March 2017

A Characterization of Hedge Fund Exposure to Systematic Risks and Market Correlation

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March 2, 2017

Abstract: Alternative investment vehicles, such as hedge funds, offer potentially high returns for investors willing to stomach the corresponding high-risks and opportunity costs. Additionally, depending on the fund's methodology, some funds purport to offer limited market exposure in conjunction with their high return potential: they act as true "alternative" investments to the market. The objective of this paper is to analyze hedge funds to determine in what respects they are exposed to the market and systematic risk factors. Using a 21-year basis for data (1994-2015), we will examine fund performance versus the market for a variety of hedge indices. Our analysis provides insight into hedge fund performance during bull, bear, and crash market conditions. By capturing these market cycles, we can measure how exposed the hedge fund returns are to traditional measures of systematic risk in the market. Using a Macro-Market model for our fund returns, we characterize significant factors for modeling fund returns, with respect to each strategy we examine. The intra-strategy analysis allows us to both draw conclusions about market independence for each strategy and compare respective strategies over the 21-year period. In conclusion, we determine to what extent our strategies offer an "alternative" investment. With the present popularity of hedge funds, understanding their correlation with market behavior is more important than ever. This paper strives to provide insight into that relationship and hedge fund dynamics in general.

1 Introduction

To understand how hedge funds act as alternative investments, we must consider how to model the returns of these funds. Previous efforts to model hedge fund returns are (logically) aimed at predictability and strategy implementation for respective funds and indices. While our concern is the macroeconomic factors affecting these returns, our analysis conducts a regression study similar to those conducted to examine strategies surrounding hedge funds.

For instance, Amenc, El Bied, and Martellini (2002) performed a study of both predictability and tactical asset allocation for hedge fund returns.[1] Brooks and Kat (2001) conducted a thorough statistical analysis of hedge fund returns, a study which this paper will reexamine.[2] Both Hamza, Kooli, and Roberge (2006) and Avramov, Barras, and Kosowski (2013) characterize the predictability of hedge fund returns; however, HKR examines the use of tactical asset allocation as an investment strategy, while ABK devises a rationale behind fund predictability, based on fund characteristics.

This paper provides a basis for intra-fund comparison for investing strategies based on multiple regression. The implementation of our model is meant to determine variable significance and return correlation with the broader market; similar analyses could be carried out for mutual funds, bond funds, or alternative investments. The diversity of hedge fund strategies and their growth over the past decade make these funds prime candidates for this analysis. Using the data available from the Credit Suisse Hedge Fund Indices, we will conduct a statistical and

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[1] Their study includes a study of hedge fund return persistence and stability, as well as an extended Macro Model, measuring return exposure to systematic risks. Our study also develops a Macro Model for hedge fund returns; however, our model analysis stresses exposure to systematic risks, not predictability and strategy development surrounding the model.

[2] Their analysis considers monthly hedge fund returns for various indices from 1995 to 2001. By considering a larger pool of data in our study, 1994-2015, we can examine changes in the statistical properties of the returns and reevaluate the corresponding conclusions.

modeling-based study of hedge fund returns. The analysis will individually cover each index, as they correspond to different hedge fund strategies: Convertible Arbitrage, Event Driven Strategies, and Emerging Markets for example.[3] By stratifying the analysis by investment strategy, we characterize market exposure holistically for each strategy. Hence, we can gauge just how "alternative" investment strategies are within certain hedge funds.

By considering a 21-year period of available data, we can survey how hedge funds act in both bull and bear markets from a statistical standpoint. Finally, we will examine the exposure of hedge fund returns to both systematic risk and traditional drivers of equity returns. Using Fama and French (1992) and Carhart (1997) as bases for modeling fund returns, this paper measures hedge fund dependence on effects traditionally associated with equities and mutual funds. Hence, we will examine to what extent hedge funds offer alternative investments as compared to market, equity, and even mutual fund characteristics. The returns of these instruments have been written about extensively, compared to hedge funds. By characterizing hedge fund returns in greater detail, we can gain insight into market behavior and strategy development surrounding theses returns.

Interdisciplinary Importance

This paper strives to characterize hedge fund returns in 3 respects: statistical properties, exposure to market growth and systematic risks, and exposure to drivers of mutual fund growth. By taking a holistic approach to studying the returns, this paper strives to understand how hedge funds act as alternative investments. With a record $3 trillion in assets-under-management (AUM) for hedge funds, the need for understanding their return properties is greater than ever.[4] By

[3] See Appendix, Figure 1 for description of each strategy studied in this analysis
[4] Source: http://www.barclayhedge.com/research/indices/ghs/mum/HF_Money_Under_Management.html

considering the indices of different hedge fund strategies, we examine aggregate behavior for each strategy, not the performance of individual funds. By examining through a broader scope, this paper provides a basis for modeling returns for individual hedge funds, assuming they follow a strategy prescribed in the indices we examine. Predictability studies done on hedge fund returns benefit from both the statistical and market correlation analyses. Accordingly, strategies surrounding the hedge fund returns can also be adjusted to reflect fund behavior over their lifetime or in present market conditions. Our study provides a basis for future modeling of hedge fund returns, as well as adjusting present portfolio strategies.

Finally, hedge funds are mystifying as investment vehicles. Known primarily for offering more return with more risk (and less regulation), these funds stand apart from equities, ETFs, and options in their characteristics. Unlike like other publically traded securities, hedge funds maintain limited liability partnerships (LLPs) with their investors; this allows the funds to maintain limited liability for poor returns for their investors. Additionally, some fund managers may not be required to file public reports with the SEC, adding opaqueness to the fund's characteristics and strategies.[5] By using a more holistic analysis towards their return properties, we attempt to demystify their characteristics and clarify the risks and benefits of the methodologies we consider. Comparing our results with those of similar studies, we can interpret how hedge funds are effected by market dynamics and how the returns change over time.

[5] Source: https://www.sec.gov/fast-answers/answershedgehtm.html

2 Review of Literature

2.1 Hedge Fund Industry

The hedge fund industry has expanded immensely over the past 20 years. From 230 billion in AUM in 2000, the industry has ballooned to over 3,000 billion. Stultz (2007) proposes that industry expansion can be attributed to hedge funds offering returns and investment strategies that traditional mutual funds cannot offer. By offering more diversified investment strategies, hedge funds have experienced more growth than the mutual fund sector in recent years. The largest contribution to hedge fund growth has come from large, institutional investors, willing to stomach high risk potentials.[6]

However, with the rising popularity of hedge funds, strategies have become more sophisticated to offer lucrative returns to their investors. As money saturates funds following traditional hedge fund methodologies, capitalizing on mispriced assets becomes more completive and assets are priced more efficiently.[7] This "return hunting" mandates that new techniques emerge to capitalize on market phenomena. Accordingly, the past decade has seen a rise in the Fund-of-funds (FOF) investment strategy, wherein money is pooled and is invested following different strategies by multiple managers. FOF investment offers access to diverse securities, strategies, and risks; expertise is an expectation for money managers involved in FOFs. Unfortunately, the whole stock market suffered from the financial collapse of 2007-2008; [8] across strategies, hedge funds suffered losses and, by reducing exposure to the market, contributed to market decline.

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[6] Source: https://www.thehedgefundjournal.com/sites/default/files/citi_institutional_report1.pdf

[7] Stultz hypothesizes that this rise in pricing efficiency will reduce the average returns of hedge funds following these mispricing strategies (CON, EDD, EDRA, FIA, for example). Hence, the need for developing new strategies that can exploit other market characteristics.

[8] Notable strategies that were not adversely effected by the collapse include Dedicated Short Bias and Managed Futures; See Figure 1.

Following the 2007-2008 financial crisis, hedge funds faced both additional regulation and academic study, specifically surrounding how hedge funds affect systematic risks in the market. Kaal and Krause (2016) outline research on how hedge funds influence systematic risk, including the role they played in the crisis. Such studies prior to 2007 yield mixed results, with some suggesting that hedge funds disperse their diversified risk to a large number of investors. However, after 2007, studies have suggested that hedge funds contribute large liquidity risks; by liquidating large stock holdings, the funds catalyze falling prices and contribute to systematic risk.[9]

Following the market collapse, the SEC began collecting data on hedge funds for measuring systematic risk associated with hedge funds. Additionally, the 2010 Dodd-Frank Act created Financial Stability Oversight Council (FSOC) for monitoring the financial practices of private, non-bank institutions, including hedge funds. Among its responsibilities, the FSOC is charged with making recommendations about financial regulation to Congress and determining which institutions qualify as systemically important to market dynamics.[10] This wave of regulations has effected hedge funds by mandating more transparency to federal institutions about their investment strategies. Presumably looking to limit position leverage, the monitoring of the FSOC will likely push hedge funds to behave more like mutual funds: more stable institutions, offering unorthodox investment strategies to riskier investors.

Hedge funds are more mainstream than ever as an investment vehicle. Hence, understanding their influence on market dynamics and correlation with market movement is imperative for investor's portfolio strategy, market makers, and regulators. By considering the

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[9] Ben-David, Franzoni, and Moussawi (2011) perform a study of hedge fund market withdrawal during the crisis, finding the industry sold 29% of their aggregate portfolio in the last two quarters of 2008. Pressured by both their investors and leverage lenders, hedge funds sold high volatility securities and liquid assets as protection from market downturn. Hedge funds reacted more quickly to the collapse than mutual funds, who suffered greater losses by retaining more of their equity investments.

[10] Source: https://ssrn.com/abstract=2748096

aggregate body of data available on hedge fund indices, our analysis offers broad-based conclusions about hedge fund strategies and their exposures. While industry is continuously changing and adapting, the mainstream strategies used offer little deviation from their prerogatives and provide a basis for comparing alternative returns.

2.2 Stock Return Predictability

There exists a huge body of work surrounding modeling investment returns for stocks. While not as extensive, analyses of mutual funds also strive to determine if their returns can be predictable and modeled appropriately. For our holistic analysis of hedge funds, we draw on these previous efforts to examine how hedge funds compare with different investment vehicles. The exposure of our hedge fund returns to regressors traditionally associated with market, stock, and mutual fund returns will be one of the bases for the analysis.

Security return predictability is primarily studied in the context of portfolio strategy and optimization. Consider Sharpe (1964) who generalized portfolio's based on an individual's risk preference, introducing an asset-pricing model. Additionally, Sharpe (1966) performed analyses of like mutual fund returns to gauge money manager performance. This study introduced the Sharpe ratio as a basis for comparing like securities; accordingly, our study includes a true and modified Sharpe ratio for comparing hedge fund indices.

Fama and French (1992, 1993) outlined how a firm's size and book-to-market can be indicators of a stock's average return, proving a basis for comparing like equities. Constructing a capital asset-pricing model (CAPM) expansion, the Fama-French 3-Factor Model models equity returns based on these indicators: small market cap and low book-market ratio. Their time series approach for examining exposure to "common risk" (systematic risk) is reutilized in our analysis.

Carhart (1997) expanded the 3-Factor Model to include equity momentum, the tendency for a rising stock to continue rising, as an explanatory variable. Using the 4-Factor model, Carhart studied modeled mutual fund returns and concluded their returns were attributable in-part to these effects, not brilliant money management. Since some hedge funds also rely on money managers to invest, Carhart's analysis lends itself to study how hedge funds are exposed to these factors. More recent studies of mutual fund return, such as Avramov (2006) and Kacperczyk (2005), also utilize the Carhart 4-factor model. Whether devising investment strategies or examining how mutual fund return has changed with industry evolution (as above, respectively), the Carhart model is used to determine two fund characteristics: exposure to market effects (value, small firm, and momentum) and significant excess returns. Our analysis utilizes both the 4-Factor and an extended Macro model for hedge fund returns with similar considerations in mind: exposure to systematic market risks and excess returns.

Predictability and strategy have been two cornerstones of analysis for equity and mutual fund returns. Drawing on these efforts, our analysis studies hedge fund exposure to variables traditionally associated with market, equity, and mutual fund returns.

2.3 Literature Gap

Current analyses of hedge funds primarily consider predictability and corresponding investment strategies surrounding their returns. Our work serves a complementary piece to those analyses by reconsidering hedge funds statistically and rigorously examine how hedge funds act as alternative investments. By comparing hedge fund returns to market and mutual fund returns, we can characterize the exposures faced by hedge funds, as well as the significance of their returns.[11]

[11] While return data will be considered from a "traditional" excess returns standpoint, there is a significant body of research indicating this measure is inept for hedge fund returns. Amin and Kat (2003) characterize both Jensen's alpha and Sharpe Ratio as being inept at measuring hedge fund performance,

Additionally, we can compare different facets of the hedge fund industry by gauging how fund strategy effects exposure to market returns and systematic risks. Doing so, we can determine how directional/non-directional (with the market) the strategies are, considering how well the strategies track market gains and losses.

Our analysis has two primarily goals: characterize how hedge funds act as alternative investments and cross-examine hedge fund strategies for benefits and disadvantages. Finally, the scope of our analysis is the aggregate hedge fund industry. By considering index performances, we take consideration of only the largest portions (in AUM) of the industry. Hence, we ignore any abnormal success of smaller funds, but also inherit a survivorship bias from analyzing only the surviving, larger firms.[12]

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as return data tends to be non-normal and non-linear in relation with equity returns. Time-varying alphas are disparaging for analyzing excess returns. However, as part of our analysis, we will consider excess returns and Sharpe Ratios when comparing respective hedge fund strategies.

[12] Survivorship bias occurs when funds that have dissolved due to poor returns are not considered in measuring the returns of an index; these biases are most prominent in mutual and hedge funds. Liang (2000) performs an analysis of hedge fund performance for “living” and dissolved funds. For the data considered, he finds an average bias of 2% per year, across different hedge fund methodologies; hence, returns are exaggerated by 2% when not considering dissolved funds. For our analysis, we do not take this or other biases under consideration.

3 Analysis

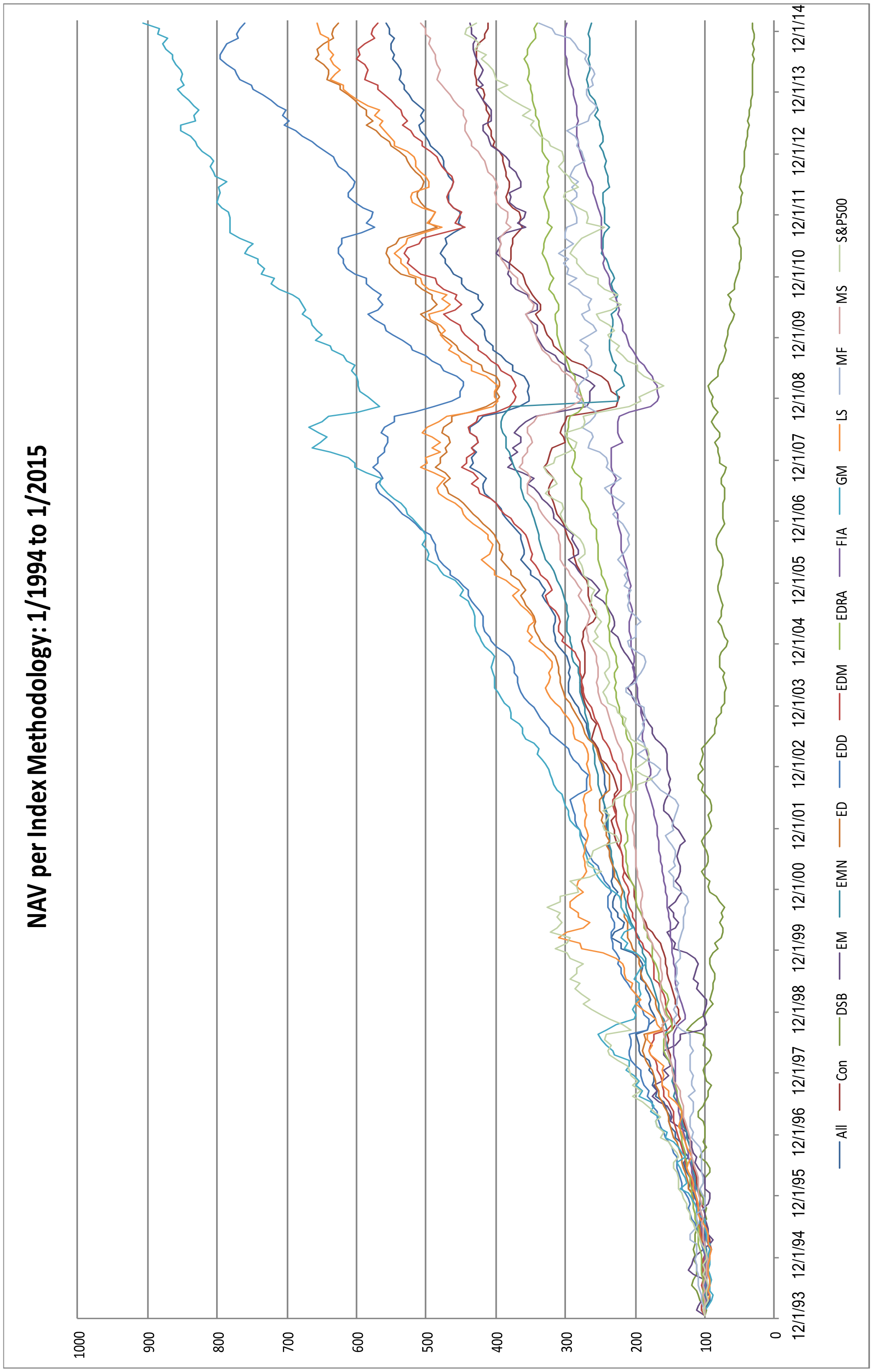

Figure 1: The evolution of $100 invested in each hedge fund index and the S&P

3.1 Summary Statistics

Figure 1 illustrates that, over the 21 years we consider, these indices display some common return characteristics, with varying degrees of volatility. Looking at 2007-2009, nearly every index, including the S&P, depreciates with the collapse of the housing bubble and Lehman Brothers. The lone exception, DSB, maintains a net short market position and bolstered in the crash market of the collapse. During the 2002-2005 bull market, all funds, minus DSB, appreciate, with GM and MF experiencing the highest returns over this period; this trend repeats following 2010 as well. Most indices also display large volatilities, gaining and losing very quickly compared to the market. Clearly, there is some interaction between S&P movements and hedge fund returns. Developing a holistic characterization of this interaction is the objective of subsequent analysis.

By considering monthly returns, Figure 1 represents a *smoothed* net asset value plot. The volatility of each index is actually greater than what analyzing monthly returns indicates, as indices vary on a daily basis. Additionally, return data may be subject to the discretion of money managers, who self-report their individual fund returns.[13] However, since our analysis considers industry indices, we will neglect smoothing efforts by individual managers; we will take smoothing from using monthly data into consideration in our study.

Note that some of the indices follow very similar strategies and some funds' return date are dependent on one another; for example, All is a compound index of all the other funds considered. In Figure 1, ED, LS, and EDM track each other extremely closely. However, throughout our analysis, we will consider each strategy's characteristics independently of each

[13] Cassar and Gerakos (2011) find evidence that funds with more manager discretion for pricing fund value display evidence of intentional smoothing. Additionally, they find asset illiquidity in fund positions to be a driver of the properties of self-reported returns.

other for completeness.[14] Accordingly, we can compare event-driven and arbitrage strategies against one another to understand how strategy changes influence their return profiles.

Table 1 displays an arithmetic summary of monthly real-return percentages for each industry index and the S&P 500 (our market proxy). Of the hedge funds, 6 offer average returns

Summary Statistics: Credit Suiss Hedge Fund Indices Monthly Return Data 1/1994 to 1/2015 (%ages)

Fund Methodology	Mu	Sigma	Skewness	Kurtosis	Min	Max	Sharpe Ratio	Non- Adj. Sharpe Ratio
All	0.6798	2.0570	-0.3261	3.0736	-7.8493	8.1837	0.2224	0.3305
Convertible Arbitrage	0.5587	1.9379	-3.0503	20.2782	-13.4583	5.6450	0.1736	0.2883
Dedicated Short Bias	-0.4648	4.6633	0.5292	0.9863	-11.9704	20.4667	-0.1473	-0.0997
Emerging Markets	0.5840	4.1090	-1.2673	8.0961	-26.1703	15.1995	0.0880	0.1421
Equity-Market Neutral	0.3832	3.4775	-13.5593	203.7372	-51.8404	3.5928	0.0463	0.1102
Event Driven	0.7251	1.7858	-2.4131	12.8178	-12.5274	4.1321	0.2816	0.4061
Event Driven Distressed	0.8015	1.8558	-2.4027	13.6586	-13.3015	4.0691	0.3121	0.4319
Event Driven Multi-Strategy	0.6877	1.9259	-1.9187	9.1158	-12.2442	4.6703	0.2417	0.3571
Event Driven Risk Arbitrage	0.4851	1.1719	-1.0284	4.9539	-6.3521	3.7396	0.2243	0.4140
Fixed Income Arbitrage	0.4325	1.6084	-5.0207	39.5292	-15.1235	4.2436	0.1307	0.2689
Global Macro	0.8715	2.6302	-0.1812	4.7491	-12.2745	10.0721	0.2468	0.3313
Long/Short Equity	0.7434	2.7115	-0.2523	3.7633	-12.1433	12.2284	0.1922	0.2742
Managed Futures	0.4824	3.3230	-0.0777	0.0040	-9.8211	9.4873	0.0783	0.1452
Multi-Strategy	0.6500	1.4857	-1.8852	7.3543	-7.6311	4.1882	0.2881	0.4375
S&P 500	0.6702	4.3115	-0.7060	1.2002	-16.9425	10.7723	0.1039	0.1554

Table 1

Column Min | Column Max

[14] Additionally, the Event Driven, Long/Short Equity, and S&P 500 returns demonstrate degrees of multicollinearity with other indices. For a complete breakdown of return association, see Appendix Figure 2 for a complete look at strategy correlation.

which exceed the market and 10 offer Sharpe Ratios which exceed that of the market. However, Sharpe ratios are consistently overestimated in this framework, including with the S&P. Volatility smoothing that results from using monthly data makes Sharpe ratio comparison ambiguous. Where S&P volatility can be calculated with more accuracy, hedge funds offer only monthly return data, perhaps to smooth excess volatility.[15] Regardless, certain strategies offer excess market returns, while some seriously underperform the market; here and for the rest of the analysis, DSB will generally behave as an outlier, as it bets against the market as a strategy.

The return distributions also display consistent negative skewness and high kurtosis, compared to a standard normal with a skewness of 0 and a kurtosis of 3. Negative skewness implies that monthly losses tend to tail off, being more severe than monthly gains; this can be seen comparing the min and max columns. Even with S&P returns, large losses tend to be more frequent than large gains. The distributions also demonstrate high kurtosis, implying they are highly centralized; in this case, they are centralized on the interval (-1,2). Notable exceptions to this centralization are All, DSN, MF, and the S&P. Oddly, All is the distribution that most closely resembles a standard normal, but the indices that contribute to All are non-normal (See Figure 2).[16] Again, DSB deviates from the rest of the market by demonstrating positive skewness and non-centralization. Since we consider a 21-year basis for hedge fund returns, there are studies which use subsets of these distributions in their data analyses. We can our compare statistical results with

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[15] Kat and Brooks (2001) find Sharpe ratios to be inept comparison tools as well. Traditional mean-variance analysis loses meaning when considering the lower-frequency data and distributional properties of hedge fund returns.

[16] The pseudo-normality of All can be viewed as a manifestation of the Central Limit Theorem. By considering aggregate return data from all the indices, All's distribution approaches the hedge fund industry's true characteristics.

those of other hedge fund studies to understand how returns have changed over time with market trends.

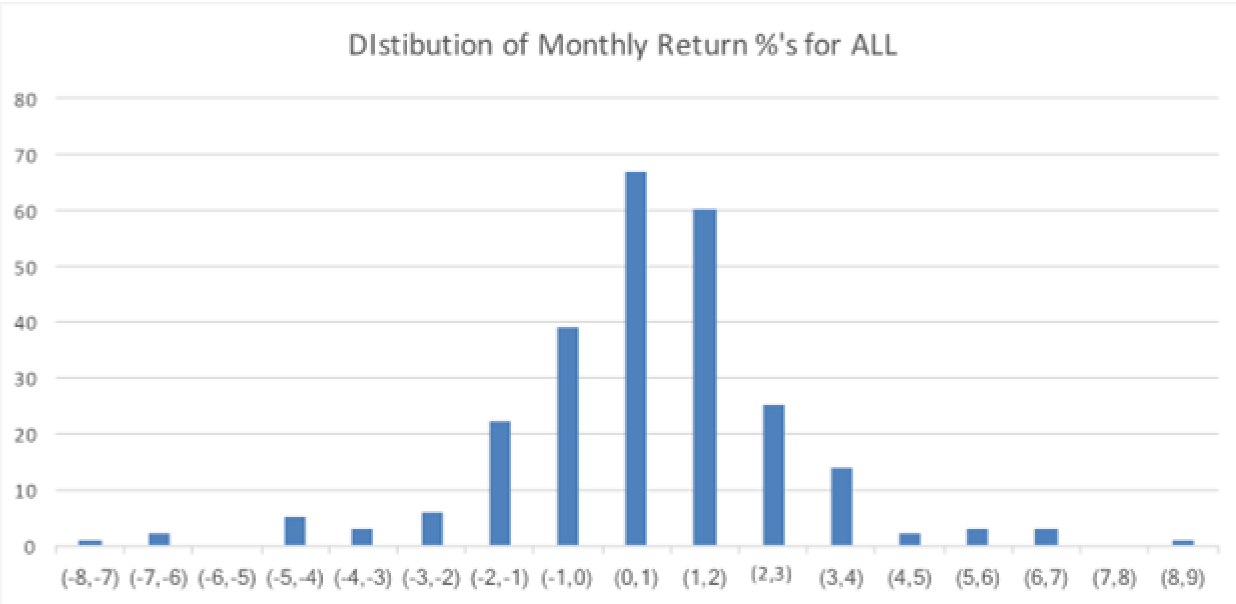

Figure 2

Comparing our statistics to Kat and Brooks' (K. and B. hereafter) (2001) breakdown of monthly hedge fund returns, returns have changed over time. While they use different databases, they consider some of the same strategies and market metrics in their analysis. Generally, sigma, skewness, and kurtosis resemble our findings. However, mean monthly return has decreased over time for CON, EDRA, EDD, LS, and EMN. Accordingly, All has also declined; the lowest average return among K. and B's considered databases for the aggregate hedge fund market is 1.13%. Our calculated mean of .6798% constitutes about 60% of the average return K. and B. found over the period 1995-2001; S&P average return today constitutes only 43% of what K. and B. found as well.[17] The stagnation of average fund returns could be attributed to the 2008 market crash or

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[17] While hedge fund returns have stagnated, market returns have actually stagnated more. This trend could contribute to the growth of the hedge funds over the past few decades: in an environment where the market appreciates slower and slower, why not seek out alternative investments that are more resilient to return stagnation?

uncharacteristically high returns during K. and B.'s analysis, 1995-2001. Another hypothesis, however, is that the expansion of the hedge fund industry actually drives down average returns for all funds. As Stulz (2007) describes, as AUM in hedge funds rise, that money goes towards, generally, securities with price discrepancies to generate a profit.[18] By raising the amount of money targeting those securities, the discrepancies are eliminated faster and the strategies become less profitable. Hence, the growth of money in hedge funds actually reduces the effectiveness of their strategies and reduces average returns, a possible explanation for stagnating returns.

Our statistical analysis allows us to compare fund performances versus the market and infer about industry evolution. Considering the shape of the return distribution is integral to defining how hedge funds behave as alternative investments. However, while summary statistics can capture average fund metrics vs. the market, it provides no information on how the indices are effected by market movements. Figure 1 illustrates that there is some correlation between market conditions and the growth in hedge fund indices; however, our statistical analysis does not provide a comparison for performance in bull and bear markets.[19] To characterize the relationship between market and hedge fund returns, we will consider a regression and correlation analysis of the returns. By utilizing capital asset pricing models associated with equities and mutual funds, we can compare hedge funds to these securities, in terms of their market exposure.

3.2 Return Market Exposure

For gauging alternativeness for each fund, we can measure market exposure in terms of a simplified Capital Asset Pricing Model, outlined by Sharpe (1964). Determining the simple market Beta for each strategy allows for cross comparison between strategy; presumably, directional

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[18] Arbitrage and event-driven strategies especially focus on mispriced securities; whether convertible bonds or stocks in distress, heavier investment in these securities mitigates strategy profitability.

[19] For a statistical comparison of hedge fund performance in bear and bull markets, see Appendix Figure 3 and Figure 4: a stratified look at the data contained in Table 1.

strategies offer significant market betas, while non-directional strategies do not. As certain strategies purport to maintain gains across market conditions, simple market beta provides basic insight into average market conditions. Finally, we expect to see some significant excess returns to justify investors seeking out alternative investments.

$$\textbf{Model 1}:^{20} \quad \mathbf{R_i} = \boldsymbol{\alpha} + (\boldsymbol{\beta}_{\mathbf{MKT}} * \mathbf{x_i}) + \boldsymbol{\varepsilon}_{\mathbf{i}}$$

Simple Market Betas

Methodology	$\boldsymbol{\beta}_{\mathbf{MKT}}$	$\boldsymbol{\alpha}$
All	1.2001*	-0.1456
CON	0.8191*	0.2126
DSB	-0.7025*	0.3436
EM	0.5682*	0.3384
EMN	0.3357*	0.5416*
ED	1.5248*	-0.4354
EDD	1.4319*	-0.4774*
EDM	1.3078*	-0.2292
EDRA	1.8397*	-0.2223
FIA	0.8972*	0.2822
GM	0.3811*	0.3380
LS	1.0726*	-0.1272
MF	-0.0970	0.7170*
MS	1.1402*	-0.0456
S&P 500	1.0000*	0.0000

Column Min	Column Max

Table 2: R_i denotes monthly hedge fund return, x_i denotes corresponding S&P monthly return. Note the color scale maps low-to-high in blue-to-red. All significance testing is performed with a 95% confidence level and significance is denoted by *.

[20] Note this model does not risk-adjust returns as Jensen (1968) does by considering returns over the risk free rate. By utilizing the simplified model, we wanted to provide as much evidence towards alpha significance as possible.

Table 2 diverges from our original inferences about hedge fund behavior. While directionless strategies CON, EMN, FIA, and EMN maintain lower betas than directional strategies, they still maintain significant positive market association in their betas. Every fund, besides MF, is significantly exposed to the market: DSB showing negative association, the rest positive. Finally, only EMN and MF offer significant excess returns over the market. Only the MF index sits in the favorable position of offering excess returns with insignificant market exposure, one of the purported benefits of alternative hedge fund investment. The event-driven strategies display betas comparable to equities, but offer alphas showing signs of significant excess losses compared to market returns. Generally, the indices display significant market betas and non-significant excess returns, as the metrics of All indicate. Table 2 illustrates that even alternative investments experience significant market exposure.

While simple market betas illustrate on average how volatile strategies are with the market, they fail to describe market association across different market conditions. Presumably, as the market fluctuates, the return profile of the hedge funds also changes;[21] the diverse investments of the funds also expose them to a diverse set of risks. However, alternative investments should maintain some degree positive returns in presence of bearish market conditions: otherwise, why seek out alternative investment? Non-directional strategies especially should offer similar return profiles across bull and bear markets.

To examine bull market vs bear market performance for the indices, we will reclassify monthly S&P returns into two data classes: strictly positive and strictly negative. We classify months in which the market had a positive yield as bull, with negative yield implying a bear month. By regressing index returns on these two data sets, we generate two market betas: one bull and one

[21] See Appendix Figure 3 and Figure 4

bear (See Model 2). The new model offers a stratified version of Model 1 which measures index exposure to bull and bear periods, respectively. Accordingly, strategies can be evaluated in terms market correlation, across market conditions.

$$\textbf{Model 2:}^{22}\quad \mathbf{R_i} = \boldsymbol{\alpha} + (\boldsymbol{\beta}_{\mathbf{Bull}} * \mathbf{x}_i^+) + (\boldsymbol{\beta}_{\mathbf{Bear}} * \mathbf{x}_i^-) + \boldsymbol{\varepsilon}_i$$

Methodology	$\boldsymbol{\beta}_{\mathbf{Bull}}$	$\boldsymbol{\beta}_{\mathbf{Bear}}$
All	0.1948*	0.3423*
CON	0.0846	0.2369*
DSB	-0.9245*	-0.7312*
EM	0.2900*	0.7156*
EMN	0.1287	0.2975*
ED	0.1480*	0.3619*
EDD	0.1190*	0.3945*
EDM	0.1637*	0.3468*
EDRA	0.1048*	0.1634*
FIA	-0.0218	0.2543*
GM	0.0950	0.1832*
LS	0.3794*	0.4638*
MF	0.1290	-0.2224*
MS	0.0726	0.1905*
S&P 500	1.0000*	1.0000*

Table 3: R_i denotes hedge fund return for each strategy, x_i^+ denotes non-negative market returns and x_i^- denotes non-positive market returns. Significance denoted with *.

Column Min	Column Max

Table 3 displays the stratified market betas for each index, a decomposed version of the β_{MKT}s from Table 2. Ideally, the indices would maintain significant, positive β_{Bull}s and significant, *negative* β_{Bear}s, maintaining positive returns across all market conditions. However, the indices

[22] The two regressors of the models are modified forms of the monthly returns of the S&P. x_i^+ is defined as max(S&P$_i$, 0) , while x_i^- is defined as min(S&P$_i$, 0). By stratifying the S&P returns, we can decompose the simple market betas outlined in Table 2.

display more significant association with bear markets than bull markets. All indices except DSB and MF maintain significant, positive association with bear markets, indicating an inability to maintain positive returns during bear markets. Meanwhile, only EM, LS, and the event driven strategies maintain significant, positive association with bull markets. While these strategies are generally directional, they all display more significant association with losses during bear markets, with larger positive β_{Bear}'s. Accordingly, they lose money faster in bear markets than they gain in bear markets. Even DSB, which takes a short position in the market, loses far more in bull markets than it gains in bear markets.[23] Again, the aggregate All index captures the fund tendency: positive exposure to market growth, but more significant positive exposure to market loss. MF is the only fund that maintains significant gains in bear markets, while maintains some degree of gains in bull markets.

By decomposing simple market betas, we can see that generally indices, regardless of strategy, maintain more significant exposure to market losses than to market gains. While some funds maintain significant excess gains over the market, they stand to lose value quickly in bear markets. Perhaps, as Stulz (2007) outlines, the lack of leverage restrictions makes hedge funds extremely sensitive to market shocks. Market drops can pressure over-leveraged positions to liquidate and repay lenders, likely incurring a loss on the position being liquidated. While leverage can greatly improve growth potential, it places a large liquidity risk on the assets when they depreciate. Hence, the indices generally capture market growth, but are more significantly exposed to market losses, even for directionless strategies. By decomposing simple β_{MKT}s, we see how the indices grow or shrink across bull and bear conditions.

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[23] The betas can be interpreted, respectively, as %age of bull and bear market growth/loss captured by the fund. Hence, the S%P captures 100% of S&P growth in bull markets and 100% of S&P loss during bear markets.

3.3 Extended and Carhart Models

While these indices do maintain significant market exposure, perhaps "alternative" implies independent of systematic market risk. Academic literature has detailed analyses of stock, mutual fund, and hedge funds, prying for indicators of security returns. Outside of the traditional CAPM used in Model 1, extended models offer a larger number of explanatory variables to measure significance. However, these models can suffer from subtractive predictive power if too many variables are included: the effects of one variable may not be distinct from another, leading to convoluted models with little predictive application.

Balancing this tradeoff, we model the hedge fund index returns using regressors traditionally utilized in measuring equity exposure to systematic risks. Drawing on previous efforts, we prescribed variables representing a cross-section of undiversifiable market risk.[24] With these variables, we modeled the index returns, as summarized in Table 4. The variables used in our extended model include:

Unemp: Unemployment Rate – Serving as a lagging economic indicator, economy growth generally implies a drop in employment, as jobs are being created.
WTI: West Texas Intermediate – Used as a benchmark for oil prices affecting American industry and consumption.
VXO: S&P 100 Volatility Index – Measuring the implied volatility of various options for the largest 100 US companies, this index serves as a fear gauge, like the VIX.
SR: Savings Rate – A measure of average money saved from paychecks, a high savings rate indicates slowed consumer consumption.
BS: Bond Spread – Defined as the difference between BAA and AAA corporate bond yield, with risky bonds needing larger yields to attract investors in volatile markets, indicating systematic risk.
TS: Treasury Spread – Defined as difference between 10-year and 3-month yield, this is a proxy for credit risk in the market, stemming from changing interest rates.
Gold: Gold Price/oz. – A leading market indicator, this commodity experiences growth in the face of market uncertainty.

[24] Bali, Brown, and Caglayan (2014) and Amenc, El Bied, and Martellini (2002) in particular outline similar cross-sections for modeling hedge fund returns. Drawing on their models, we selected our variable set and checked the variables for serial correlation to mitigate subtractive predictive power. See Appendix Figure 5, the correlation matrix for our variables.

MS: Money Supply – Here, the M1 money supply proxies for liquidity risk and inflation in the market, as it measures liquid portions of American currency.

$$\textbf{Model 3}: \quad \mathbf{R_i} = \boldsymbol{\alpha} + (\boldsymbol{\beta}_{\mathbf{Unemp}} * \mathbf{x1_i}) + (\boldsymbol{\beta}_{\mathbf{WTI}} * \mathbf{x2_i}) + (\boldsymbol{\beta}_{\mathbf{VXO}} * \mathbf{x3_i}) + (\boldsymbol{\beta}_{\mathbf{SR}} * \mathbf{x4_i}) + (\boldsymbol{\beta}_{\mathbf{BS}} * \mathbf{x5_i}) + (\boldsymbol{\beta}_{\mathbf{TS}} * \mathbf{x6_i}) + (\boldsymbol{\beta}_{\mathbf{Gold}} * \mathbf{x7_{i}}) + (\boldsymbol{\beta}_{\mathbf{MS}} * \mathbf{x8_i}) + \boldsymbol{\varepsilon}_{\mathbf{i}}$$

Extended Macro Model: Systematic Risk Measure

Methodology	α	β_{Unemp}	β_{WTI}	β_{VXO}	β_{SR}	β_{BS}	β_{TS}	β_{Gold}	β_{MS}
All	0.7061*	-0.8318	0.0443	0.0686*	0.0501	-6.8949*	0.0586	0.0048	-0.0067
CON	0.6191*	0.2257	0.0639*	0.0520*	-0.0649	-9.1748*	-0.2455	0.0052	-0.0112
DSB	-0.2759	1.3255	-0.0381	0.0464	-0.7104	6.8996*	-2.7365*	-0.0086	-0.0225
EM	0.5405*	-2.6687	0.0061	-0.0155	0.2054	-11.2214*	1.0205	0.0159*	-0.0015
EMN	0.7181*	-3.4870*	0.1197*	0.2554*	0.0521	-7.5317*	2.9840*	-0.0078	-0.0454*
ED	0.7629*	-1.0836	0.0318	0.0482	0.1103	-6.4375*	0.5906	0.0042	-0.0076
EDD	0.8523*	-1.2511	0.0229	0.0429	0.1207	-6.2434*	0.8570	0.0026	-0.0085
EDM	0.7199	-1.0902	0.0396	0.0565	0.1163	-6.7132*	0.3322	0.0048	-0.0073
EDRA	0.5026	-0.0968	0.0384*	-0.0357	0.0439	-1.5624*	0.0912	0.0030	-0.0043
FIA	0.5033*	-0.8064	0.0603*	0.0918*	0.0474	-7.0480*	-0.5444	0.0022	-0.0121*
GM	0.8901*	-0.0271	0.0219	0.0605	-0.0329	-4.9989*	-0.2012	0.0075	-0.0062
LS	0.7040*	-1.2731	0.0702	0.0180	0.1261	-7.3350*	0.1482	0.0058	0.0014
MF	0.4076	1.0523	-0.0429	0.0774	-0.3196	-1.1962	-0.3119	0.0101	0.0067
MS	0.6844*	-0.9586*	0.0517*	0.0794*	0.0533	-6.7649*	0.1081	0.0041	-0.0070
S&P 500	0.5605*	-3.5491*	0.0592	-0.1473*	0.5102	-9.8212*	0.3327	0.0013	0.0128

Significance*

Table 4: Ri corresponds to index return, α corresponds to excess return, and xk_i corresponds to the month over month change in the variable defined in the respective beta ($x1_i$ corresponds to month over month change in unemployment rate, for example).

Our extended model shows that that hedge funds vary by strategy in exposure to systematic risk. Strategies, like CON, EMN, FIA, and MS, show considerable exposure to our variable basis, while LS, GM, and the event driven strategies show little far less exposure. All indices demonstrate significant excess returns, except DSB and MF, which show minor exposure altogether; the market also displays significant excess returns.[25] Overall, the indices show resilience to these sources of systematic risk, producing significant returns, in excess of the market in some cases.

Considering the betas of Model 3, β_{WTI}, β_{VXO}, and β_{BS} display the most significance across the indices.[26] The indices and the market display significant negative exposure to bond spread, heavily depleting returns during periods of market uncertainty. Counterintuitively, the indices display positive exposure to market volatility in the VXO, improving returns with higher volatility, contrasting with the market returns which deteriorate. Perhaps, through the use of options or some rise in mispricing during the periods, the indices capitalize on volatile market conditions, whereas S&P investors withdraw money and drive value down. Indices generally maintain long positions in oil prices and suffer from rises in employment, save CON, DSB, and MF. Overall, commodity exposure was menial for the indices, between oil and gold, while savings rate and money supply offered little significance for both the market and the indices.

Overall, the indices display similar systematic risk exposures compared to market, under our variable basis. Individual strategies, like EMN and FIA, display more exposure than other

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[25] The S&P showing significant excess returns can be interpreted as Model 3 not adequately capturing systematic risk in the market place, driving market prices. Permutations of the variable list also yielded this result, indicating some significant sources of market risk are not included in this model.

[26] Note that the xk_is are correspond to monthly change in the variable considered, for ease of beta interpretation. For instance: β_{WTI} corresponds to the change in percentage monthly return per dollar change price of a barrel of oil, β_{BS} corresponds to change in monthly return percentage per percent change in bond spread.

indices and the market, but the overall exposure of hedge funds is limited. MF paradoxically displays no significant variable exposure, but also no significant excess return: the model as a whole account for significant return variation in its basis, but no one variable maintains 95% significance in its association. Our basis reveals the All index maintaining comparable systematic exposure that the market does. From an alternative standpoint, the indices do benefit more on average from market volatility than the actual market does, while suffering less from credit risk. However, both the market and hedge funds maintain diverse risk exposures, likely outside of the scope of our basis. The indices indicate that they do maintain alternative systematic risk exposures, compared to the market. From this standpoint, we can conclude that the indices differ with one another in exposure to systematic risk, but, within our basis, operate similarly to the market: with respect to market returns, the indices maintain alternative systematic risk profiles.

With alternative risk profiles in mind, our final model gives consideration to if hedge funds behave similarly to mutual funds. With both security types investing according to a money manager's guidance, the criteria used for determining valuable assets may be similar between the two fund types. Unlike hedge funds, mutual funds maintain publically available holdings and are regularly audited, more transparency with their shareholders than hedge funds.[27] While mutual funds have more legal restrictions than hedge funds, their investment strategies, like hedge funds, depend on finding mispriced securities and taking positions speculating on the price changes. Utilizing the persistence framework of Carhart (1997), we can compare index exposure to the excess returns of small firms over big firms, high book-to-market over small book-to-market, and momentum stocks. Carhart determined the 4-factor model accounted for nearly all the

[27] Source: https://www.thebalance.com/regulations-of-mutual-funds-2466589

variation in expected mutual fund return, primary due to the SMB and MOM factors. By comparing index exposures to the exposures Carhart original findings for mutual funds, we can qualitatively compare investment strategies. While the time frames of the two studies are different, the non-dynamic strategies of the indices likely maintain exposures across both time bases, warranting the exposure comparison.

$$\textbf{Model 4: } \mathbf{R_i - Rf_i = \alpha + (\beta_{MKT-RF} * x1_i) + (\beta_{SMB} * x2_i) + (\beta_{HML} * x3_i) + (\beta_{MOM} * x4_i) + \varepsilon_i}$$

Carhart 4-Factor Model: Likeness to Mutual Funds

Methodology	α	β_{MKT-RF}	β_{SMB}	β_{HML}	β_{MOM}
All	0.1972*	0.3198*	0.0504	0.0321	0.1198*
CON	0.2125	0.1644*	0.0224	0.0999*	-0.0290
DSB	-0.1686	-0.8444*	-0.1873*	0.0462	-0.0706*
EM	-0.0074	0.5474*	0.1315	-0.0079	0.1015*
EMN	-0.0307	0.2152*	0.0835	0.2114*	-0.0278
ED	0.2897*	0.2748*	0.1080*	0.0917*	0.0425*
EDD	0.3858*	0.2658*	0.1179*	0.0798*	0.0238
EDM	0.2312*	0.2861*	0.0991*	0.1063*	0.0590*
EDRA	0.1526*	0.1446*	0.0354	0.0536*	0.0089
FIA	0.1033	0.1277*	0.0395	0.0976*	-0.0107
GM	0.4785*	0.1798*	0.0043	0.0267	0.1074*
LS	0.1442	0.4990*	0.0978*	-0.0343	0.1971*
MF	0.2296	-0.0329	0.0544	0.0164	0.1092*
MS	0.3106*	0.1429*	0.0391	0.0666*	0.0100
S&P 500	-0.1286*	0.9543*	-0.1004*	-0.0033	-0.0529*

Table 5: The Model is the true Carhart (1997) model, incorporating market returns over the risk free rate, excess returns by small firms over large, excess returns by high book-to-market firms, and momentum equities as the xk_is for modeling hedge fund return over the risk free rate.

Significance*

Table 5 shows the indices' exposure to the traditional drivers of mutual fund return. As Carhart originally found within mutual fund returns, there is evidence of momentum in hedge fund returns, with exposure to various market effects, though not at the same magnitude as mutual funds.[28] Market betas aside, the indices display similar exposure levels to the value effect in β_{HML} and to momentum stocks in β_{MOM}, both with 8/14 indices displaying significant betas. The indices demonstrate limited exposure to the small-firm effect, with event-driven strategies, LS, and DSB having significant β_{SMB}s. Note that only some of the alphas in Model 4 display significant excess returns, namely the event driven strategies, GM, and MS. Compared with Model 3, Model 4 captures far more variation in the index returns, leading to less alpha significance. This implies that the indices are more exposed to market phenomena which drive mutual fund returns than to larger systematic risks effecting the market. Generally, the money managers of both fund types try to exploit value, small firm, and momentum equities in maintaining returns.

Model 4 illustrates that hedge funds maintain similarities with mutual funds; the lack of significant excess returns for 6 funds testifies to money managers adopting similar equity valuation strategies. However, like Model 3, several strategies display excess returns over the variable basis. Hedge fund returns demonstrate a diversity of exposures in their returns, including traditional systematic risk indicators and drivers of mutual fund returns. A rigorous model of hedge fund returns would entail a large variable basis, including elements of Models 3

[28] Baquero, Horst, and Verbeek (2005) strengthen this conclusion, concluding that hedge funds demonstrate more persistence than mutual funds. They theorize this may be due to restricted capital movement for hedge funds, relative to mutual funds who may move money with more liquidity. We reevaluate this finding in Appendix Figure 6, defining autocorrelations for the indices, for a variety of lag times and period bases.

and 4.[29] However, diagraming return variation for one strategy might not diagram another strategy with the same sophistication. With closely held portfolios and investment strategies, holistically documenting hedge fund exposure, even for well-defined strategies, is not feasible.[30] Again, the diversity of exposures sourcing hedge fund returns makes the funds difficult to sufficiently model. Alternative investment again partially maintains the exposure profile of a traditional investment vehicles: in this case, mutual funds.

4. Major Findings

Evaluating hedge fund indices as alternative investments, our analysis reveals several like characteristics across the industry. Specific strategies differ in their specific exposures, but overall the following patterns emerge which guide our understanding of the returns and the larger industry.

1) Non-Normal Return Distribution: The indices display negative skewness and considerable kurtosis, indicating a left-skewed return distribution with tail losses exceeding tail gains. The skewness makes traditional mean-variance analyses, like Sharpe ratios, ill-conditioned, as tail events tend to be negative with increased variation. The monthly frequency of the data implies that volatility is underestimated, as daily price fluctuations are not accounted for.

2) Return Decay: Over time, index returns, including the aggregate index, have decreased. Comparing with older statistical analyses, the average returns of the indices over their lifetime have decreased over the past 20 years, coinciding with large growth in hedge fund industry. This trend pushes new strategies to be developed to capitalize on market movements.

3) Market Exposure: While most funds maintain significant excess returns over the market, indices wallow in bear markets. The indices display more significant exposure to losses in bear markets than gains in bull markets, MF being an exception. The alternative investments tend to gain with the market, but they will consistently dive sharply with market drops. Across market conditions, even hedge fund returns fluctuate.

4) Systematic Risk Exposure: The indices display excess returns over traditional measures of systematic risks in the market. While bond spread, volatility, and oil prices do account for some variation in the index returns, our basis failed to capture more of the returns that desired. On our basis, the indices displayed similar systematic exposure compared to the S&P 500.

[29] See Appendix, Figures 7&8 for an attempt.

[30] For our attempt at this holistic variation capturing, see Appendix Figures 7 and 8, a composite model of Models 3 and 4 in Analysis.

5) Mutual Fund Likeness: The Carhart 4-Factor Model eliminated significant excess returns for half of the indices examined. The hedge funds demonstrated significant exposure to value, small firm, and momentum equites, which are traditionally viewed as mutual fund performance drivers. While not capturing as much return variation as Carhart did with mutual funds, the model demonstrates that money managers in both industries utilize these phenomena in their holding and strategy implementation.

6) Diversity: Pinning down the drivers of hedge fund returns is not as clear cut as mutual funds. Drivers likely vary strategy to strategy and with the opaqueness that money manager invest with, risks might be too diversified to succinctly capture in a model. The presence of excess returns across Model 3 and Model 4 speaks to the unknown where money is allocated, even if it is outlined in a fund strategy.

7) Excess return demands excess risk.

5. Conclusions

The hedge fund industry demonstrates an ability to offer significant returns, with diverse risk profiles and market access. Their unique exposure and return properties offer an alternative to vanilla investing in the S&P or bonds. However, the proposition that they offer favorable returns across market conditions is, on average, false. The indices still maintain exposure to bear markets and are adversely affected by market dives, save DSB. The indices have systematic risk exposure that is comparable to the market, but suffer from liquidity risk from leveraged positions during market downturns. Finally, hedge funds share significant exposure to variables traditionally associated with mutual funds, implying some inspection between manager strategy for each industry. Overall, hedge offer *unique* investment opportunities and strategy access to investors who don’t have the capital to support the strategies independently. Unfortunately, even these investments face market exposure. Alternative investments offer high average returns by taking on additional sources of risk in their respective strategies. Pinning down the drivers of their returns is ambitious because of this diversity.

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Appendix

Figure 1: Hedge Fund Strategy Breakdown[31]

Credit Suiss Hedge Fund Index (All) – Representing the aggregate performance by the Credit Suisse hedge funds (outlined below), this index is a benchmark for average hedge fund performance. Respective strategies can be compared to this index as a measure of how closely correlated the fund's returns are with broader market growth.

Convertible Arbitrage (CON) – This market-neutral strategy entails taking a long position in a company's convertible securities and a short position in the company's common stock. The convertible security acts as insurance in case the stock price rises and the short position is out of the money, as the security can be redeemed for common stock and the short position closed. CON maintains that the convertible securities are priced less efficiently than the common stock, implying the opportunity for "arbitrage".

Dedicated Short Bias (DSB) – This directional trading strategy holds both long and short positions in market, with a larger proportion of the portfolio being short. The bias towards more short assets allows the portfolio to benefit from market declines, while mitigating growth during bull markets. The balance of long and short assets allows the portfolio to be more resilient than a pure dedicated short portfolio to market growth.

Emerging Markets (EM) – This strategy specializes in investing in emerging country markets. Unlike EM mutual funds, the hedge fund strategy includes more investment options under its portfolio, including commodities, forex, and real estate. EM provides the investor access to international markets and the growth opportunities for the developing nations; however, that opportunity necessitates exposure to risk in foreign markets.

Equity Market Neutral (EMN) – This market-neutral strategy takes a mixture of long and short positions in the market, based on a belief in pricing inefficiency in the portfolio's investments. EMN attempts to circumvent systemic risk in the market by maintaining a beta of nearly zero. By maintaining long and short positions, with the appropriate hedging, the portfolio exhibits lower volatility than the volatility of the larger market.

Event Driven (ED) – This strategy tries to take advantage of pricing inefficiencies resulting from corporate events; bankruptcies, acquisitions, and mergers, for instance. The uncertainty of the corporate event occurring provides an opportunity for ED managers to take a position in the company's offerings to exploit the uncertainty. ED strategy can be further broken down into how the managers try to exploit the pricing uncertainty (see below).

Event Driven Distressed (EDD) – This strategy is a complementary, sub-section of Event Driven strategy, wherein investment is focused around the securities of a firm going through distress: a bankruptcy or scandal for instance. The firm's securities – corporate bonds, for example – are

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[31] Sources: http://www.barclayhedge.com/research/educational-articles/
http://www.investopedia.com/university/hedge-fund/strategies.asp

speculated on with the belief that their value stands to decline. Accordingly, EDD tends to be more successful in periods where the market is performing poorly and more firms are distressed.

Event Driven Mutli-Strategy (EDM) – A subsection of Event Driven strategy in which both positive and negative events in the corporate world are speculated on. Likely more market-neutral than EDD, this strategy stands to gain from favorable firm events as well (positive earnings reports, for instance).

Event Driven Risk Arbitrage (EDRA) – This subsection of Event Driven strategy tries to capitalize on the price change resulting from the merging of two companies. By longing the company lower-valued company stock and shorting the higher-valued company's stock, the strategy assumes the merger will occur and the two stock prices will converge somewhere in the middle. However, there is risk associated with the transaction not occurring.

Fixed Income Arbitrage (FIA) – This market-neutral strategy tries to exploit pricing inefficiencies by simultaneously selling and buying similar securities, namely bonds. As the prices for the securities approaches their fair value, the FIA managers settle their position to exploit the original inefficiency in the price. "Arbitrage" is misleading in this scenario because of the possibility that the company goes bankrupt, while netting small gains from the owned bonds.

Global Macro (GM) – This strategy speculates on the overall political and economic climate of a country and buys/shorts securities according to the perception of that country. This strategy attempts to exploit trends in sentiment about a nation through currency exchanges and taking positions in the country's indices and bond offerings. The macroeconomic events that can influence market direction (elections, political events, recessions…) are exploited through this strategy.

Long/Short Equity (LS) - This strategy entails taking long positions in stocks expected to gain and short positions in stocks expected to fall, with minimal market exposure in the resulting portfolio. The resulting portfolio can take either a long or short bias in the market, or could be market-neutral. Additionally, this strategy maintains flexibility as to which markets and stocks it takes a position in: small or large cap, domestic or foreign, any stock could be incorporated in to the strategy.

Managed Futures (MF) – This strategy allows a money manager to allocate an investor's assets according to strategies that they deem prudent. The managers, known as CTAs (Commodity Trading Advisors), take positions in future contracts on prominent commodities, foreign currencies, and indices to offer a return. The management they do is subject to heavy federal scrutiny to ensure they are not engaged in illicit activities.

Multi-Strategy (MS) – This strategy is defined firm-to-firm and acts as a blend of all aforementioned hedge fund strategies. The flexibility of multi-strategy provides more access to opportunities in the market; however, it also exposes to fund to a diverse number of risks arising from all the previous strategies.

Figure 2: Correlation Matrix for Index Returns

Min	Max

-	All	Con	DSB	EM	EMN	ED	EDD	EDM	EDRA	FIA	GM	LS	MF	MS	S&P 500
All	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CON	0.555	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-
DSB	-0.488	-0.265	1.000	-	-	-	-	-	-	-	-	-	-	-	-
EM	0.714	0.448	-0.537	1.000	-	-	-	-	-	-	-	-	-	-	-
EMN	0.282	0.195	-0.157	0.143	1.000	-	-	-	-	-	-	-	-	-	-
ED	0.756	0.647	-0.584	0.702	0.289	1.000	-	-	-	-	-	-	-	-	-
EDD	0.692	0.600	-0.564	0.649	0.329	0.941	1.000	-	-	-	-	-	-	-	-
EDM	0.757	0.632	-0.542	0.694	0.242	0.962	0.820	1.000	-	-	-	-	-	-	-
EDRA	0.511	0.478	-0.465	0.509	0.165	0.683	0.600	0.667	1.000	-	-	-	-	-	-
FIA	0.542	0.779	-0.201	0.411	0.306	0.511	0.495	0.491	0.304	1.000	-	-	-	-	-
GM	0.807	0.344	-0.105	0.450	0.064	0.387	0.340	0.414	0.231	0.401	1.000	-	-	-	-
LS	0.834	0.458	-0.699	0.674	0.199	0.750	0.680	0.737	0.598	0.376	0.448	1.000	-	-	-
MF	0.198	-0.076	0.069	-0.015	-0.003	-0.022	-0.047	-0.010	-0.047	-0.054	0.311	0.081	1.000	-	-
MS	0.517	0.701	-0.261	0.304	0.350	0.561	0.495	0.565	0.355	0.620	0.275	0.478	0.071	1.000	-
S&P 500	0.573	0.368	-0.760	0.541	0.271	0.632	0.616	0.584	0.500	0.335	0.233	0.675	-0.075	0.393	1.000

This correlation matrix describes the associations between the returns of each index used in our analysis, the R_i's in all the models we consider. Since some of these indices are composed of one another, the various event driven strategies, for example, we would expect to observe multicollinearity between some of these strategies. This co-movement is most consistent across the aggregate index, the All index of the considered hedge funds, with r's consistently above .7. Additionally, the most heavily correlated returns are the pairs (ED, EDD) and (ED, EDM); with EDD and EDM being subsets of ED, this also aligns with our expectations.

Considering S&P 500 correlations, we see which strategies maintain a net long position (significant, positive correlation) with market returns: All, EM, ED, EDD, EDM, EDRA, LS.[32] Dedicated Short Bias, again, displays returns inversely related with S&P growth.

Note that Equity Market Neutral and Managed Futures maintain little correlation with both other hedge fund strategies and the market. By definition, EMN attempts to maintain a β_{MKT} as

[32] These correlations corroborate the results displayed in Tables 2 and 3, that strategies maintaining significant, positive β_{Bull} and β_{Bear} experience high degrees of positive market correlation.

close to 0 as possible, so its independence is unsurprising. MF's independence can be interpreted as money manager's tendency to maintain market-neutral positions, a hedge against large market corrections. From an 'alternativeness' standpoint, EMN and MF display superior independence from market and other hedge fund methodologies.

Figure 3: Summary Statistics of Strictly Bull S&P Months

Column Min	Column Max

Summary Statistics: Credit Suisse Hedge Fund Indices Monthly Return Data: Strictly Bull S&P Market

Methodology	Mu	Sigma	Skewness	Kurtosis	Min	Max	Non- Adj. Sharpe Ratio*
All	1.4290	1.6908	0.3544	3.2741	-4.6807	8.1837	0.8452
CON	0.9098	1.3377	-0.1956	3.6310	-4.7883	5.6450	0.6801
DSB	-2.7366	3.2728	-0.0204	-0.2236	-11.9704	5.0261	-0.8362
EM	1.8794	3.5164	-0.1292	3.1774	-10.5153	15.1995	0.5345
EMN	0.9045	0.9415	0.3620	0.4491	-1.3634	3.5928	0.9607
ED	1.4115	1.1364	-0.6600	1.4564	-3.0078	4.1321	1.2421
EDD	1.4931	1.1945	-0.4090	0.7015	-2.5718	4.0691	1.2500
EDM	1.3673	1.3691	-0.6045	2.4467	-4.8530	4.6703	0.9987
EDRA	0.8181	0.9383	-0.0245	1.1279	-2.3785	3.7396	0.8719
FIA	0.7033	1.1037	-2.6387	18.1636	-7.2191	4.2436	0.6372
GM	1.2843	2.6152	-0.2047	6.4303	-12.2745	9.9507	0.4911
LS	1.9074	2.0060	0.9880	4.3020	-4.0618	12.2284	0.9509
MF	0.6774	3.2174	-0.3636	0.4244	-9.8211	9.0409	0.2105
MS	1.0109	1.2105	-1.4806	4.9184	-4.8737	4.1882	0.8352
S&P 500	3.2624	2.3219	0.8847	0.2663	0.0087	10.7723	1.4050

By only taking consideration of months where the S&P 500 had positive returns, we generated the table above for comparison with Table 1 of raw return data. Generally, we see marked improvement to average monthly return, DSB being an outlier, and lowered volatility across the returns. Accordingly, non-RF-adjusted Sharpe Ratios (simply Mu/sigma) show dramatic improvements during these bull months; across all indices, they improve by an average of over 160%.

For strategies which display significant, positive β_{Bull}'s (EM, ED, EDD, EDM, EDRA, and LS), this table defines the "best case" return properties for these funds. Volatility is reduced by the presence of fewer negative returns, and mu increases appropriately. Investors considering the potential of these hedge fund strategies can look to the average performance outlined above and ask themselves, "What if this is as good as it gets?'

Figure 4: Summary Statistics of Strictly Bear S&P Months

Column Min	Column Max

Summary Statistics: Credit Suisse Hedge Fund Indices Monthly Return Data: Strictly Bear S&P Market

Methodology	Mu	Sigma	Skewness	Kurtosis	Min	Max	Non- Adj. Sharpe Ratio*
All	-0.5875	2.0063	-0.6048	4.3817	-7.8493	6.2870	-0.2928
CON	-0.0352	2.5630	-3.0497	14.2143	-13.4583	5.5595	-0.0137
DSB	3.3778	4.1206	0.5321	2.8072	-9.0448	20.4667	0.8197
EM	-1.6072	4.1256	-2.7611	13.4433	-26.1703	5.8665	-0.3896
EMN	-0.4984	5.4784	-9.0476	85.3922	-51.8404	1.8195	-0.0910
ED	-0.4359	2.0686	-2.7587	12.3201	-12.5274	2.2775	-0.2107
EDD	-0.3683	2.1696	-2.7581	13.1596	-13.3015	3.0709	-0.1698
EDM	-0.4619	2.1773	-2.3152	9.3222	-12.2442	4.2903	-0.2121
EDRA	-0.0780	1.3099	-1.3154	5.4937	-6.3521	3.4618	-0.0596
FIA	-0.0257	2.1454	-4.7080	28.0438	-15.1235	1.9987	-0.0120
GM	0.1732	2.5184	-0.2303	2.9817	-7.2281	10.0721	0.0688
LS	-1.2255	2.6175	-0.3014	6.9077	-12.1433	10.5640	-0.4682
MF	0.1526	3.4871	0.3474	-0.2614	-7.5469	9.4873	0.0438
MS	0.0302	1.7023	-1.9686	7.1877	-7.6311	3.5419	0.0177
S&P 500	-3.7144	3.2080	-1.5821	3.1341	-16.9425	-0.0143	-1.1579

By only taking consideration of months where the S&P 500 had net negative returns we generate the table above, the complement of Figure 3. Compared with Figure 3, there are paltry non-adjusted Sharpe Ratios and higher volatilities, as losses tend to be more severe and spread out.[33] With the exception of MF, MS, and GM, average return flipped sign for the strategies, with DSB benefitting immensely from bear market conditions.

For strategies which displayed significant, positive β_{Bear}'s, this table represents a worst case scenario for monthly return properties. Note that every methodology, except DSB and MF, is exposed to market decline; this table corresponds to a worst case for a majority of the indices.

Figure 5: Correlation Matrix of Macro Model Regressors

Min	Max

X-vars	Δ_{Unemp}	Δ_{WTI}	Δ_{VXO}	Δ_{SR}	Δ_{BS}	Δ_{TS}	Δ_{Gold}	Δ_{M1}
Δ_{Unemp}	1	-	-	-	-	-	-	-
Δ_{WTI}	-0.0661	1	-	-	-	-	-	-
Δ_{VXO}	-0.0535	-0.2846	1	-	-	-	-	-
Δ_{SR}	-0.0117	-0.1153	0.0509	1	-	-	-	-
Δ_{BS}	0.0488	-0.4432	0.3764	0.0972	1	-	-	-
Δ_{TS}	0.0780	0.1465	-0.0086	-0.0262	0.0002	1	-	-
Δ_{Gold}	0.0874	0.1256	0.1214	-0.0096	-0.1237	-0.1234	1	-
Δ_{M1}	-0.0038	-0.1483	0.1176	0.1281	0.1435	-0.0638	0.2008	1

Model 3:

$$\mathbf{R_i = \alpha + (\beta_{Unemp} * x1_i) + (\beta_{WTI} * x2_i) + (\beta_{VXO} * x3_i) + (\beta_{SR} * x4_i) + (\beta_{BS} * x5_i) + (\beta_{TS} * x6_i) + (\beta_{Gold} * x7_{i)} + (\beta_{M1} * x8_i) + \varepsilon_i}$$

Note that all the x-variables we consider for our regression are deltas: month-over-month changes in our desired regressors, for ease of beta interpretation in our analysis. Additionally, each variable delta corresponds to an xk_i in our model, according to the appropriate beta coefficient; hence, $\boldsymbol{x1_i}$ corresponds to $\Delta_{\mathbf{Unemp}}$, $\boldsymbol{x2_i}$ corresponds to $\Delta_{\mathbf{WTI}}$, and so on, again for ease of beta interpretation in our analysis.

Examining our correlations, we find no evidence of multicollinearity across our regressors. With the maxima in |r| between the pairs (Bond Spread, West Texas Oil Index) and (Bond Spread, VXO), we find only moderate correlations and no basis for subtractive predictive power between regressors. We concluded that these variables provide a cross section of systematic risk within the market, with little subtraction between predictive power. Hence, they became our basis for our macro model examining exposure to systematic risk across hedge fund returns.

[33] Consider skewness and kurtosis in Table 1 and Figure 2 of Analysis.

Figure 6: Autocorrelation Matrix for Hedge Fund Indices

Column Min	Column Max

	Monthly Returns			Quarterly Returns			Yearly Returns	
Strategy	1-Month Lag	2-Month Lag	3-Month Lag	1-Q Lag	2-Q Lag	4-Q Lag	1-Y Lag	2-Y Lag
All	0.2095	0.1061	0.0560	0.2134	0.0675	-0.1358	-0.2372	-0.0815
CON	0.5552	0.2953	0.1562	0.4219	0.0158	-0.1191	-0.3105	-0.2646
DSB	0.0854	-0.0453	-0.0183	-0.0455	-0.0935	-0.1154	-0.1378	-0.1969
EM	0.3010	0.0539	0.0442	0.1084	-0.1215	-0.1092	-0.4962	-0.1052
EMN	0.0543	0.0305	0.1360	0.1610	-0.0394	0.0376	0.0745	0.0986
ED	0.3615	0.2168	0.1598	0.2752	-0.0241	-0.1119	-0.3101	-0.2394
EDD	0.3938	0.2430	0.1649	0.3111	-0.0190	-0.1059	-0.2654	-0.0180
EDM	0.3140	0.1944	0.1468	0.2517	-0.0125	-0.1250	-0.3334	-0.3727
EDRA	0.2784	0.0162	-0.0271	0.0433	0.1401	-0.0553	0.0684	-0.0682
FIA	0.5232	0.2016	0.1148	0.3093	-0.0197	-0.0863	-0.2913	-0.2288
GM	0.0922	0.0453	0.0725	0.1870	0.1348	-0.0776	-0.0121	-0.0806
LS	0.1945	0.0733	0.0061	0.0866	0.0027	-0.0749	-0.0850	-0.1288
MF	0.0332	-0.1092	-0.0949	-0.1684	-0.1791	-0.1588	-0.3792	0.1973
MS	0.3269	0.2199	0.1782	0.3048	-0.0391	-0.1262	-0.3320	-0.2071
S&P 500	0.0812	-0.0251	0.0984	0.0869	0.0620	0.0658	0.1218	-0.0495

For a k-period lag: $\mathbf{R_i = R_{i-k} + \varepsilon_i}$

The correlations above characterize persistence across hedge fund strategies, a corollary to the Carhart 4-factor model analysis.[34] By considering the autocorrelations of each fund, we can accurately gauge momentum in fund growth, based on the available data frequency (monthly).

In the 1-Month Lag framework, we see strong evidence of persistence for the two arbitrage strategies (Convertible and Fixed Income) and moderate evidence for event driven strategies, as well as Multi-Strategy and Emerging Markets. With net positive average returns for these funds, positive autocorrelation is a desirable characteristic, as the fund efficiently maintains gains. The 2-Month Lag autocorrelations show reduced persistence across the funds mentioned above and next to no persistence in the other funds considered. Even the highest 2-month auto correlation, in

[34] With $\boldsymbol{\beta_{MOM}}$, the model measure return exposure to market securities with persistent returns. Hence, funds using this tactic can be seen plainly, implying that expert money management may not be the source of the fund's returns. For our autocorrelation analysis, |r| >.3 will be considered significant.

Convertible Arbitrage, shows only moderate persistence with previous returns, at +0.2953. 3-Month lags show little return persistence across all strategies.

Net quarterly returns display little autocorrelation for 2-Quarter and 4-Quarter lag times. However, for a 1-Q lag, momentum is displayed for CON, ED, EDD, EDM, FIA, and MS; note that these funds are a subset of the funds that display monthly momentum with a 1-month lag. From a momentum standpoint, these funds demonstrate the most consistent returns over time, considering different periodic returns and lag times. Unfortunately, this conclusion is confounded by consideration of annual returns.

Differing from the monthly and quarterly, annual returns are predominantly negative; in fact, there are no significant positive autocorrelations among annual returns, regardless of lag time, with a positive max of .1973. For 1-Y lags, significant negative autocorrelations for CON, EM, ED, EDM, MF, MS indicate that a fund with a positive yield over the last year will revert to have losses over the coming year, and vice versa. Even funds that display monthly and quarterly momentum do not maintain their annual returns. While this draws attention to aggregate money managers' expertise, the finding exposes the high degree of volatility associated with these funds; investments in hedge funds fundamentally should not be actively managed, specifically because of the expectation for growth swings and inconsistent returns.

Hence, we conclude that some hedge fund indices, namely the arbitrages, the event driven, EM, and MS, display momentum in their returns, but only over very short lag times. Unfortunately, annual returns indicate that short term persistence may be offset by expected losses in the future. Broadly speaking, there is momentum in hedge fund returns, but calling it persistence may be a mischaracterization.

Figures 7&8: Composite Model, Correlation Matrix and Betas

This composite model incorporates the 3 most significant regressors from the Macro model and Carhart model, respectively. The goal of this model is to eliminate significant excess returns from the indices and capture the most variation of an industry whose returns demonstrate broad exposure. Model 5 is outlined below for the composite.

Model 5: $$\mathbf{R_i = \alpha + (\beta_{WTI} * x1_i) + (\beta_{VXO} * x2_i) + (\beta_{BS} * x3_i) + (\beta_{MKT-RF} * x4_i) + (\beta_{SMB} * x5_i) + (\beta_{HML} * x6_i) + (\beta_{MOM} * x7_i) + \varepsilon_i}$$

Figure 7: Correlation Matrix

X-vars	Δ_{WTI}	Δ_{VXO}	Δ_{BS}	MKT − RF	SMB	HML	MOM
Δ_{WTI}	1.0000	-	-	-	-	-	-
Δ_{VXO}	-0.2846	1.0000	-	-	-	-	-
Δ_{BS}	-0.4432	0.3764	1.0000	-	-	-	-
MKT − RF	0.2318	-0.2394	-0.3516	1.0000	-	-	-
SMB	0.0824	0.0112	-0.1145	0.1972	1.0000	-	-
HML	-0.0047	0.1419	0.0478	-0.1921	-0.3446	1.0000	-
MOM	-0.0887	0.1876	0.2280	-0.2719	-0.1907	0.0281	1.0000

Here again, we say no evidence of serial correlation across our variable basis, so we continue with our multiple regression, trying to capture additional return variation in our models.

Figure 8: Composite Model Betas

Strategy	α	β_{WTI}	β_{VXO}	β_{BS}	β_{MKT-RF}	β_{SMB}	β_{HML}	β_{MOM}
All	0.4383	0.0264	0.0915	-5.2567	0.2878	0.0200	0.0113	0.1280
CON	0.4709	0.0620	0.0606	-8.6376	0.0901	-0.0102	0.0781	-0.0059
DSB	0.0653	0.0130	-0.0801	-3.0642	-0.8858	-0.1873	0.0607	-0.0483
EM	0.2424	-0.0107	0.0623	-7.2956	0.5026	0.1060	-0.0222	0.1189
EMN	0.2109	0.1470	0.2562	-5.2178	0.1828	0.0183	0.1494	-0.0378
ED	0.5263	0.0198	0.0671	-4.2285	0.2485	0.0833	0.0771	0.0504
EDD	0.6202	0.0134	0.0627	-3.7753	0.2441	0.0949	0.0670	0.0308
EDM	0.4699	0.0244	0.0736	-4.6752	0.2561	0.0724	0.0897	0.0676
EDRA	0.3739	0.0303	-0.0262	-0.4194	0.1303	0.0291	0.0594	0.0167
FIA	0.3514	0.0545	0.0958	-6.6119	0.0783	0.0046	0.0721	0.0017
GM	0.7183	0.0145	0.0720	-4.9712	0.1496	-0.0217	0.0109	0.1169
LS	0.3815	0.0356	0.0605	-4.2455	0.4674	0.0728	-0.0491	0.2061
MF	0.4577	-0.0410	0.0674	-2.8235	-0.0322	0.0361	0.0087	0.1117
MS	0.5622	0.0507	0.0914	-6.2283	0.0961	0.0061	0.0427	0.0213
S&P 500	0.0875	-0.0020	0.0050	0.3212	0.9598	-0.1082	0.0003	-0.0518

Significance*

Our composite model actually suffers from convoluted variables; the simple Carhart 4-factor explained more variation than this mode, even if the funds demonstrate significant exposure across a wider array of variables. The number of funds displaying excess returns speaks to the diversity of exposures that hedge funds maintain to accrue their returns.