i) = Hedge_Variables_Master(Period_Start:Period_End, i);
    else
        Hedge_Variables_Master_Rolling(:, i) = 0;
    end
end

% II. Rolling Windows - Stepwisefit
[B,SE,PVAL,INMODEL,STATS,NEXTSTEP,HISTOR] = stepwisefit(X, Y, 'display', 'off');

Coefficient = B';
Pvalue = PVAL';

II. Prepare Variables for OLS
num_variables_used = 0;
result_column = num_variables_used + 1;
ar_result(count_row, result_column) = Hedge_Index_Header(1, i);
ar_result(count_row, result_column+1) = raw_date(i, 1);
ar_result(count_row, result_column+1) = cellstr(int2str(i));

for count_column = 1:1:cols
    if INMODEL(1, count_column) == 1
        num_variables_used = num_variables_used + 1;
        result_column = count_column + 2;
    end
end
Hedge_Variables(:, num_variables_used) = X(:, count_column); 

%Header 
ar_results(count_row, result_column) = Hedge_Variables_Header(1, count_column); 

%Coefficient 
ar_results(count_row+1, result_column) = {Coefficient(1, count_column)}; 

%P-Value 
ar_results(count_row+2, result_column) = {Pvalue(1, count_column)}; 

end 
end 

% III. Perform OLS 

if num_variables_used == 0 
else 

OLS_X = [ones(size(Hedge_Variables(:,1))) Hedge_Variables]; 
OLS_Y = Y; 
ar_results_ols = ols(OLS_Y, OLS_X); 

dv = num_variables_used; 

num_samples_used = length(OLS_X); 
ns = num_samples_used - 2; 
f_stat = sum(ar_results_ols.yhat.A2) / sum(ar_results_ols.resid.A2)/ ns; 
f_inv = finv(0.95, dv, ns); 

col_indi = num_variables + 10; 
ar_results(count_row, col_indi) = {'# Var'}; 
ar_results(count_row, col_indi+1) = {'# Sample'}; 
ar_results(count_row, col_indi+2) = {'R-sqr'}; 
ar_results(count_row, col_indi+3) = {'R-bar'}; 
ar_results(count_row, col_indi+4) = {'DW'}; 
ar_results(count_row, col_indi+5) = {'F-stat'}; 
ar_results(count_row, col_indi+6) = {'F-inv'}; 

ar_results(count_row+1, col_indi) = num_variables_used; 
ar_results(count_row+1, col_indi+1) = num_samples_used; 
ar_results(count_row+1, col_indi+2) = ar_results_ols.rbar; 
ar_results(count_row+1, col_indi+3) = ar_results_ols.dw; 
ar_results(count_row+1, col_indi+4) = f_stat; 
ar_results(count_row+1, col_indi+5) = f_inv; 

% % V. Cusum Test 

% cusum_r = cusums(OLS_Y, OLS_X); 
% num_res_sum = 0; 
% num_check_out = 0; 
% for g = 1:interval
num_res_sum = num_res_sum + cusum_r.rres(g);
if (num_res_sum > cusum_r.lower95(g)) && (num_res_sum <
cusum_r.upper95(g))
else
    num_check_out = num_check_out + 1;
end
ar_results(count_row, col_indi+7) = {'CUSUM_Out'};
end
count_row = count_row + 4;
count_row_full = count_row_full + 4;
Period_Start = 1;
Period_End = num_row;
clear B
clear SE
clear PVAL
clear INMODEL
clear STATS
clear NEXTSTEP
clear HISTORY
clear X
clear Y
clear Hedge_Variables_Master_Rolling
Hedge_Variables_Master_Full(:, :) =
    Hedge_Variables_Master(Period_Start:Period_End, :);
for I = 2:1:num_variables
    Hedge_Variables_Master_Full(:, 1) =
        Hedge_Variables_Master(Period_Start:Period_End, 1);
    row_nan = 0;
    for k = Period_Start:1:Period_End
        if isnan(Hedge_Variables_Master(k, I))
row_nan = row_nan + 1;
end
end
if row_nan == 0
Hedge_Variables_Master_Full(:, :) = Hedge_Variables_Master(Period_Start:Period_End, :);
else
Hedge_Variables_Master_Full(:, :) = 0;
end
%
X = Hedge_Variables_Master_Full(Period_Start:Period_End, :);
Y = Hedge_Index(Period_Start:Period_End, :);
[B, SE, PVAL, INMODEL, STATS, NEXTSTEP, HISTORY] = stepwisefit(X, Y, 'display', 'off');
Coefficient = B';
Pvalue = PVAL';

% II. Prepare Variables for OLS
num_variables_used = 0;
result_column = num_variables_used + 1;
ar_results(count_row, result_column) = Hedge_Index_Header(1, j);
ar_results(count_row, result_column+1) = cellstr('full');
%
ar_results_full(count_row_full, result_column) = Hedge_Index_Header(1, j);
ar_results_full(count_row_full, result_column+1) = cellstr('full');
for count_column = 1 : num_variables;
    if INMODEL(1, count_column) == 1
        num_variables_used = num_variables_used + 1;
        result_column = count_column + 2;
        Hedge_Variables_Full(:, num_variables_used) = X(:, count_column);
ar_results(count_row, result_column) = Hedge_Variables_Header(1, count_column);
%Coefficient
ar_results(count_row+1, result_column) = Coefficient(1, count_column);
%P-Value
ar_results(count_row+2, result_column) = Pvalue(1, count_column);
end
end

% III. Perform OLS
OLS_X = [ones(size(Hedge_Variables_Full(:, 1))) Hedge_Variables_Full];
OLS_Y = Y;

ar_results_ols = ols(OLS_Y, OLS_X);

dv = num_variables_used;

% dv = size(OLS_X(:, 1));
num_samples_used = length(OLS_X);
ns = num_samples_used - 2;

f_stat = sum(ar_results_ols.yhat.^2)/(sum(ar_results_ols.resid.^2)/ns);
f_inv = finv(0.05, dv, ns);

col_indi = num_variables + 10;

ar_results(count_row, col_indi) = {'# Var'};
ar_results(count_row, col_indi+1) = {'# Sample'};
ar_results(count_row, col_indi+2) = {'R-sqr'};
ar_results(count_row, col_indi+3) = {'R-bar'};
ar_results(count_row, col_indi+4) = {'DW'};
ar_results(count_row, col_indi+5) = {'F-stat'};
ar_results(count_row, col_indi+6) = {'F-inv'};

ar_results(count_row+1, col_indi) = num_variables_used;
ar_results(count_row+1, col_indi+1) = num_samples_used;
ar_results(count_row+1, col_indi+2) = ar_results_ols.rsqr;
ar_results(count_row+1, col_indi+3) = ar_results_ols.rbar;
ar_results(count_row+1, col_indi+4) = ar_results_ols.dw;
ar_results(count_row+1, col_indi+5) = f_stat;
ar_results(count_row+1, col_indi+6) = f_inv;

ar_results_full(count_row_full, count_row+2,:) = ar_results(count_row,count_row+2,:)

%% % Cusum Test
%%
%% % cusum_r = cusums(OLS_Y, OLS_X);
%%
%% % count_cusum = count_cusum + 6;
%%
%% % num_res_sum = 0;
%%
%% for g = 1:1:num_row
%%
%% % num_res_sum = num_res_sum + cusum_r.rrest(g);
%%
%% if (num_res_sum > cusum_r.lower95(g)) && (num_res_sum < cusum_r.upper95(g))
%%
%%    num_check = 1;
%%
%% else
%%
%%    num_check 0;
%%
%% end
%%
%% % ar_cusum_results(g, count_cusum) = cusum_r.lower95(g);
%%
%% % ar_cusum_results(g, count_cusum+1) = cusum_r.cusums(g);
%%
%% % ar_cusum_results(g, count_cusum+2) = num_res_sum;

48
ar_cusum_results(g, count_cusum+3) = cusum_r.upper95(g);
ar_cusum_results(g, count_cusum+4) = num_check;
end

numgrint = 1;
num_ar_results_column = 4;
for I = 1 : I : num_ar_results_column
    row_string = 0;
    for m = 1 : I : num_ar_results_row
        if iscellstr(ar_results(m,I))
            row_string = row_string + 1;
        end
    end
    if row_string == 0
        else
            ar_resultsgrint(1 : num_ar_results_row, num_print) = ar_results(1 : num_ar_results_row,I);
            ar_resultsprint(num_ar_results_row + 2, num_print) = num2cell(row_string);
            num_print = num_print + 1;
            end
    end
    ar_resultsprint(num_ar_results_row + 4, 1) = cellstr(strcat('Period (month): ', int2str(num_row)));
    ar_resultsprint(num_ar_results_row + 5, 1) = cellstr(strcat('Size of window: ', int2str(interval)));
    ar_resultsprint(num_ar_results_row + 7, 1) = cellstr(strcat('# Variables-Total: ', int2str(num_variables)));
    ar_resultsprint(num_ar_results_row + 8, 1) = cellstr(strcat('# Variables-Signif(95%): ', int2str(num_print-6-3-1)));
end

file_name = strcat(S_Results_2.FINA", int2str(interval), ", datestr(rolling_start));
M = ar_results_print;
sheet = char(Hedge_Index_Header(1,1));
range = 'A1';
xlswrite(file_name, M, sheet, range);
end

%----------------------------------------------------------------------------------
% Remove Empty Columns: full
%----------------------------------------------------------------------------------

ar_column = size(ar_results_full);
num_ar_results_column = ar_column(1,2);
num_ar_results_row = ar_column(1,1);

num_print = 1;
% num_ar_results_column = 4;
for i = 1:1:num_ar_results_column
    row_string = 0;
    for m = 1:1:num_ar_results_row
        if iscellstr(ar_results_full(m,i))
            row_string = row_string + 1;
        end
    end
    if row_string == 0
    else
        ar_results_full_print(1:num_ar_results_row, num_print) = ar_results_full(1:num_ar_results_row,i);
        ar_results_full_print(num_ar_results_row + 2, num_print) = num2cell(row_string);
        num_print = num_print + 1;
    end
end

%-------------------------------------------------------------------------------
% Writing on Excel: Full
%-------------------------------------------------------------------------------

M = ar_results_full_print;
sheet = 'REG FULL';
range = 'A1';
xlswrite(file_name, M, sheet, range);

50
REFERENCES


Burki, Valentin and Larque, Rodolphe, 2001, “Hedge Funds Returns and Their Drivers,” University of Lausanne, Working paper


