PERFORMANCE, MANAGERIAL SKILL AND FACTOR EXPOSURES IN COMMODITY TRADING ADVISORS AND MANAGED FUTURES FUNDS

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To my family

ABSTRACT

Understanding risk is important. Prior to 2008, as the yields on safe assets hit rock bottom, investors turned their focus to an alphabet soup of more complex instruments. These complex securities were rated AAA, they appeared as safe as U.S. Treasuries, yet with much higher yields. The financial crisis of 2008 revealed that higher yields on these instruments in fact came with higher risk, albeit too late for these investors. The focus of this research is to understand the risk-return tradeoff in two financial instruments that have not been currently investigated, commodity trading advisors (CTAs) and managed futures funds (MFFs).

This study starts with documenting the differences of CTAs and MFFs with hedge funds and mutual funds: We start with legal and operational differences. Next, performance analysis indicates that CTAs and MFFs, as stand-alone investment vehicles, provide higher returns than the average market returns in bear markets; while carrying a lower level of risk. CTAs' and MFFs' strong standing in bear markets let them deserve their so-called title "downside risk protectors." CTAs and MFFs are profitable individual assets, but addition of these funds to classical asset portfolios enhance portfolio performance significantly. This feature makes them strong hedging assets. As expected, in up markets, their performance is below standard asset performances.

I find that the superior performance of CTAs and MFFs can be explained by managerial skill. Positive and significant Jensen alphas are evidence of good performance; moreover, persistence of Jensen alphas is supported by both parametric and non-parametric tests. Incentive fee and age of the fund are found to positively related to managerial skill; while somewhat surprisingly, management fee is found to be negatively related to managerial skill.

I also find that many financial and macroeconomic factors are statistically unrelated to CTA and MFF performances. However, the value premium (HML) factor and industrial production growth (IPG) are correlated with the performance of these funds. HML has a positive effect on one-month-ahead fund returns whereas IPG has a negative effect on one-month-ahead fund returns. Nonparametric tests support these results marginally. These findings suggest that both CTAs and MFFs use well-known and well-established predictors of expected returns to generate their alphas.

Keywords: Commodity trading advisors, managed futures funds, performance analysis, managerial skill, factor exposures.

ÖZET

Karmaşık finansal ürünler, aşırı risk üstlenme, ve finansal kurumların aşırı kredi arzı 2008 finansal krizinin oluşmasında önemli rol oynamıştır. Bu dönemde yatırımcılar daha güvenilir yatırım araçlarına yöneldiklerinden klasik yatırım araçları yeniden önem kazanmaya başlamıştır. Ancak, hisse sendi ve sabit-getirili menkul kıymetlerdeki aşırı düşük getiriler, yatırımcıları daha yüksek getirili yeni finansal araçlar aramaya sürüklemiştir. Elde ettiğimiz bulgular, emtia ticaret danışmanları (CTA'lar) ve vadeli sözleşme fonlarının (MFF'ler), gerek risk gerek getiri açısından risk sermayesi ve yatırım fonları arasında bir yerde durmakta ve yatırımcılarına uygun getiriler sağlamakta olduğunu göstermektedir.

Bu çalışma CTA'lar ve MFF'ler arasındaki yasal ve uygulamadan kaynaklanan farkları inceleyerek başlamaktadır. Performans analizleri göstermektedir ki, söz konusu fonlar fiyatların düşmekte olduğu yani resesyon piyasalarında yatırım aracı olarak tercih edildiğinde piyasadki ortalama yatırım performansından daha yüksek performans sağlamaktadır. Bu özellikleri onlara iddia ettikleri gibi 'yüksek riskten koruma araçları' olma özelliği kazandırmaktadır. Söz konusu fonlar, bireysel yatırım aracı olarak karlı olduğu gibi portföy içine dahil edildiklerinde portföyün Sharpe rasyosunu hızla yükselterek ideal çeşitlendirme aracı olduklarını da göstermektedir. Bu anlamda, söz konusu fonlar riskten korunma araçları olarak kabul edilmelidir. Fiyatların yükselmekte olduğu piyasalarda ise fon performansı ortalamanın altında kalmaktadır.

Fonların başarısını fon yöneticilerinin yetenekleri ile açıklamak mümkündür. Regresyonlardan ele edilen pozitif Jensen alfa değerleri yüksek fon performansının bir kanıtıdır. Alfaların uzun vadede devamlılığı ise fon yöneticilerinin başarılarına atfedilebilir. Hem parametrik ve nonparametric testler bu sonuçları doğrulamaktadır. Yönetici yetkinliği, fonların yaşları ve teşvik primleri ile doğru orantılı; yönetici primleri ile ters orantılı bir ilişkiye sahiptir.

Fonların başarısını açıklayan iki adet finansal ve makroekonomik değişkene ulaşılabilmiştir. Birinci değişken değer primi (HML), ikinci değişken ise endüstriyel üretimin büyümesi (IPG)'dir. Değer primi, bir ay sonraki fon getirisi ile doğru orantılı, endüstriyel üretimin büyümesi ise bir ay sonraki getiri ile ters orantılı bir ilişki sergilemektedir. Hem parametrik hem de nonparametrik testler sonuçları desteklemektedir.

Anahtar Kelimer: Emtia ticaret danışmanları, vadeli sözleşme fonları, performans analizi, yönetici yetkinliği, fonları etkileyen faktörler.

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LIST OF ABBREVIATIONS

AUM: Assets under Management
BDTF: Fung and Hsieh Bond Trend Followıng Factor
CDS: Credit Default Swaps
CFNAI: Chicago FED National Activity Index
CFTC: Commodity Futures Trading Commission
CMA: Fama-French Investment Factor
CMTF: Fung and Hsieh Commodity Trend Followıng Factor
CRSP: CRSP Value-Weighted Market Index
CTA: Commodity Trading Advisor
DEF: Default Spread
DIV: Aggregate Dividend Yield
EW= Equal- weighted
E(INF): Expected Inflation
FINRA: Financial Industry Regulatory Authority
FX: Foreign Exchange
FXTF: Fung and Hsieh Currency Trend Followıng Factor
GDPPCG: U.S: Monthly Growth Rate of Real GDP per Capita
Gov: Government
HML: Fama-French Book-to-Market Factor
INF: Monthly U.S. Inflation Rate
IPG: FED FRED Industrial Production Index
IRTF: Fung and Hsieh Short-Term Interest Rate Trend Followıng Factor
LT: Long- Tem
MFF: Managed Futures Funds
MMIFF: Money Market Investor Funding Facility
MOM: Carhart Momentum Factor
MPMM: Manipulation-Proof Performance Measures
NAV: Net Asset Value
NFA: National Futures Association
OTC: Over-the-Counter
PRYL: FED FRED Total Nonfarm Employment
R_F: One-Month Treasury Securities
RMW: Fama-French Operating Profitability Factor
RREL: Relative T-Bill Rate

SEC: Securities Exchange Commission

SKTF: Fung and Hsieh Stock Index Trend Followıng Factor

SMB: Fama-French Size Factor

TED1M: LIBOR 1-Month Treasury Bill

TERM: Term Spread

UNEMP: U.S: Monthly Unemployment Rate

UNE(INF): Unexpected Inflation

VW= Value- weighted

Δ10Y: Monthly Change in TERM

ΔCredSpr: Monthly Change in DEF

CHAPTER 1

INTRODUCTION

Managed futures funds are alternative investment vehicles available to investors who wish to participate indirectly in commodity markets (Edwards and Liew, 1999a). Managed futures funds trade in exchange-traded derivatives such as futures, options and swaps on physical commodities, financial assets and currencies. The managers of these funds profit from the changes in asset prices by deploying long- and short-strategies and by making use of leverage, just like hedge funds. Similar to hedge funds, managed futures funds industry is a skill-based industry. Investment managers buy and sell assets based on their proprietary strategies. Furthermore, MFFs argue that any positive return that they generate is the consequence of their individual success (Anson, 2002) since overall correlation with the market portfolio is typically small.

This dissertation examines commodity trading advisors (CTAs) and managed futures funds (MFFs) from several dimensions. Legal definitions of the funds, their investment criteria, their differences from hedge funds and mutual funds are analyzed. I find that CTAs and MFFs stand between hedge funds and mutual funds on the risk spectrum. CTAs are more similar to hedge funds, while and MFFs are more similar to mutual funds. The basic difference between CTAs and hedge funds is that CTAs are registered with the SEC and CFTC, and therefore, they are audited. Moreover, these funds are more flexible for investors than the hedge funds. The difference between mutual funds and MFFs is basically that MFFs invest in derivative markets while many mutual funds do not.

The data for MFFs and CTAs are provided by Lipper TASS hedge fund database. Time frame is from January 1994 to December 2014. Even though the data are available from 1973, we start analysis in 1994, because the database did not report deactivated hedge funds until 1994. Excluding deactivated hedge funds would have caused a serious survivorship bias, since most hedge funds collapse and deactivate after large losses. The database provided us with data on 2,737 funds.

Summary statistics show that the number of CTAs in the database declines while total volume of assets under management (AUM) increases in time. MFFs, on the other hand, grow both in number and in AUM. Both types of funds attract investments during the crisis periods. Average monthly return of a CTA is 0.81% during the life of a fund, average age is 58 months, average AUM is $54 million, average annual management fee is 2% of assets, and incentive fee is 20% of returns. On the other hand, average monthly return of an MFF is 0.23% during the life of a fund, average age is 71 months, average AUM is $107 million, average annual management fee is 1.85% of assets, and incentive fee is 17.3% of returns.

We guard against three types of potential biases in this study. The first is the survivorship bias, which shows spurious high returns in the absence of deactivated funds. We compute the annual average returns of active funds and inactive funds in the database. The difference in returns between inactive and active funds is 1.87% for CTAs and 4.10% for MFFs. These numbers indicate a huge survivorship bias issue for MFFs. The second bias is backfill bias, which is an artifact of backfilling earlier returns to a database. Funds that have good nesting period performance before registering the fund prefer backfilling the earlier pre-registration returns. Therefore, backfilling would cause spurious higher returns. As a general approach, we cleanse the data going back twelve months from the registration period to eliminate backfilled returns.

The results show that CTAs suffer 3.05% and MFFs suffer 0.58% return from backfill bias. Since, CTAs cannot use advertising, backfilling is an important tool for attracting new investment. The last bias type is multi-period sampling bias. Because investors seek a return history of funds to make investment decisions, we eliminate funds having less then twelve-month history of returns. Multi-period sampling bias is 0.21% for CTAs and 0.34% for MFFs.

Having cleansed our database from potential biases, we next analyze CTAs and MFFs as standalone investment vehicles as well as portfolio assets. We use four performance measures: Sharpe ratio, Roy's criterion, Kataoka's criterion, and Sortino ratio. CTAs and MFFs rank very high as standalone investment vehicles based on these performance measures in the whole sample period. Their performance is compared with those of stock markets, corporate bond market, long-term government bond market, and foreign exchange market. Next, we evaluate CTAs and MFFs as portfolio assets. Their contribution to standard asset portfolios enhance portfolio performance measures significantly. They optimize performance measures when they are included around 15%-55% to portfolios.

Performance analysis is a rough measure because many assets behave differently in up- and down-markets due to their differences in risk. To understand a broad measure of risk better, we repeat the same analysis by dividing the sample period into two, up and down (or bull and bear) markets. The results show that CTAs and MFFs yield much better than standard assets in down markets. Their performance is astonishing both as stand-alone and portfolio assets. On the other hand, these funds perform worse-than market-average in up markets. Thus, CTAs and MFFs have strong negative correlations with standard assets in down market, and weak negative correlations with other assets in up markets. CTAs perform slightly better than MFFs in all market types.

Is the superior performance of CTAs and MFFs due to market conditions or do fund managers also play a significant role in the success? There is no straightforward method of testing managerial skill. The classical approach suggests computing Jensen alphas and then measuring persistency in Jensen alphas. Persistent alphas are an indicator of successful fund managers. We compute Jensen alphas by using 4-factor and 11-factor models. Around 10% of all funds has positive and significant alphas. Alphas are positively correlated with fund age and incentive fee, and somewhat surprisingly, they are negatively correlated with management fee. We use parametric and nonparametric methods to measure persistency. The results indicate that there is persistency in fund returns.

Another way of measuring managerial skill is to observe fund inflows and outflows. If investors are sensitive to returns, flows should chase higher returns. The results show that fund flows do chase higher returns. However, the opposite is not true: There is no reliable relationship between current flows and future returns. There is no guarantee that a fund makes higher level of profits after getting higher levels of inflows. Therefore, flows cannot be a good predictor of future fund returns. The only exception is highly successful and highly unsuccessful funds. Highly successful funds attract higher levels of flows and they perform better once they receive these higher flows. In contrast, investment flows run away from highly unsuccessful funds, and these funds perform worse in the next period.

We also test if CTA and MFF performance can be explained by well-known risk factors. Parametric and nonparametric tests show that value premium (HML) and ındustrial production growth (IPG) are significant factors in CTA and MFF performance. HML has a positive effect on one-month-ahead fund returns. HML is related to growth potential in the economy. As the growth potential in the economy is bigger, these funds perform better. HML is also related to financial distress risk (Fama and French, 1993). Thus, this outperformance can also represent compensation for distress risk. IPG has a negative correlation with one-month-ahead fund return. This can be due to the negative correlation between industrial growth and derivatives.

This study is organized as follows: This chapter continues with industry overview and literature review. Chapter 2 introduces data, summary statistics and potential data biases. Chapter 3 is dedicated for performance analysis of CTAs and MFFs. Chapter 4 provides analysis for managerial skill and persistency in fund returns. Chapter 5 documents the factor exposures for the performance of CTAs and MFFs. Finally, Chapter 6 concludes.

INDUSTRY OVERVIEW

The first funds were established in order to reduce riskiness in investments without understanding the mathematics behind it, much before Harry Markowitz improved his portfolio selection theory (1952). The industry flourished both in Europe and in the U. S., making it a necessity in time to analyze the building blocks behind fund portfolios. In order to understand the nature of funds, one needs to revise the definition of asset classes, asset allocation, and diversification.

We can define asset classes as set of assets that has some fundamental economic similarities and characteristics that make them distinct (Greer, 1997). Greer distinguishes asset classes into three groups as capital assets, consumable/ transformable (C/T) assets, and store of value (SOV) assets. Capital assets are assets whose value is dependent on the ongoing value of a company. Typical capital assets are stock and bonds. C/T assets are consumable; but also transformable assets, which have economic value already without binding to another asset. Physical commodities are a typical example for this group. The transformation mechanism of these assets is commodity futures. Since the value of these assets is not bind to discount rates, instead they depend on commodity prices; they might potentially be very good diversification tools. SOV assets store value; they do not generate income or are not consumed. A good example is fine arts. The author argues that C/T assets and SOV assets are very low or even negatively correlated with capital assets and therefore these asset classes should be included in portfolios in order to increase diversification.

Sharpe (1992) defines asset allocation as allocation of investors’ portfolio among a number of major asset classes. He uses a factor model in order to compute the exposure of factors to different asset classes. The asset classes in his study were comprised of only capital assets (mainly stock and bonds). Similarly, SEC (2014) uses the same definition for asset allocation and categorizes asset classes into three as stocks, bonds, and cash. We can possibly extend Sharpe's study by using the newly defined asset classes by Greer (1997), i.e., C/T and SOV.

Markowitz (1952) showed it is more profitable to have a portfolio of assets than having a single asset even when the expected returns of both are the same. Portfolios allow lower expected risks thanks to diversification. Diversification is the averaging out of independent risk in a large portfolio (Berk and DeMarzo, 2007). Diversification is possible by investing different assets within only one asset class (Campbell, 2007); but it is stronger if investment is allocated into different asset classes (Lintner, 1983; Jensen et al, 2002). Diversification is important for long-term investors; researchers are looking for the most efficient ways of diversification. For example, Campbell and Viceira (1998 and 2002, p. 2) find the solution in investing in long-term indexed capital assets or Lintner (1983) suggests that managed futures should be included in portfolios.

Another view seperates asset allocation into two: Strategic and tactical (Anson, 2004). Strategic asset allocation is a long-term asset allocation and it contains capital assets basically. It targets higher expected returns as well as lowered risk. Diversification is the basic method to mitigate risk. Tactical asset management has a shorter-term horizon. It aims to benefit from current market conditions; therefore, one asset may be more preferred over another for a while due to its speculative returns. Reducing risk is not the main target. Alternative asset classes can be preferred not because of hedging, but because of their expanding nature; they can be considered as a broader asset class (Anson, 2002, p: 6).

What is the expanding nature of an asset class? Anson (2002, p: 6) discovers this attribute of portfolios composed of different asset classes. Different asset classes not only provide diversification, but also increase the exposure to other industries in order to increase returns. A best means of achieving this target is to use C/T and SOV assets. Assume returns in metal markets are high for a certain period. Having metal futures in a portfolio might increase returns available in metal markets; also reduces risk by having a negatively correlated asset in the portfolio. This occurrence leads us to the fact that futures and futures funds can be used as both individual assets and portfolio assets because they provide not only low risk, but also increased return.

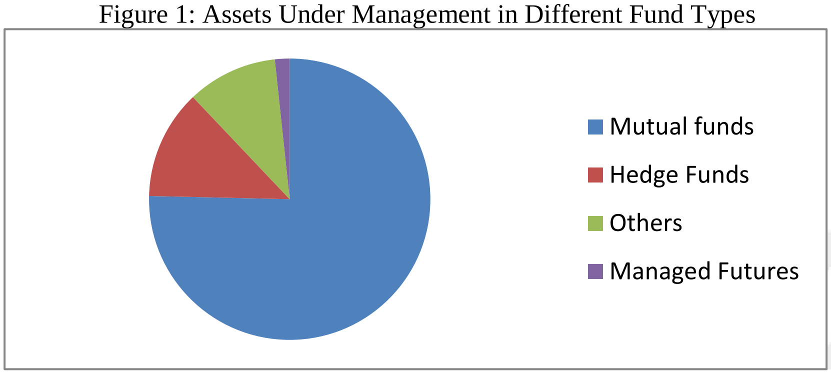
Mutual Funds Industry

A mutual fund is an investment company that pools money from many investors and invests it on behalf of the fund. The number of investors usually varies from a few hundred to thousands. Mutual funds typically invest in stocks, bonds, and money markets instruments. There are many types of mutual funds. The types are usually determined by the assets, in which they invest. Funds can have different strategies, such as real estate, international, specialty funds, etc. However, their basic investment assets are usually stocks and bonds. Mutual funds disclose their investment strategies and can invest only in the assets that are specified in their prospectuses.

Mutual funds are the oldest fund type; they are also the widest-known funds among many investor groups. Therefore, the word “funds” resemble mutual funds, not other types of funds, to many people. Even though there are advantages of other fund types, investments to mutual funds take the largest share from the funds market. Assets under management of mutual funds are about

$15 trillion at year-end 2013 (2014 Investment Company Factbook). The estimated magnitude of the funds types at the end of 2013 can be found in figure 1.

Figure 1: Assets Under Management in Different Fund Types



Source: Managed Funds Association Fact Sheet and 2014 Investment Company Factbook.

Other funds in Figure 1 are comprised of exchange traded funds, closed-end funds, and unit investment trusts. The table clearly shows the size of the mutual funds comprises almost 75% of the total industry.

Mutual funds emerged in the second half of the eighteenth century in Europe as an outcome of mercantilism. After the discovery of new continents by the Europeans not only enriched by gold and silver that flew from the new lands, but also finding new markets to sell their high-tech products. New companies were founded in order to trade in new lands, the stocks and bonds of these companies were seized by all types of investors. Lack of immediate information about company operations and transparency of company books was accompanied by positive expectations of investors. Monetary growth played into speculators' hands and prices of stocks and bonds jumped up and down instantly. Speculation in stock market was followed by several crises (Kindleberger, 2008, Section 3 and 4; Fridson et al., 1996). Given the communication technologies of the time, the transoceanic trade was very risky for small investors and small investors started looking for more stable assets than stocks and bonds. As a response to seeking a safer asset, the first mutual fund was emerged in 1770s. The primary purpose of mutual funds was to arrange a diversified investment basket for the small investor (Rouwenhorst, 2004).

After growing in the Europe, the funds industry jumped to the United States. Firstly, closed-end funds arrived in the US market at the end of the nineteenth century; the first open-end mutual fund was established in 1924 in the US market, and this very new industry became popular in the same decade. 1929 Great Depression forced funds to use more leverage and be more flexible in order to survive under hard economic conditions. The establishment of the Securities Exchange Commission (SEC), which administers the federal securities laws; and the establishment of Revenue Act of 1936, which regulates tax treatments for mutual funds and shareholders owe their existence the emergence of stocks and funds industry at the beginning of the twentieth century (Fink, 2009; Blakey and Blakey, 1936).

The difference between open-end and closed-end companies is explained in Investment Company Act of 1940. “Open-end company means a management company which is offering for sale or has outstanding any redeemable security of which it is the issuer” (Sec 5. (a)). In practice, this definition points out “mutual funds” that we know; yet many mutual funds are open-end companies. These funds are not traded in public exchanges. If investors want to buy any shares, they buy it from the fund or from fund’s broker; if investors want to sell any shares they sell it to the fund or to fund’s broker (Investment Company Act of 1940, Sec. 22). Even though there are some limitations or restrictions based on fund charter or economic conditions, the funds may issue as many shares as they can. Selling shares back to the issuer is called redemption. A fund may have to sell some of its assets in order to shrink its NAV to the circulating value of shares.

The investor yield can be computed from difference between sales and purchase prices and any fee charged by the fund and the broker.

There are also closed-end companies, as defined in Investment Company Act of 1940, sec 5. (a) (2), they are management companies other than open-end companies. These funds are launched through IPOs and are traded in open markets. Closed-end funds issue a pre-determined number of shares and the shares are not redeemable. Supply and demand conditions determine the prices of shares in the open market just like stocks or exchange traded funds. The number and NAV of closed-end funds are very limited compared to open-end funds, and they are not as well-known by the investors as open-end funds. This study refers to open-end funds for the term “mutual fund”.

An important issue for this study is the relationship between funds and derivatives. Can mutual funds invest in derivatives? There is no direct restriction in securities laws to prohibit investment in derivatives. However, mutual funds were distracted from derivative investments until 1997 due to tax regulations. The Revenue Act of 1936 organized mutual funds as pass-through entities: The funds did not pay any taxes; they conveyed the taxes to investors. Investors pay individual revenue taxes due to capital and dividend gains (Kinlay and Kinlay, 1936; Koski and Pontiff, 1999). In turn, the Act imposed “short-short rule” (Internal Revenue Service Code Section 851 (b)(3)) on mutual funds. Short-Short Rule prohibited mutual funds to collect more than 30% of their revenues from the sale of securities held for less than 3 months. Many derivatives such as futures and options have less than 3-month maturities. The purpose of the Short-Short Rule is to promote mutual funds as long-term investment vehicles (Koski and Pontiff, 1999; Barnhart, 1997). The Short-Short Rule was repealed in 1997; from then on mutual funds can invest in derivatives without limitations. Bae and Yi (2008) show that the repeal improved timing ability of mutual funds, causing mutual funds to be more profitable.

There are also other practical restrictions regarding use of derivatives. Mutual funds have to disclose their risks to the SEC; however, there are conflicts about reporting derivatives risk. Derivatives increase leverage and mutual funds are restricted on their leverage ratio. The measurement of leverage is of some doubt (Spangler, 2011). Moreover, some mutual funds hesitate to invest in derivatives because public sees them as speculative, high-risk assets (Sivy, 2013). Especially, the trust to exotic toxic derivatives mitigated during the 2007 financial crisis. For example, on October 21, 2008 the reserve Board opened Money Market Investor Funding Facility (MMIFF) in order to fund money market mutual funds due to large amount of redemption requests (St. Louis FED Timeline, 2008).

Mutual funds are exposed to four federal securities acts: The Securities Act of 1933, which organizes registration of funds shares, prospectus disclosure, and advertising. The second act is Securities Exchange Act of 1934, which regulate brokers' and dealers' activities, and also define SEC as a controlling body on securities markets. The third one is the Investment Advisors' Act of 1940, which regulates registration of investment advisors. And the last one is the Investment Company Act of 1940, which provide an oversight on mutual fund industry. Mutual funds and mutual fund managers have to be separately registered to the SEC. SEC regulates mutual funds and mutual fund managers due to Investment Company Act of 1940 (Fink, 1996).

Securities Exchange Act of 1934 enforces some operational restrictions on mutual funds, such as purchasing securities on margin (Section 7), borrowing by members, brokers, and dealers

(Section 8), affecting short sales, and buying more than 3% of the outstanding voting rights of equity (Section 10-d).

Investment Advisers' Act of 1940 makes emphasis on shareholder rights and disclosure. According to the law, a mutual fund company may borrow money, make loans, buy or sell real estate, or underwrite securities issued by other companies only under the authorization of the SEC (Almazan et al., 2004). A mutual fund company must declare its objectives in the prospectus, and it may not change them without the majority of shareholder votes. Similarly, a mutual fund company may not change the nature of its business; and also cannot change from a diversified form to an undiversified company without the majority votes of shareholders.

Disclosure policy enforced by Investment Company Act of 1940 has great remarks. Mutual funds have to issue semiannual balance sheet, income statement and a statement of total investment value, the list of securities amounts and values, total dollar amounts of sales and purchases of securities, salaries and other bonuses or fees paid to officers, directors, and advisory board members (Frank et al., 2004).

Disclosure policy, shareholder rights and other regulations render mutual funds open-strategy companies. They have to reveal all strategies, investments, even salaries to the investors. They cannot change their objectives, or they cannot move to a riskier form from the existing one. All these attributes make mutual funds more static and reliable; nevertheless, less profitable investment assets.

Hedge Funds Industry

A hedge fund definition cannot be found in any of the laws that regulate securities markets. The term emerged as an exception to investment companies, and gained great importance in time. It is not an investment company type; rather it is a private company, whose investors are limited in number and qualified for the amount of investments they make. The activities of hedge funds are not regulated; the companies prefer keeping their activities private. In turn, they are restricted from enlarged marketing. As a result, hedge funds are not public companies that any investor can invest.

"A hedge fund is a privately organized investment vehicle that manages a concentrated portfolio of public securities and derivative instruments on public securities, that can invest both long and short, and can apply leverage" (Anson, 2002, p: 11). Hedge funds can invest in national or international markets to offset losses during market downturns and also generate better returns than traditional capital assets in rising markets. They are assumed to be zero-beta investment vehicles, which are expected to make positive excess returns in any market conditions. In order to achieve this goal, they are given flexibility to use dynamic trading strategies, and invest in many assets without restrictions (Fung and Hsieh, 1997). Hedge funds are legal entities formed to collect money from investors and make investments in diverse markets. A hedge fund is different from a mutual fund in number of investors, and magnitude of investments it receives. The number of investors under the umbrella of a mutual fund can be as much as possible. Investors can be individuals as well as corporate customers. On the other hand, hedge funds prefer less than 100 investors in order not to have to register as an investment company. (Investment Company Act of 1940 requires a hedge fund to register to SEC if it represents more than 100 customers. However, there is an exemption to that law. Section 3(c)(1) of the Investment Company Act of 1940 allows funds to have less than 100 investors, 35 of whom can be non-accredited investors. If the hedge fund does not register, the SEC cannot impose a limit to the amount that it collects from investors). A hedge fund can require her customers to invest a minimum of $ 1 million.

Therefore, investors of hedge funds are usually institutions and limited number of exclusive persons.

Better yet, hedge funds have more privileges in their investments. They are practically unregulated and unmonitored. They are exempt from many restrictions that mutual funds are exposed to. For example, they can benefit from high levels of leverage, and short sales; they can invest in complex derivatives or they can invest any percentage of the total fund on a single asset without a concentration issue. Moreover, they do not have to reveal their investment strategies, and since the custody of the invested amount is in the hedge fund, the investor does not even know where her money is. Hedge funds do not have to pay back the invested money back immediately upon request; usually there is a lock up period about 6 months, which make these funds quite liquid and viable for long-term investment opportunities.

The first hedge fund, which can be classified as equity long/ short fund, was set up in 1949. The success of the fund attracted many other money managers to the industry. Industry grew fast until 1970 bear market. The growth was slow during 1970s and 1980s. However, the market accelerated again in 1990s and 2000s. The total assets under management in the U. S. market are estimated to be $2,5 trillion at year-end 2013 (Ritholtz, 2013). The reason of the fast growth seems to be the net positive returns of hedge funds for several years due to their privileges.

However, these funds have disadvantages that keep many investors away from them. For example, hedge funds are prohibited from broad advertising or solicitation of new funds (Securities Act of 1933, 502 (c)). They choose to self-report the commercial databases in order to attract more investors (Getmansky, 2012; Ackermann et al, 1999; Aiken et al, 2013).

Moreover, since they do not have to reveal their strategies, hedge fund customers are investing in black boxes. Prohibition of advertising along with their unregulated nature makes these funds mystique to many investors.

Managed Futures Industry

Managed futures industry is a type of alternative investment industry, which makes it available for investors wishing to participate indirectly in commodity markets (Edwards and Liew, 1999a). Managed futures funds trade in exchange traded derivatives such as futures, options and swaps markets on physical commodities, financial assets, and currencies. The industry makes profit from the changes in asset prices by deploying long- and short-sales, and leverage like hedge funds. Similar to hedge funds, this is a skill-based industry. Investment managers buy and sell assets by applying their private strategies. And they have right to argue that any positive return is the consequences of their individual success (Anson, 2002). From this operational point of view, we can see no difference between hedge funds and managed futures. The difference originates mostly from legislation and regulation.

Before diving into regulatory issues, we can have a look at the history of commodity trading and managed futures. Chicago Board of Trade was established in 1848 and forward contracts started trading. At the beginning, forward and future trading was perceived as gambling by the society and some disputes involved the industry until 1921. Futures Trading Act of 1921 (later changed to Grain Futures Act of 1922) was the first regulation in the industry. The Act designated the market as contract markets and the traders were to be licensed. Later, the act was amended and renamed as Commodity Exchange Act of 1936 (Stassen, 1982). This Act defines the basics of futures markets.

A decade after the Commodity Exchange Act of 1936 was enforced, the first public futures fund began trading (in 1948) and was active until mid-1960s (Irwin and Brorsen 1985). Several other public futures funds were started trading in early 1970s, but they were ceased due to unsuccessful results (Irwin and Brorsen, 1985). 1970s were a period, in which managed future industry was introduced to large number of investors and regulations accelerated. Commodity Exchange Act of 1974 established Commodity Futures Trading Commission (CFTC), which is the regulatory body for future markets and managed futures funds (Stassen, 1982). In spite of heavy legalization, the industry was expected to be a dubious one; an average investor would believe that institutional investors and trade advisors use futures for speculative reasons and to cheat the small investor. Institutional investors would use the industry for hedging purposes or in order to balance the cash inflows and outflows. The industry was respected as a standalone asset class after John Lintner presented his seminal paper in Annual Conference of the Financial Analysts Federation in 1983 (Lintner, 1983). The industry used this chance to grow tremendously after the perception towards managed futures changed (Chance, 1994). The CFTC established National Futures Association (NFA) in 1982 as a self-regulatory organization, which is responsible for developing and enforcing rules, safeguarding market integrity, and protecting investors (National Futures Association Annual Report, 2007). 1990s and 2000s were bright years of managed futures investments. Commodity Exchange Act was amended in 2000 in order to enlarge the industry into swaps and hybrid product markets (Rosen, 1983a).

It is hard to estimate the size of the industry due to the CTAs that do not report to any database. However, it is known that liquidity requirements in the last crisis, and fraud cases such as Madoff Ponzi scheme, attracted a number of CTA investors (Barclays Capital, 2011). Here, we elaborate to use an average estimate among extremes: The AUM in the US industry is expected to be around $ 337 billion at November 2013 (Managed Funds Association Fact Sheet).

An investor can invest in managed futures markets in three ways. First, an investor can invest her money in a public commodity fund (with another name, managed futures fund), which works almost the same way a mutual fund does. Edwards and Liew (1999b) states that “a commodity fund is the futures markets’ rough equivalent of mutual funds”. These funds are named as commodity futures, because in 1948 futures contracts were exclusively written on commodities. Starting from 1970s futures contracts can be written on financial instruments and currencies, but the name is still in use. The difference between a public managed futures fund and a mutual fund is basically the assets, in which they invest. Managed futures funds invest in futures and commodity options and swaps, using long and short positions and margin. Public funds are appropriate for retail investors because their minimum investment requirement for a managed future fund is very low, such as $2.000. These funds charge front-load and back-load fees like mutual funds (Edwards and Liew, 1999b). Some managed futures guarantee the initial investments. Similar to mutual funds, they must issue prospectuses. Since they are offered to public, they must be registered with the SEC; and moreover Commodity Futures Trading Commission is a regulatory body over these funds. These funds represent about 15% of all managed futures (Chance, 1994).

Second, an investor can place funds in a private commodity pool operator (CPO). CPOs pool investors’ money and hire commodity trading advisors (CTAs) to manage the pooled money. The required minimum investment amount for a CPO is usually higher than a managed futures fund (Edwards and Liew, 1999b; Kat, 2004). The minimum required amount may change from hundreds to thousands. These pools work like hedge funds; they are usually offered to a limited number of investors due to the limitations in number of investors in Investment Company Act of 1940. CPOs are usually organized as limited partnerships, like hedge funds, which limits investors' liabilities to the amount they initially invested (Rosen, 1983b). The pools have to be registered to CFTC and NFA. CPOs represent about 55% of all managed futures accounts (Chance, 1994).

Lastly, an investor can hire a private CTA to manage her money on an individual basis. Since the CTA is managing one person's or a small number of people's money, he sets a very high minimum investment requirement, usually at least $1 million. The minimum required investment is usually so high that only institutional investors or high net worth individuals can invest in private CTA accounts, just like hedge funds (Edwards and Liew, 1999b; Kat, 2004). One advantage of a private CTA account is that arrangements are customized to the investor, and investor can bargain for the best terms. Individual accounts comprise about 30% of all managed future accounts (Chance, 1994). Contrary to hedge funds, these accounts are regulated by the CFTC; and therefore subject to regulation and supervision.

It is also possible to invest in passive managed future indexes. The most famous managed futures index is MLM, which is based on actual market prices for a basket of passively traded futures contracts consisting of commodities, global bonds, and currencies (Ingarm, 2009). However, the differences between returns of indexes (tracking errors) and CTAs could be quite large (Schneeweis and Spurgin, 1997)

The legal definition of a CTA and CPO can be found under Commodity Exchange Act Sec. 1a [7 U.S.C. 1a] Definitions. A CTA is any person who, for compensation or profit, advises others directly or through publications, writings or electronic media as to the value of or the advisability of trading in commodity futures and options using leverage. Practically, a CTA is a professional money manager, whose expertise is in futures market (Chance, 1994). A CPO is any person engaged in a business that is of the nature of an investment trust, syndicate, or similar form of enterprise, and who, in connection therewith, solicits, accepts or receives from others, funds, securities, or property, either directly or through capital contributions, the sale of stock or other forms of securities, or otherwise, for the purpose of trading in any commodity for future delivery on or the subject to the rules of any contract market or derivatives transaction execution facility, except that the term does not include such persons not within the intent of the definition of the term as the Commission may specify by rule, regulation, or order. Practically, a CPO is an experienced CTA, who organize private commodity pools and promote the product to investors (Chance, 1994).

CTAs and CPOs are regulated by government entities and an industry-wide self-regulatory organization. The Commodity Futures Trading Commission (CFTC) is the government entity responsible for regulating commodity trading. The national Futures association (NFA) is the self-regulatory organization responsible for regulating futures markets. [Public pools are considered “uncovered securities” and are therefore regulated by individual state regulators, the Securities and Exchange Commissions (SEC), the CFTC, the NFA, and the Financial Industry Regulatory Authority (FINRA)]. All CTAs have to register to CFTC, and those CTAs who manage customer accounts must be members of the NFA.

Similarities and Differences Among Managed Futures, Mutual Funds and Hedge Funds

Investment methods of managed futures resemble both mutual funds and hedge funds. There are three types of investments in managed futures industry. A managed futures fund is similar to a mutual fund from many aspects, whereas a private CTA is very similar to a hedge fund investment. CPOs are similar to both mutual funds and individual CTA accounts, but in principal they work like CTA accounts.

Public managed futures funds have fee structures, legal sanctions, and customer profiles very similar to mutual funds. After the repeal of Short-Short rule, mutual funds use more derivatives in their investments; so the similarity soared after the repeal. The repeal of Short-Short Rule reinforced the similarities between mutual funds and managed futures funds. On the other hand, there are also private pools and individual managed futures accounts, which resemble more of hedge funds. Fee structure of private CTAs and public CPOs is similar more to hedge funds. CTAs charge 2% management fee of AUM and 20% incentive fee on annual profits, just like hedge funds (Edwards and Liew, 1999b). Both hedge funds and managed futures are marketed as alternative investment vehicles which are not correlated with stock and bond markets. However, the difference is originated from the legal definition and regulations on CTAs. As hedge funds are imposed almost no regulations, CTAs are subject to strict ones. Both funds are restricted from enlarged marketing.

The first difference between hedge funds and managed futures is about custody of funds. Investors hand over their money to the fund manager in hedge funds. It becomes fund’s money until the investor quits the fund. In turn, the investor has a share of fund’s total assets. It is costly for an investor to quit a fund. On the other hand, the investor does not submit her money to the fund in an individual managed future account. Investors are generally required to have a futures commission merchant (FCM) as a custodian of the fund. The FCM has the custody of funds, but the CTA has right to access the account and place orders on it (INGARM, 2009). She keeps her money in her account; the fund manager has a right to access the account and place orders on it.

(Investor can check her account every day close to see the changes. Commodity pools can be regarded similar to hedge funds. CPOs pool the money, investors have shares on the total assets, and CTA runs the pool’s money that belongs to CPO) (Barclays Capital, 2011; Attain Capital, 2011).

A drawback to the investor owning her own account is the fiduciary liability. Hedge funds are constructed as limited liability companies; however private CTA investors have to cope with the sudden liquidation burden. Investors have to conduct the due diligence process on their own; they must choose the CTA and all other responsible people and authorize them, the liability is on the investor (Barclays Capital, 2011).

A hedge fund does not have to register any state institution or organization. However, a CTA has to register to CFTC and NFA in order to offer a managed futures program. A public managed futures fund also has to register to SEC. The registration requirement reduces fraud risk, yet it imposes more restrictions on managed futures, such as types of assets and amount to invest; communication and performance reporting (Barclays Capital, 2011).

Managed futures can invest only in exchange traded markets. However, there is a growing over-the-counter (OTC) market including derivatives such as forward contracts on commodities or currencies, equity derivatives, credit default swaps (CDS), interest rate and return swaps. The only exception to this rule is swaps markets. After the Dodd-Frank Act was enforced, managed futures can invest in swaps markets upon required authorization. However, hedge funds can always invest in both exchange traded markets and OTC markets. This difference makes hedge funds more profitable and riskier than managed futures (Managedfunds, 2012).

Because managed futures do not take over investor’s money in their accounts, investors can liquidate in a few days or in a night in many cases, without even consulting the fund manager. On the other hand, liquidation can take months (lock-up period is 1 year in many hedge funds) in hedge funds, and it can be a complicated process. Early withdrawals can also be punished by redemption fees in hedge funds. Therefore, managed futures provide much more liquidity to investors than hedge funds do. The easiness in liquidation is expected to lower average managed future returns compared to hedge fund returns. The lock-up period and redemption fee requirements allow hedge funds to invest in illiquid assets, and yield higher than managed futures (Economist, 2007). Managed futures invest in more liquid products such as stock indexes, fixed income, and commodity derivatives (CME, 2012; Barclays Capital, 2011).

Neither hedge funds managers nor managed futures managers have to reveal their trading strategies. However, managed futures investors can see their positions at the close of every day, because they keep the custody of their money and see the account balance every day-end. Moreover, regulations and supervisions bind them. Therefore, the trading process is more transparent than hedge fund trading process. Since hedge funds do not have to report to any regulatory agency, it is difficult for investors to keep track of them (Barclays Capital, 2011; Attain Capital, 2011).

Hedge funds can use more leverage than managed futures use. Both hedge funds and CTAs use leverage via margin trading or short selling. In CTA accounts, both margin trading and short sales are realized based on investor’s permission. The permission can be acquired through the service contract. Investors determine the conditions of their contracts (Barclays Capital, 2011). Therefore, leverage is limited to investor’s risk appetite. On the other hand, hedge fund managers can use leverage based on their own risk appetite, without any knowledge of the investor. Leverage has a positive effect to increase returns whereas it can cause problems, such as margin calls in crisis periods (Barclays Capital, 2011; Attain Capital, 2011).

Hedge funds can invest in bulk amounts; therefore, they move the market dynamics; however managed futures usually do not invest in bulk, due to the regulations of NFA and CFTC. Their investments are well-diversified, and usually does not exceed 1% of their assets under management. So, they do not harm the markets they invest in. Some studies of investment firms, such as Attain Capital Management (2011), measure the correlation between hedge funds and managed futures close to zero. This shows that managed futures market is very different from hedge fund market.

Because hedge funds carry more risks than managed futures, their returns and risks are expected to be higher. Even though both asset types are marketed as absolute return instruments, many times managed accounts are perceived as diversification instruments whereas hedge funds are perceived as absolute return assets. In line with the perception, there is a rank order in the success of funds. Hedge funds almost always outperform mutual funds (Schneeweis and Spurgin, 1998; Ackermann et al, 1999) and they always beat the market after the internet bubble (Huang and Wang, 2013). Investment in derivatives increases efficiency, it is not due to advisor opportunism (Deli and Varma, 2002). Managed futures outperform mutual funds. Some research about subgroup of funds support this finding: Funds that resemble hedge funds, for example hedge fund mimicking mutual funds outperform mutual funds; however, underperform hedge funds (Agarwal et al., 2009).

Liability on complexity of hedge funds is on the shoulders of hedge fund managers. However, the complexity and costs of a managed futures is shared by the investor, money manager, and the third parties related. The third parties may be prime broker, custodian, fund administrator, or a managed account platform. In addition to complexity of managing these people, infrastructure and manpower problems, data collecting and analysis might also be a burden on the investor (Barclays Capital, 2011).

Regulation in The Financial Services Industry

During the stock market crash of 1929 and the following Great depression, many investors lost their fortunes in the securities markets, and the country had to pay the price for mal-or mis-practices in the industry. Starting from 1933, a process of regulation is ongoing. By every amendment or new law, the system is progressing to respond the up-to-date requirements of the investors. This section gives a brief chronology about the development in securities law in the US.

<u>Grain Futures Act of 1923:</u> After the Chicago Board of Trade was established in 1948, futures and forward trading started. However, such activities were perceived as gambling and were subject to several banning through time (Stassen, 1982). In order to settle the disputes in the industry, the Act was legislated, so that futures market was settled on a ground. The law was repealed and replaced by Commodity Exchange Act of 1936.

<u>Securities Act of 1933:</u> The aim of the Act is to preserve investor rights. In order to protect investors, it imposes registration process. Registration provides transparency for the securities offered for public sale, and prohibits all kinds of fraud in the sale of securities. Registered companies have to disclose a description of the business (prospectus), its properties, assets to be offered for sale, information about the management, and certified financial statements. The exemption of the registration includes private offerings to a limited number of

investors, such as hedge funds; governmental securities; intrastate offerings or offerings of limited size.

Even though the Act enforces rules for registration, the body of registration, SEC, was formed based on Securities Exchange Act of 1934.

<u>Securities Exchange Act of 1934:</u> This act regulates the rules that govern securities exchanges, brokers, and dealers. However, the most important contribution of this act to the securities industry is the foundation of SEC. By enforcing this act, The Congress formed and empowered the SEC with broad authority to register, regulate, and oversee many financial institutions and self-regulatory organizations in the finance industry. The SEC is the body that executes the regulations determined in Securities Act of 1933.

<u>Commodity Exchange Act of 1936:</u> Several amendments were required to Grain Futures Act of 1923 in the aftermath of the crisis. The new Act embraces all goods in futures markets and was more restrictive in operations in favor of consumers (Stassen, 1982). The Act is still in force.

<u>Public Utility Holding Company Act of 1936:</u> This act basically regulated electric utility industry; however, it also regulated utility of holding companies in regulated businesses, such as investment holding companies. The act was repealed and replaced by Energy Policy Act of 1992. Investment Company Act of 1940 took on the duty of regulating investment companies before the act was repealed.

<u>Revenue Act of 1936:</u> The purpose of the Act is to regulate revenues of companies and individuals. Companies were held subject to taxes on net income, excess profits and capital stocks; whereas individuals were subject to taxes on revenues from corporation dividends (Blakey and Blakey, 1936). Mutual funds are organized as pass-through entities by means of this

Act: They do not incur any taxes; rather investors are subject to pay taxes on capital gains and dividends they earn as if they earn it from their personal accounts (Koski and Pontiff, 1999).

Trust Indenture Act of 1939: This act regulates fixed-income security issuances, in which fund industry is very interested. However, it does not regulate the fund industry directly. It regulates the trust indenture, which is an agreement between the issuer and the holder of fixed income securities in a public sale.

Investment Company Act of 1940: The motivation of this act is to regulate the organization of investment companies, whose securities are offered to the public. The act focuses on disclosure of financial statements, registration to the SEC, investment policies and objectives, other public information, company structure and operations. The act also defines interested persons to a fund, and restricts some activities of interested people in order to avoid fraudulent activities. SEC was founded by the Securities Act of 1934; however, its scope of oversight on funds is enforced by Investment Company Act of 1940.

Investment Advisers Act of 1940: This Act defines the term "investment advisor" and requires investment advisors to register to the SEC. Advisors who manage at least $100 million of AUM or who work for a registered investment company must register to the SEC. Hedge fund managers are exempt from this law. Together with Investment Company Act of 1940, this law requires both investment companies and investment advisors to register to the SEC. By this means, private funds are also monitored by the SEC.

Commodity Exchange Act of 1974: The Act was legislated in order to amend the Commodity Act of 1936. The most significant contribution of the Act is the establishment of Commodity Futures Trading Commission (CFTC). The CFTC was officially founded in 1975 as a regulatory jurisdictive body over futures markets (Stassen, 1982). The Act was amended in 1982 and 2000 in order to extend the life of the CFTC (Rosen, 1983a) and legislative operations to hybrid instruments and swap transactions.

<u>Taxpayer Relief Act of 1997:</u> The concern of the Act mainly about percentage taxes on individuals. More importantly, it repealed the Short-Short Rule (Internal Revenue Service Code 851 (b) (3)) on mutual funds. This repeal paves the way for derivatives use in mutual fund industry (Koski and Pontiff, 1999).

<u>Sarbanes-Oxley Act of 2001:</u> The Act enforces reforms about corporate social responsibility, financial disclosures, and precautions for accounting fraud. The act regulates auditing profession as a part of its objectives.

<u>Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010:</u> The act focuses on consumer protection, trading restrictions, credit ratings, corporate governance, transparency, regulation of financial products, and more. The act allows managed futures to invest in swap agreements, which is an OTC product. The CFTC is working on other OTC products to make them available for CTAs.

<u>Jumpstart Our Business Startups Act of 2012:</u> The act aims to help businesses raise funds in capital markets by reducing regulatory requirements.

LITERATURE REVIEW

Performance Analysis of Managed Futures Funds

The first study conducted on managed futures funds was prepared by Lintner (1983). He prepared his paper in order to demonstrate the performance of managed futures funds/ accounts to the finance community. In his paper, he shows that a portfolio of managed accounts would have a large return/ risk ratio than a well-diversified stock portfolio. He also notes that the same ratio is higher for a well-diversified stock portfolio than a well-diversified bond portfolio. Moreover, there are additional benefits of managed futures accounts, such as they increase the return/ risk ratio of a traditional portfolio when added. They substantially reduce the total risk. Such augmented portfolios dominate stock- or bond-alone portfolios by using very considerable margins. Thus, managed futures funds are successful as a standalone asset class, but the funds perform magically in asset portfolios: They increase the reward-to-risk ratio of traditional portfolios. The results hold for nominal and real terms as well as risk-adjusted returns.

Lintner's study was echoed back by many researchers. Some researchers analyzed managed futures funds as individual assets. Results are contradicting: Many researchers find that CTAs and managed futures funds are successful individual investment vehicles (Schneeweis et al., 1991; Edwards and Liew, 1999a; Lamm, 2005; Gregoriou et al., 2010; Till and Eagleeye, 2011; Martellini and Vaissie, 2004). On the other hand, many other researches find that CTAs and managed futures cannot provide any positive excess returns; they are usually beaten by the market or even bond portfolios (Murphy, 1986; Elton et al., 1987; Edwards and Liew, 1999b; Kat, 2004; Christopherson et al., 2004; Bhardwaj et al., 2008; Irwin et al., 1993). It is noteworthy that all databases are limited and analysis periods of sturdies vary by time.

Risk and return studies concentrate more on portfolio analysis and benefits of diversification as Prof. Lintner recommends them as portfolio assets. Some studies find CTAs and MFFs enhance risk-return tradeoff of portfolios (Irwin and Brorsen, 1985; Schneeweis et al., 1991; Schneeweis and Spurgin, 1999; Edwards and Park, 1996; Edwards and Liew, 1999b; Schneeweis, 2001; Liang, 2003; Kat, 2004; Rollinger, 2012; Christopherson et al., 2004; Lamm, 2005; Schneeweis and Gupta, 2006; Martellini and Vaissie, 2004). Scherer (2013) imply that there is no such thing as over-diversification in CTA industry; as risk-aversion increases, the number of CTAs may increase. There are contrary findings as well. Though general perception of CTAs being appropriate diversification assets, some researchers conclude that CTAs and MFFs do not affect volatility so they do not enhance the diversification benefits of portfolios and moreover reduce the overall return (Murphy, 1986; Elton et al., 1987 and 1990; Irwin et al. (1993). It is noteworthy to repeat that methods to measure performance, weights of assets in portfolios and analysis periods of analysis vary in all of these studies.

The relationship between asset classes and inflation is important, especially when we consider their performance in up and down markets. CTAs and MFFs have negative relationships with inflation, in contrast to other asset classes. The behavioral difference between standard assets and commodity futures causes a positive correlation between inflation and commodity futures. This would make commodity futures good hedgers against inflationary pressures (Gorton and Rouwenhorst, 2005; Kat and Oomen, 2006; Erb and Harvey, 2006). Edwards and Park (1996) measure correlation between standard assets and managed futures funds and they find the same results: Managed futures are good hedges against inflation whereas common stocks are not. On the other hand, Bernard and Frecka (1987) point common stocks can also hedge against inflation as well as commodity futures.

Some authors argue that managed futures perform better than other asset classes in hard economic times. Schneeweis et al. (2013) show that CTA performance is temporal; in order to understand the current shifts in the market, performance analysis should be repeated time to time. Edwards and Liew, 1999a; Liang, 2003; Christopherson et al., 2004; Bhardwaj et al., 2008; Till and Eagleeye, 2011) state that CTAs are better downside protectors than hedge funds. Their reasoning is that CTAs have low correlation with other assets; and the correlation coefficients are especially negative in down markets. Jensen et al. (2003) argue that futures (and indirectly managed futures funds) have a time-varying effect in portfolio performance. They increase the performance in restrictive monetary environments whereas mitigate performance under expansionary monetary policies. Hübner and Papageorgiou (2004) find that performance of CTAs changes in different states of the world. Mayer (2009) observes that money managers make more speculation in commodity markets when prices are higher. Commodity prices are usually higher when stock market is down. This observation indicates a time-varying feature of managed futures funds. Bjornson and Carter (1997) find that expected returns to commodities are lower in high interest rates, expected inflation, and economic growth. Therefore, commodities are natural hedges against business cycle risks. Martellini and Vaissie (2004) find that financial and macroeconomic factors' exposure on CTA returns evolves over time. Therefore, they do not suggest using multi-factor models in CTA return prediction.

Performance of CTAs and MFFs against inflationary pressures pose a question for their behavior in business and monetary cycles. Jensen et al. (2000, 2002, and 2003) examine monetary policy and benefits of futures. They differentiate between expansionary and restrictive monetary policies by using interest rate changes. Then, they compute averages and standard deviations of assets in these periods and compare the results. They find that managed futures behave contrarily to standard asset classes, and therefore they hedge against business cycle risk. Vrugt et al. (2004) analyze dynamic commodity strategies in expansion and contradiction periods by using several parameters. They find that volatility of commodities is high and therefore it is possible to come up with different investment strategies with commodities. Their results are in line with earlier studies: Commodities hedge against business cycle risk and they contribute traditional portfolios a lot in terms of diversification.

It is possible to rank order CTAs, CPOs, and MFFs. The order is that CTAs perform the best whereas MFFs perform the worst. Performances of CTAs and CPOs are comparable but the underperformance of MFFs is significant (Edwards and Park, 1996; Edwards and Liew, 1999a). Edwards and Park believe that the underperformance of MFFs lies under the high cost structure. (Bhardwaj et al., 2008) support his idea and claim that high fees take all the profits away from MFF industry.

Some studies argue that CTAs and MFFs are positively skewed; therefore, they are preferred by investors. Even though they do not generate higher than market returns; their positive skewness make them lottery-like assets, so the demand for CTAs and MFFs do not reduce in time (Lamm, 2005; Bali et al., 2011; Bhardwaj et al., 2008). On the other hand, Elton et al., (1990) find that MFFs have negative skewness.

Managerial Skill and Persistence

Maybe because there is no direct measure of managerial skill, researchers have not directly examined it in CTAs and MFFs. However, persistence is studied as a partial measure of managerial skill. We can split earlier literature as managerial skill literature and persistency literature.

Managerial skill literature concentrates basically on hedge funds and mutual funds. Many researchers measure managerial skill by using Jensen alpha as long as it is persistent throughout time. Jensen alphas are computed as using factor regressions. Positive and significant alphas refer to successful funds. But the source of success is not known. If the success is sustainable over time, then managerial skill is accepted as a likely source of success. Moreover, the factors that affect managerial skill can also be detected by using regression analysis. Incentive fees in hedge funds (Edwards and Çağlayan, 2001) and managerial compensation in mutual funds (Berk and Binsbergen, 2012) are important factors that is related with managerial skill. Aggarwal and Jorion (2010) examine managerial skill of emerging hedge funds by using this measurement. They compute abnormal returns of hedge funds and check persistence of Jensen alphas in cross section. They find that emerging hedge fund returns are significantly higher than established hedge fund returns. They also find persistency up to 5 years in emerging hedge funds but performance loses its persistence after the first 5 years. Arnold (2012) makes a large analysis of systematic versus discretionary CTAs in terms of their performance and persistency. She finds that CTAs are absolute positive value funds under several multi-factor models. There are managerial alphas in many funds. Additionally, she finds persistency in fund returns and alphas. So, she concludes that there is managerial skill in the CTA industry.

There are other measures of managerial skill. Titman and Tiu (2011) argue that hedge funds less exposed to systematic factor risks have better information than other hedge funds. The hedge funds that show lower R^2s from factor models have higher Sharpe ratios, information ratios, manipulation-proof performance measures (MPPMs) and managerial alphas. These funds also charge higher management and incentive fees. Avramov et al. (2011) examine managerial skill and effect of macroeconomic variables in the hedge fund industry. They argue that hedge fund managers should be evaluated under the effect of macroeconomic variables such as default spread and volatility. They classify investor types with different beliefs about managerial skill and predictability. Predictability is modelled based on macroeconomic factors. The strategy that allows for predictability in managerial alpha, fund betas, and benchmark returns outperforms other strategies by selecting positive and significant alpha funds. Agarwal et al. (2011) show that hedge fund managers inflate December returns in order to reach their hurdle rate and earn incentive fees by the end of the year. Their results are valid for high incentive fee hedge funds. This result brings a different interpretation for the hypothesis that the incentive fee has a positive effect on fund returns. Hedge fund managers inflate their returns on December by mostly “saving” (accruing reserves) over the months prior to December if they are high enough. Sun et al. (2012) measure a strategy distinctiveness index (SDI) based on hedge fund strategies. Each strategy is assumed to be a cluster and SDI measures the distance from each hedge funds returns to cluster’s average returns. It is defined as 1 minus the correlation coefficient between each fund and cluster. They show that SDI increases in funds’ returns and persistency; therefore, it can be used as a measure of managerial skill. There are many determinants of SDI such as incentive fee and age. They suggest SDI as a future-looking, fund-specific variable to detect managerial skill in a hedge fund selection period. Brown et al. (2001) analyze competition and risk in terms of career and survival issues in hedge funds and the CTA industry. They control age, volatility, and absolute and relative performance by means of high watermark return benchmark and median return benchmark. An important contribution of this paper is that both hedge fund and CTA managers care about relative return compared to absolute return. The funds that have lower-than-median returns take excessive risk in the second half of the year in order to increase their returns. And the funds that have higher-than-median returns reduce their volatility in the second half. But this is not true when the authors break up firm returns from their high watermark ratios. Funds do not change their risk level in order to reach for high watermark rate. The results suggest that absolute return is not as important as relative performance. This finding contradicts with the perception that defines hedge funds as market neutral and hedge funds managers care about absolute returns. The authors also find that CTAs are more sensitive to short-term poor performance whereas hedge fund managers are interested in longer-term performance. This fact probably originates from the legal differences. Hedge funds do not have to report their returns; however, CTAs are forced to inform their clients regularly. On the other hand, hedge funds are more sensitive to marginal risk than CTAs are, and higher risk is a factor for termination of hedge funds, whereas CTAs are not affected that much.

Many researchers argue that there is persistence in CTA and MFF returns. Gregoriou et al. (2010) measure return and persistence of CTAs by categories. They find that 9 out of 12 categories outperform the market by using CAPM equations and FF 3-factor and Carhart 4-factor models). They find positive and significant alphas from regressions. They apply winner-and-loser contingency tests to measure persistency in alphas (not returns). They run the analysis for 1-, 3-, 6-, and 12-month periods. They find that persistence in alphas is observable for 3 months and longer periods, but not shorter periods. Thus, they find a significant difference between 1-month persistence and 3-month persistence. They also apply acid-test to measure persistency in top-quartiles. But the results are not affirmative. There is no persistence in extremes. Pojarliev and Levich (2007) analyze only managed currency funds and they come up 4 factors that explain positive alphas of these funds. These factors are carry trade returns, trend-following returns, volume-trading returns, and currency volatility. Still there is some positive and significant alpha that these factors cannot explain. The authors refer to this residual alpha as managerial skill.

Contrarily there is evidence that there is no persistence in CTA and MFF returns (Elton et al., 1987; Bhardwaj et al., 2008; Irwin et al., 1994; Brorsen and Townsend, 1998; Brorsen and Townsend, 2002). Irwin et al. (1994) analyze 363 CTAs for an 11-year period to analyze persistence and predictability of returns. They use correlation and portfolio analysis in their study. Their results suggest that returns and correlations prove little evidence of predictability but standard deviations are predictable for almost all holding periods. They come up with three primary implications for CTAs. First, a naïve strategy would not help investors select profitable CTAs in the future. Second, investors have to search for additional information to help them choose a more persistent (in returns) CTA. Third, CTAs have their specific risk in selection. Strategies for selecting CTAs that have their own risks consistent with an investor's risk tolerance are likely to be successful. Brorsen and Townsend (1998 and 2002) use regression analysis, Monte Carlo simulations, and some out-of-sample tests as Elton et al. (1987) to check the persistency in CTA and MFF returns. They also explain return and risk attributes by some CTA characteristics, using OLS. Their analysis show that there is some performance persistence, but it is small relative to noise in the data. Return/risk measures, such as appraisal ratio (α/σ) show more persistence than returns.

Some researchers show that persistence in CTA and MFF returns is temporary and may change over time (Lamm, 2005; Marshall et al., 2008). Lamm (2005) claims that positive skewness and kurtosis are an origin for CTA returns. He develops theories to explain why both trend-followers and discretionary CTAs earn momentum profits. He argues that loss-limit orders are a source of persistent returns. He also notes that persistence of trading patterns may change over time, so there is short-term persistence; the return pattern is contemporaneous. Therefore, data should not be extrapolated into the future. Marshall et al. (2008) argue that even though futures have diversification benefits, their profitability is sustainable at short-term contrarian strategies or medium-term momentum strategies. The reason for this short-term persistence is data-snooping bias. It is possible that there are very successful individual CTAs that yield higher than average. But for the entire industry, the success rate is lower than that which could be generated by chance. Commodity futures are not the only market, in which CTAs and MFFs invest; but also these funds use short-selling and leverage which would reverse or reduce momentum or reversal profits. The findings for CTAs and MFFs should be expected to be time-varying and not-persistent.

Diz (2003) looks at managerial skill from a different perspective. He finds that CTA leverage is positively related to performance. CTA diversification leads to higher levels of leverage and volatility. However, leverage is negatively related to survival. This affects managers' decision making and alphas.

McCarthy et al. (1997) use 40 CTAs to compare their pre- and post-selection returns. They use an adjusted beta measure and several risk measures. When data are selected based on historical beta and standard deviation, post-selection returns underperform historical returns. However, they also add that the amount of upward bias is based on the different approaches in portfolio selection and measurement. Beta adjusted models show a more persistent return relationship between past and future. They suggest that pre-selection returns are still beneficial to forecast pro-forma return distribution; however, investors should take "selection bias" into consideration when they decide. Measures based on naïve projections would overestimate future returns.

Abdou and Nasereddin (2011) use a support vector machine approach to measure the persistence of hedge fund strategies in different economic periods. Their results show that many hedge fund strategies are non-persistent through economic periods.

Predictability of Future Returns

Some authors compare managed futures funds with hedge funds. Comparison is an easy way of understanding one of the two similar assets. Hedge funds are well-known by many investors, but managed futures funds are not so much popular. We believe, these studies help understand the features of managed futures industry. Edwards and Liew (1999) find that both managed futures and hedge funds are successful standalone investments but hedge funds have better performance. They find a decreasing rank order in Sharpe ratios of hedge funds, CTAs, CPOs, and publicly traded managed futures funds. The difference between hedge funds and managed futures is their correlation with traditional asset classes. Hedge funds are positively correlated with traditional assets, usually correlation coefficients are high. However managed futures funds have low or even sometimes negative correlation with other asset types, including hedge funds. They argue that the diversification power of managed futures come from this negative correlation with other assets. Brown et al. (2001) compares hedge funds and CTAs in terms of career and survival issues. They find that the attrition rates of CTAs are higher than those of hedge funds. CTAs are more sensitive to short-term poor performance; whereas hedge funds are more sensitive to marginal risk: CTAs have to provide frequent performance reports; it is likely to be a reason of liquidation after short-term poor performance. (Supporting this finding, Chong and Miffre (2010) find evidence that futures provide diversification benefits for short investment periods, the benefits reduce as investment periods get longer). On the other hand, the positive skewness might protect them from marginal risk. They find a common characteristic between these two funds: They care about relative performance rather than absolute performance: Funds that perform less than median returns take excessive risk; but funds that perform less than high water mark do not take any action. That shows the importance of relative performance.

Bhardwaj et al. (2008) find evidence to support this fact: High water mark is not a signal for higher performance. In their paper, Bhardwaj et al find almost zero excess returns in the CTA industry. The low performance is explained by high fee structure: High fees sweep away the profits originated by managerial skill. The authors are surprised by the permanent inflows to the industry. They explain the inflows to the CTA industry as a conclusion of misinformation and misperception, partly by data vendors due to survivorship and backfill biases and partly by the skewness of the funds. Positive skewness attracts investors with less frequent but high positive returns. Schneeweis (2001) argues that hedge funds do not provide diversification benefits, and they can be categorized into groups by their styles. Future return patterns can be predicted at least within styles. However, it is not possible to classify CTAs in that way. Most CTAs are trend followers by nature. The diversification benefits of CTAs can increase if trend followers can be distinguished from other styles. A blend of trend followers and other styles would provide higher diversification benefits. Liang (2003) finds that CTAs are slightly or even negatively correlated with hedge funds. CTA strategies are different from hedge fund strategies. He suggests using option trading factors in explaining CTA returns, and argues that option trading factors have no power in explaining hedge funds. Bali et al. (2012) show that option trend following factors cannot explain the variability in hedge funds). Liang finds that attrition rates of CTAs are higher than hedge funds; however, attrition rates of CTAs in bear markets are much lower compared to hedge fund attrition rates. The possible reason is that CTAs are negatively correlated with other assets and hedge funds in bear markets. Therefore, CTAs are good candidates of downside risk protectors. Christopherson et al. (2004) compare risk and return metrics of hedge funds and CTAs. Both risk and return measures of hedge funds are more preferable than those of CTAs. However, due to the negative correlation of CTAs with other assets, they provide downside protection and diversification benefits, and therefore they should be included in portfolios.

There are papers that find common factors that would help predict future fund returns of managed futures. For example, Elton et al. (1987) find that standard deviations of managed futures funds are persistent through time; and they can be used to model estimation of future returns. Edwards and Ma (1988) and McCarthy et al. (1997) reveal a significant difference between pre-public returns and post-public returns of managed futures funds; however, they could not find a common factor for return estimation. Elton et al. (1990) find no relationship between fund returns, size, and experience of the general partner. However, the funds managed by partners with above-average prior experience outperform the funds managed by partners with below-average prior experience. This might be a sign for managerial skill or luck, even though they do not emphasize it. They conclude that fund returns are affected by the relative experience of the fund manager. Schneeweis and Spurgin (1999) reveal that MLM trend following index, USDX index, and intra-month standard deviation of the USDX are correlated with CTA returns; therefore, they can be used in predicting future CTA returns. Lamm (2005) argues that the style of CTAs does not matter in return prediction. Trend follower CTAs replicate straddles, and discretionary CTAs use loss limits in order to protect their returns. Independent of the style, all CTAs have high return and considerable risk, positive skewness and kurtosis. Hübner and Papageorgiou (2004) use a 5-factor market model (MRKT, HML, SMB, MOM and HDMZD) for bull and bear markets separately. The results are weak, and there is no consistently significant factor that explains fund returns. Moreover, they also use a three-moment factor in order to check the power of moments of excess return of the market index on fund returns. Multi-moment model results more powerful than multi-factor model however R^2 of the regressions are still very low. And there is no persistent significance between different states of the world. The authors additionally use several other factors to strengthen the power of the tests. We use some of these factors in this study. The authors find that these factors contribute a lot to increase the R^2 of the regressions. Martellini and Vaissie (2004) use S&P 500 index, a bond index, two currency indexes, and a commodity index in order to explain CTA returns. All factors were significant in parametric tests, however only S&P 500 index and bond index got significant results in non-parametric tests. They find that the exposure of the factors on fund returns is nonlinear. The exposure evolves through time, so one multifactor model may not be adequate to use in measurement purposes.

Fung and Hsieh (1997a) apply principal component analysis in order to determine investment styles of CTAs. The first component explains much of the variability in CTAs. So, there is only one dominant investment style in the industry. The authors argue that this style is a dynamic trading strategy since it is correlated with 2 of Fung and Hsieh hedge fund styles. They also argue that CTAs have option-like (u-shaped) return profile. Fung and Hsieh (2001) improve their findings and model hedge fund returns by using trend-following lookback straddles. They also find that many CTAs are trend followers.

The effects of systematic and unsystematic risk were not measured in managed futures industry. However, there are studies conducted for futures markets. Dusak (1973) analyze approximately 300 futures contracts between 1952 and 1967. Using CAPM, she finds almost zero systematic risk in futures markets. Depending on systematic risk, the returns were also close to zero. Bessembinder (1992) finds some evidence for systematic risk effects in futures markets. But the effect is not significant for all futures types. He argues that asset markets and futures markets may both be subject to the same degree of systematic risk due to the integration between these two markets (Domanski and Heath (2007) support this finding by arguing that commodity markets have become more like to financial markets in terms of motivations and strategies of participants). He also finds evidence for residual risk can have explanatory power on some futures types. Kolb (1996) analyzes systematic risk of futures contracts. He finds that both returns and futures markets betas are close to zero, prepondering to positive values. He employs CAPM regressions to determine the beta in futures markets. He also finds a negative relationship between systematic risk and returns. His findings are consistent with asset market findings; only futures are less exposed to asset market risks. Till (2000) studies the sources of systematic returns in commodity futures markets. She mentions systematic risk gains originated from futures indexes. However, she warns investors that more systematic gains can be earned in investing actively managed portfolios. Actively managed portfolios provide other gains independent from indexes. De Roon et al. (2009) measures hedging effects in futures markets. They find that after controlling for systematic risk and price pressure effects, hedging pressure effects were still significant for both intra-industry and cross-industry. Hedging pressure effects were also significant for underlying assets (Therefore, there is reason to believe that managed futures funds are also exposed to hedging pressure effects). The authors measured systematic risk by following Black Scholes (1972) model. Beta for market risk premium was not significant in their analysis. However, this study can be extending to factor models. It is expected to find significant systematic or unsystematic risk effects in managed futures industry.

Mayer (2009) argues that money managers are not interested only in diversification, but they enter the market for speculation, especially in times of economic distress, when commodity prices are higher. Though not directly related, this argument highlights the importance of systematic and unsystematic risk. Distress periods might be potential candidates for one of the two risk factors are extremely important.

CHAPTER 2

DATA AND SUMMARY STATISTICS

This study uses commodity trading advisors (CTAs) and managed futures funds (MFFs) dataset from Lipper TASS (Trader Advisor Selection System) database. The Lipper TASS database distinguishes between CTAs and MFFs, yet presents them together. Return and AUM records, along with other fund wise characteristics, are kept starting from May 1973 permanently on a monthly basis. The database defines CTAs as individuals or firms, registered with the CFTC, who receives compensation for giving advice on options, futures and the actual trading of managed futures accounts. A CTA is a separately managed account. MFFs are defined as funds like mutual funds that accept positions in government securities, futures contracts, and options on futures contracts.

The analysis period of this study is January 1994 to December 2014. We start analysis in 1994 as the database started keeping the records of defunct funds on January 1994. Excluding records before 1994 from analysis period saves us from facing inevitable survivorship bias.

The database contains 1250 MFFs and 1183 CTAs, in total 2433 funds. 2003 of the all funds are from the graveyard database, and 430 of them are alive as of December 31, 2014. Table 1 shows the numbers of live and dead CTAs and MFFs in the database. We deleted funds that do not report any returns or AUM. The total assets under management, as of December 13, 2014 are $103 billion.

Table 1: Number of CTAs and Managed Futures in Lipper TASS Database

	Live Funds	Graveyard Funds	Total Funds
MFFs	342	912	1254
CTAs	88	1395	1483
Total	430	2307	2737

In order to compare CTAs' and MFFs' returns with those of standard asset classes, we use proxies for standard assets. Indices that represent stock markets are value-weighted CRSP (CRSP), U.S. Small Stock Market Index (Russell2000), and developed market stock index (MSCI World index). Fixed income market is represented by long-term (10 year) government bond returns (LT Gov Bond) and corporate bond (BUSC) indexes. We also use a foreign exchange index (DXY Curncy index), which is an index of the value of the USD relative to a basket of foreign currencies. This index represents FX market in our model.

Table 2 shows summary statistics of CTAs and MFFs. Table 2-Panel A reports the total number of CTAs and MFFs existing in the database at the beginning of a year, entrances and exits into and from the database within a certain year, total assets under management (AUM) as of the year end. Between 1994 and 2014 total number of funds declined from 675 to 390. In contrast to this decline, AUM increased from $19 billion to$103 billion. This can be an indication for elimination of small CTAs and MFFs. Small funds are replaced by bigger funds. The subprime mortgage crisis has a positive effect on the growth rate of the industry. However, there is a sharp decline in total AUM after 2011: The total AUM declined to $102 billion from $169 billion in 4 years.

The right hand side of the table shows descriptive statistics on the equal-weighted CTA and MFF portfolio. Average returns are highest in crisis years: The mean return is 1.11% in 1997; 0.95% in 2000; 1.20 in 2008, which can be described as crisis years. The last two columns, minimum and maximum, show that there are funds making big losses and profits each year in the industry, regardless of market conditions.

Panel B of Table 2 displays the cross sectional statistics for CTAs and MFFs. Descriptive statistics for average monthly return and average monthly AUM over the life of a fund; age of fund, management fee, and incentive fee for all funds in the database can be found under this panel. Average monthly return over the life of a fund is 0,51%; the median is 0.42, with a standard deviation of 9,28%. Average assets under management is $81 million. Average life of a fund is 65 months, average management fee is 1.98%, and average incentive fee is 18.68%.

Table 2: Summary Statistics for CTAs and MFFs

Panel A: Summary Statistics Year by Year (1994- 2014)

							Equal- Weighted (EW) Portfolio Monthly Returns						
Year	**Year Start**	**Entries**	**Dissolved**	**Year End**	**Total AUM (Billion $)**	**Total Flow (Billion $)**	**Mean**	**Median**	**Std. Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
1994	675	434	418	691	19.00	1.63	0.29	0.00	2.10	0.25	-1.25	-2.42	3.88
1995	691	122	139	674	18.22	-1.70	1.22	1.31	2.37	0.77	0.45	-1.49	6.30
1996	674	96	142	628	20.68	0.94	1.11	0.53	3.23	0.11	-1.13	-4.11	5.75
1997	628	82	88	622	28.16	5.40	1.11	1.08	2.59	0.06	-0.05	-3.35	5.96
1998	622	66	101	587	31.99	1.13	0.94	0.57	2.65	1.20	2.94	-3.29	7.44
1999	587	111	93	605	34.43	1.57	0.10	0.47	1.97	-0.69	-0.10	-3.93	2.59
2000	605	42	90	557	31.83	-4.34	0.95	0.28	2.73	1.34	1.98	-1.90	7.56
2001	557	67	72	552	36.54	3.35	0.42	0.57	2.50	-0.56	0.44	-4.55	4.47
2002	552	67	64	555	44.72	2.71	1.25	1.09	3.12	0.25	-0.99	-3.30	6.53
2003	555	95	44	606	69.58	17.57	1.26	0.75	3.02	0.04	-0.64	-4.06	5.78
2004	606	123	61	668	100.88	26.85	0.49	0.06	2.60	0.01	-0.10	-4.29	4.75
2005	668	85	87	666	102.97	4.79	0.21	0.23	1.93	-0.42	0.20	-3.36	3.48
2006	666	87	79	674	124.94	12.72	0.71	0.94	1.99	0.08	-0.93	-2.28	4.14
2007	674	73	93	654	129.99	1.11	0.99	0.89	2.33	0.25	-0.50	-2.60	5.27
2008	654	73	86	641	126.73	-14.77	1.20	1.19	2.53	0.35	0.85	-3.07	6.51
2009	641	105	59	687	143.29	23.78	0.08	-0.52	1.93	0.51	0.05	-3.21	3.43
2010	687	95	67	715	164.19	6.87	1.98	0.87	5.59	2.30	6.62	-3.32	17.90
2011	715	57	102	670	168.87	22.40	-0.27	-0.56	2.24	0.56	-0.38	-3.37	4.04
2012	670	74	140	604	162.99	9.09	-0.31	-0.28	1.78	-0.42	-0.65	-3.22	2.12
2013	604	49	138	515	132.93	-24.06	-0.18	-0.30	1.58	-0.19	-0.26	-3.24	2.05
2014	515	15	140	390	102.73	-22.30	0.37	0.22	1.39	0.35	-0.55	-1.63	3.02

Panel B: Cross Sectional Statistics	**N**	**Mean**	**Median**	**Std. Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Average Monthly Return over the life of the Fund (Percent)	2433	0.51	0.42	9.28	45.54	2183.02	-31.58	445.82
Average Monthly AUM over the life of the Fund ($ Million)	2433	80.81	14.01	238.22	16.46	443.23	0.00	7590.17
Age of the Fund (Number of Months in Existence)	2433	64.90	48.00	56.20	1.35	1.38	1.00	252.00
Management Fee (Percent)	2045	1.98	2.00	1.25	2.15	19.19	0.00	16.63
Incentive Fee (Percent)	2367	18.68	20.00	6.81	-1.33	3.38	0.00	50.00

Table 3 provides the summary statistics only for CTAs. As Panel A suggests that the pattern for CTA returns and number of CTAs is similar to the pattern of all funds. Number of CTAs dropped from 491 to 68; however, assets under management increased from $13 billion to $44 billion. AUM decline sharply after 2011 from $67 billion to $44 billion. Equal-weighted portfolio monthly returns of CTAs are usually positive apart from 2011-2013. Panel B shows that average monthly return over the life of a fund is 0.81%, and the median is 0.49%, with a standard deviation of 13.20%. Average life of a CTA is 58 months, average management fee is 2.08%, and average incentive fee is 20.08%.

Table 3: Summary Statistics for CTAs only

Panel A: Summary Statistics Year by Year (1994- 2014)							Equal- Weighted (EW) Portfolio Monthly Returns						
Year	**Year Start**	**Entries**	**Dissolved**	**Year End**	**Total AUM (Billion $)**	**Total Flow (Billion $)**	**Mean**	**Median**	**Std. Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
1994	491	223	249	465	13.26	1.03	0.40	0.11	2.20	0.31	-1.00	-2.44	4.37
1995	465	80	115	430	12.27	-1.37	1.25	1.13	2.31	0.88	0.57	-1.50	6.28
1996	430	52	94	388	12.91	0.00	1.21	0.74	3.26	0.14	-1.04	-4.08	6.33
1997	388	41	58	371	17.34	3.40	1.12	0.94	2.49	0.43	0.08	-2.89	5.98
1998	371	33	64	340	18.22	0.25	0.84	0.63	2.55	1.14	2.47	-3.21	6.91
1999	340	47	56	331	18.20	1.09	0.11	0.32	1.97	-0.48	0.93	-4.11	3.42
2000	331	21	56	296	15.73	-2.75	1.16	0.51	2.75	1.32	1.87	-1.65	7.78
2001	296	38	51	283	16.97	1.16	0.53	0.62	2.30	-0.55	0.81	-4.12	4.49
2002	283	33	28	288	20.59	1.62	1.32	1.26	2.83	0.22	-0.88	-2.87	6.28
2003	288	36	28	296	30.39	8.23	0.96	0.73	2.29	-0.32	-0.04	-3.56	4.65
2004	296	26	40	282	40.93	9.67	0.58	0.36	2.21	0.21	-0.59	-3.02	4.16
2005	282	19	47	254	37.54	-0.87	0.24	0.08	1.73	-0.27	0.17	-2.95	3.09
2006	254	15	38	231	39.67	0.85	0.45	0.52	1.72	0.37	-0.50	-1.98	3.59
2007	231	17	48	200	38.60	-0.62	0.92	1.03	1.81	0.57	0.36	-1.48	4.76
2008	200	26	30	196	42.30	-2.34	1.49	1.36	2.10	0.58	1.23	-2.17	6.03
2009	196	22	23	195	43.85	2.77	0.31	0.31	1.66	0.67	0.58	-2.31	3.73
2010	195	39	34	200	59.77	13.30	4.85	0.37	15.18	3.41	11.71	-2.08	52.82
2011	200	21	36	185	67.44	10.90	-0.03	0.02	1.74	0.05	-0.87	-2.64	2.90
2012	185	8	61	132	58.22	-1.13	-0.15	-0.29	1.50	0.60	0.78	-2.50	3.07
2013	132	9	32	109	50.01	-8.50	-0.02	-0.27	1.06	-0.18	-0.75	-1.97	1.51
2014	109	4	45	68	43.76	-3.57	0.34	0.43	1.69	0.28	-0.47	-2.34	3.41

Panel B: Cross Sectional Statistics	**N**	**Mean**	**Median**	**Std. Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Average Monthly Return over the life of the Fund (Percent)	1183	0.81	0.49	13.20	32.49	1094.11	-31.58	445.82
Average Monthly AUM over the life of the Fund ($ Million)	1183	53.56	7.24	279.47	19.73	481.12	0.00	7590.17
Age of the Fund (Number of Months in Existence)	1183	58.47	39.00	54.39	1.52	2.09	1.00	252.00
Management Fee (Percent)	1091	2.08	2.00	1.11	0.55	1.76	0.00	6.00
Incentive Fee (Percent)	1171	20.08	20.00	4.45	-1.40	10.54	0.00	50.00

Table 4 provides the summary statistics only for MFFs. The pattern for number of MFFs is different from that of CTAs. Number of funds increases along with the total AUM through time. There were 184 funds in the industry at the beginning of 1994, the number increased to 322 at the end of 2014. Similarly, total AUM increased from \$6 billion to \$59 billion from 1994 to 2014. However, the increase is not monotonic: The number of funds makes a top in 2010 (515 funds), and AUM makes a top in 2012 (\$104,76 billion); and they both fall down afterwards. Panel B shows that the average monthly return over the life of a fund is 0.23%, with a median of 0.35%, and a standard deviation of 1.59%. Average assets under management of an MFF is \$107 billion. Average of a MFF is 71 months, average management fee is 1.85%, and average incentive fee is 17.30%.

Table 4: Summary Statistics for MFFs only

Panel A: Summary Statistics Year by Year (1994- 2014)							Equal- Weighted (EW) Portfolio Monthly Returns						
Year	Year Start	Entries	Dissolved	Year End	Total AUM (Billion $)	Total Flow (Billion $)	Mean	Median	Std. Deviation	Skewness	Kurtosis	Minimum	Maximum
1994	184	211	169	226	5.74	0.60	0.02	0.16	1.91	0.03	-1.77	-2.44	2.69
1995	226	42	24	244	5.95	-0.32	1.18	1.33	2.53	0.48	0.02	-2.09	6.33
1996	244	44	48	240	7.77	0.94	0.94	0.36	3.24	0.06	-1.12	-4.16	5.92
1997	240	41	30	251	10.82	2.00	1.09	1.29	2.84	-0.34	-0.18	-4.05	5.92
1998	251	33	37	247	13.77	0.88	1.07	1.09	2.87	1.19	3.04	-3.41	8.20
1999	247	64	37	274	16.23	0.48	0.08	0.57	2.11	-0.63	-0.80	-3.73	2.64
2000	274	21	34	261	16.10	-1.59	0.72	0.11	2.73	1.34	1.99	-2.17	7.30
2001	261	29	21	269	19.57	2.19	0.30	0.42	2.75	-0.53	0.06	-5.01	4.45
2002	269	34	36	267	24.13	1.08	1.17	0.91	3.45	0.29	-1.07	-3.79	6.81
2003	267	59	16	310	39.19	9.34	1.58	0.77	3.88	0.37	-0.49	-4.60	8.55
2004	310	97	21	386	59.95	17.18	0.41	-0.09	2.96	-0.16	0.23	-5.38	5.18
2005	386	66	40	412	65.43	5.67	0.19	0.41	2.10	-0.48	0.10	-3.65	3.73
2006	412	72	41	443	85.26	11.88	0.85	1.27	2.21	-0.02	-1.21	-2.46	4.48
2007	443	56	45	454	91.38	1.73	1.02	0.73	2.60	0.17	-0.73	-3.14	5.50
2008	454	47	56	445	84.44	-12.44	1.08	1.09	2.81	0.27	0.50	-3.46	6.73
2009	445	83	36	492	99.44	21.01	-0.01	-0.66	2.09	0.48	-0.08	-3.57	3.75
2010	492	56	33	515	104.41	-6.43	0.87	1.06	3.11	-0.42	-1.03	-4.51	4.86
2011	515	36	66	485	101.43	11.50	-0.36	-0.52	2.50	0.60	-0.34	-3.68	4.51
2012	485	66	79	472	104.76	10.23	-0.36	-0.28	1.90	-0.56	-0.61	-3.62	2.00
2013	472	40	106	406	82.92	-15.56	-0.22	-0.36	1.78	-0.08	-0.20	-3.58	2.42
2014	406	11	95	322	58.97	-18.74	0.38	0.35	1.36	0.39	-0.73	-1.43	2.92

Cross Sectional Statistics	N	Mean	Median	Std. Deviation	Skewness	Kurtosis	Minimum	Maximum
Average Monthly Return over the life of the Fund (Percent)	1250	0.23	0.35	1.59	-4.53	68.94	-25.14	11.63
Average Monthly AUM over the life of the Fund ($ Million)	1250	106.59	26.72	187.66	4.43	38.67	0.03	2660.86
Age of the Fund (Number of Months in Existence)	1250	70.98	54.00	57.21	1.23	0.91	1.00	252.00
Management Fee (Percent)	954	1.85	2.00	1.39	3.15	27.21	0.00	16.63
Incentive Fee (Percent)	1196	17.30	20.00	8.28	-0.90	1.01	0.00	50.00

CTAs and MFFs perform best in crisis periods, therefore 2011 and following few years were quite tough for the industry. Corporate scandals and failures left their mark on the industry, e.g. Madoff Ponzi Scheme, SAC Capital, and Galleon Group.[1] Equal-weighted portfolio returns are negative for both CTAs and MFFs after 2011, and AUM declines sharply for both assets during these years. However, 2014 seems to be a recovery year with positive returns, even though AUM continues to decline.

Table 5: Time Series Statistics for EW-and VW-CTAs and MFFs

	N	Mean	Median	Std. Dev.	Skewness	Kurtosis	Maximum	Minimum
EW__All Funds	252	0.57	0.59	1.89	-0.07	0.36	6.58	-4.90
EW__CTAs	252	0.59	0.52	1.77	0.23	-0.21	5.82	-4.17
EW__MFFs	252	0.51	0.66	2.21	-0.16	0.54	7.35	-5.98
VW__All Funds	252	0.53	0.34	1.80	0.36	0.10	6.48	-4.22
VW__CTAs	252	0.62	0.36	2.15	0.36	-0.12	7.14	-4.04
VW__MFFs	252	0.25	0.07	1.63	1.28	9.56	9.93	-6.09
CRSP	252	0.86	1.53	4.44	-0.76	1.21	11.35	-17.15
Russell2000	252	0.77	1.58	5.62	-0.53	1.14	16.42	-20.90
MSCI World	252	0.51	1.07	4.35	-0.79	1.73	10.90	-19.04
LongTermGovBond	252	0.46	0.43	1.99	0.03	1.28	8.54	-6.68
Corp Bond	192	0.12	0.17	1.69	0.03	3.31	7.63	-6.43
DXY CRNCY	252	0.00	-0.12	2.31	0.21	0.61	7.78	-6.22
INF	240	-0.45	-0.32	3.72	-6.61	82.69	15.49	-44.26
E(INF)	252	0.83	0.90	1.71	-1.09	6.52	5.70	-9.80
UNE(INF)	240	-0.66	-0.53	3.72	-6.48	80.93	15.48	-44.26

Table 5 displays the time series summary statistics for equal-and value-weighted all funds, CTAs, and MFFs, along with indices as the proxies for other markets for the 1994-2014 period. Time series statistics provide information about the attributes of CTAs and MFFs. First, when we look at value-weighted funds, CTAs are yielding 0.62%per month whereas value-weighted MFFs are yielding 0.25%. Therefore, we can say that profitability of CTAs is higher than profitability of MFFs. Second, value-weighted CTAs and value-weighted MFFs are doing better than foreign

[1] See ‘The 3 Biggest Hedge Fund Scandals’ for detailed information on http://www.investopedia.com/articles/investing/101515/3-biggest-hedge-fund-scandals.asp.

exchange market, and corporate bonds; in addition to that value-weighted CTAs are doing better than long term government bonds and developed market stocks. Small stock index and market index, on the other hand, are always doing better than CTAs and MFFs. Third, CTAs have positive skewness. Positively skewed assets have rare but sharp jumps that would classify them as lottery-like. Many investors find lottery-like assets attractive (Bali et al., 2011). On the other hand, MFFs have quite high kurtosis, which would make them more protected from tail risk. They are less likely to be hit by crisis.

Table 6 shows the time series mean, median, standard deviation, minimum and maximum percentage returns of the 24 financial and macroeconomic factors used in this study. The financial factors are as follows: (1) CRSP-Rf: Value-weighted CRSP market index return net of 1-month US T-bill rate; (2) SMB: Fama-French (1993) size factor; (3) HML: Fama-French (1993) book-to-market factor; (4) RMW: Fama-French (2017) operating profitability factor; (5) CMA: Fama-French (2017) investment factor; (6) MOM: Carhart (1997) momentum factor; (7) Δ10Y: Fung-Hsieh (2004) long-term interest rate factor; (8) ΔCredSpr: Fung-Hsieh (2004) credit risk factor; (9) BDTF: Fung-Hsieh (2001) bond trend following factor; (10) FXTF: Fung-Hsieh (2001) currency trend following factor; (11): CMTF: Fung-Hsieh (2001) commodity trend following factor; (12) IRTF: Fung-Hsieh (2001) short-term interest rate trend following factor; (13) SKTF: Fung-Hsieh (2001) stock index trend following factor.

Table 6: Time Series Statistics for Financial and Macroeconomic Risk Factors

	N	Mean	Median	Std. Dev.	Minimum	Maximum
CRSP-Rf: CRSP Value-Weighted Market Index-1-Month Treasury Securities	252	0.63	1.34	4.44	-17.23	11.35
SMB: Fama and French (1993) Size Factor	252	0.20	-0.02	3.25	-15.36	19.18
HML: Fama and French (1993) Book to Market Factor	252	0.21	0.12	3.23	-13.11	13.91
RMW: Fama and French (2014) Operating Profitability Factor	252	0.36	0.33	2.78	-17.57	12.19
CMA: Fama and French (2014) Investment Factor	252	0.31	0.12	2.16	-6.81	9.51
MOM: Carhart (1997) Momentum Factor	252	0.44	0.56	5.17	-34.58	18.38
Delta10Y: Fung and Hsieh (2004) Monthly Change in TERM	252	-0.01	-0.03	0.23	-1.11	0.65
DeltaCredSpr: Fung and Hsieh (2004) Monthly change in DEF	252	0.00	-0.01	0.19	-0.99	1.45
BDTF: Fung and Hsieh (2001) Bond Trend-Following Factor	252	-0.02	-0.04	0.15	-0.27	0.69
FXTF: Fung and Hsieh (2001) Currency Trend-Following Factor	252	-0.01	-0.05	0.19	-0.30	0.90
CMTF: Fung and Hsieh (2001) Commodity Trend-Following Factor	252	0.00	-0.03	0.14	-0.25	0.65
IRTF: Fung and Hsieh (2001) Short Term Interest Rate Trend Following Factor	252	0.00	-0.06	0.26	-0.35	2.22
SKTF: Fung and Hsieh (2001) Stock Index Trend Following Factor	252	-0.05	-0.07	0.13	-0.30	0.60
TERM: Term Spread (10-Year Gov. Bond Yield-3 Month Treasury Securities)	252	1.74	1.85	1.17	-0.70	3.69
DEF: Default Spread (BAA Rated Bond Yields-AAA Rated Bond Yields)	252	0.96	0.86	0.44	0.55	3.38
DIV: Aggregate Dividend Yield on S&P 500 Index	252	1.90	1.83	0.47	1.11	3.60
INF: Monthly inflation rate based on the US CPI	252	0.19	0.19	0.35	-1.92	1.22
RREL: Relative T-Bill Rate (12 Month T-Bill rate-12 Month Backward Moving Average)	252	-0.07	-0.02	0.64	-2.36	1.35
UNEMP: U.S. Monthly Unemployment Rate	252	0.06	0.06	0.02	0.04	0.10
CFNAI: Chicago FED National Activity Index	252	0.00	-0.02	0.69	-1.62	2.33
TED1M: LIBOR-1 Month T-Bill	252	2.87	2.89	2.16	0.15	6.25
GDPPCG: U.S. Monthly growth rate of real GDP per capita						
IP Growth: FED FRED Industrial Production Index	252	0.18	0.22	0.66	-4.27	2.05
Payroll: FED FRED Total Nonfarm Employment	252	0.09	0.12	0.17	-0.62	0.42

The macroeconomic factors are as follows: (1) TERM: Term spread, measured as the difference between yields on 10-year and 3-month treasury securities; (2) DEF: Default spread measured as the difference between yields on BAA rated and AAA-rated corporate bonds; (3) DIV: Aggregate dividend yield on the S&P 500 index; (4) INF: Monthly inflation rate based on the US consumer price index; (5) RREL: Relative T-bill rate, measured as the difference between 3-month T-bill rate and its 12 month moving average backward average; (6) UNEMP: The US monthly unemployment rate, measured as the number of unemployed people as a percentage of labor force; (7) CFNAI: Chicago FED national activity index; (8) TED1M: TED spread, an indicator of credit risk and perceived soundness of the banking system, measured as the difference between 1-month LIBOR and 3-month T-bill rates; (9) GDPPCG: US monthly growth rate of real GDP per capita; (10) IPG Growth: Louisiana FED industrial production index; (11) PYRL: Louisiana FED total nonfarm employment.

POTENTIAL DATA BIASES

Not only managed futures funds are similar to hedge funds in nature but also their aggregate return and assets data can be received only from data vendors make them to be subject to the same data biases. This study covers four data biases analyzed in earlier hedge fund and CTA studies (Fung and Hsieh, 2000; Edwards and Çağlayan, 2001; Bali et al, 2011).

Survivorship Bias

In order to explain survivorship bias, we should distinguish between surviving funds and defunct funds. Surviving funds are still operating and reporting to the data vendor as of the last report date. Defunct funds have left the database due to several possible reasons such as name change, closure, bankruptcy, voluntary stoppage of reporting to the data vendor. Some data vendors keep record of only surviving funds. This would cause an upward bias in the analysis that aims to represent the whole market. Defunct funds are expected to have lower average returns than surviving funds. Low return funds are more likely to liquidate, and they leave the database. If analysis excludes them, they represent only the successful funds in the industry (Fung and Hsieh, 2000).

Schneeweis et al (1996) obtained 56 individual CTAs for the period 1985-1991 in order to compute survivorship bias. They find that live CTAs have higher returns and lower volatility than graveyard CTAs. Therefore, dead CTAs should also be included in analysis in order to avoid the spurious upward bias of returns. The difference between surviving and non-surviving CTAs is 8.14 % when measured 36 to 12 months before dissolution. The difference increases to 41,22% when measured 12 months to dissolution. They also check CTAs in portfolios and conclude that survivorship bias is not such a problem in portfolios as big as in individual assets. Survivorship bias has a minor influence in portfolios. Since indexes contain information of both live and dead funds, they are exempt from survivorship bias issue.

Lipper TASS database provide both surviving and defunct funds' records, starting from January 1994. In order to avoid from an upward bias, we start the analysis from the same date. We compute the possible survivorship bias during January 1994-December 2014 in order to compare the results to that of Fung and Hsieh (2000) and Schneeweis et al. (1996).

We compute survivorship bias following Malkiel (1995) as the difference between annual returns of all funds and annual returns of all surviving funds. Survivorship bias for all funds together and separately can be found in Table 7 Panel A. For both CTAs and managed futures, survivorship bias is 3.26% per year. It is 1.87% for CTAs and 4.10% for MFFs. These numbers are comparable to the results of Fung and Hsieh (2000). However, survivorship bias for CTAs is much lower than survivorship bias for MFFs. Since our analysis is clean from survivorship bias, our analysis is not fooled by survivorship bias.

Table 7: Survivorship, Backfill and Multi-Period Bias in CTAs and MFFs

Panel A: Survivorship Bias	All CTAs and MFFs	CTAs	MFFs
Annual Returns of Surviving CTAs and MFFs	11.21%	12.07%	10.96%
Annual Returns of all CTAs and MFFs	7.95%	10.20%	6.6%
Survivorship Bias	3.26%	1.87%	4.10%
Panel B: Backfill Bias			
Annual Returns of All CTAs and MFFs after the Returns for the First 12 Month is Deleted	6.61%	7.15%	6.29%
Annual Returns of all CTAs and MFFs	7.95%	10.20%	6.86%
Backfill Bias	1.35%	3.05%	0.58%
Panel C: Multi-Period Bias			
Annual Returns of All CTAs and MFFs after the funds that report less than 24 months are deleted.	6.90%	7.36%	6.63%
Annual Returns of All CTAs and MFFs after the Returns for the First 12 Month is Deleted	6.61%	7.15%	6.29%
Multi-Period Bias	0.30%	0.21%	0.34%

Backfill Bias

When a fund is included in a data vendor, its previous returns are automatically added to the database. This automation is called backfilling. Backfilling is voluntary and therefore it is an incentive for successful funds. They are eager to report their earlier returns as a marketing tool; however, funds that have lower returns in their past hesitate to report their results. Therefore, backfilling results that only successful funds report to data vendors. This would cause an upward bias in returns of data vendors (Fung and Hsieh, 2000). In order to provide our analysis to represent the whole market, we need to clean out backfilled returns from the data. Forasmuch, Edwards and Ma (1988) show that there is no statistically significant relationship between pre-public and post-public returns of CTAs. Moreover, McCarthy et al. (1997) reveals that CTAs provides higher pro-forma returns than post-selection returns.

Fung and Hsieh (2000) determine the average incubation period of hedge funds as 15 months in TASS database. They require deletion of minimum of 36 months' return history in order to eliminate backfill bias. On the other hand, Ackermann et al. (1999) require a minimum of 24 months' return deletion. Lipper TASS database CTAs and MFFs has average backfill less than 1 year; therefore, it is better to delete only 12 months.

In order to detect back-fill bias we deleted the first 12 months of returns using the whole dataset. The deletion started in 1973, which is the first year of reporting. We calculated backfill bias between 1994-2014. After the deletion, we lost 455 funds, and left with 2282 funds in total (1133 CTAs and 1149 MFFs). The results can found in Table 7 Panel B. All funds have 1.35% backfill bias annually. Backfill bias for CTAs is 3.05%, and it is 0.58% for MFFs. This result is not surprising, because CTAs cannot use advertising and backfilling is a strong source of attracting new customers.

Bhardwaj et al. (2008) analyze Lipper TASS CTA database for the 1994-2007 period. They argue that CTAs earn very low positive return, however compared to T-bills, the returns are not significantly different from zero. They claim that investors are fooled by the information obtained from databases. Data vendors provide information without cleaning the effects of survivorship and backfill bias; especially high backfill rates misguide many investors. Our database has high survivorship bias for MFFs and high backfill bias for CTAs.

Selection Bias

CTAs and MFFs do not have to release their performances to the third parties (apart from regulatory institutions). Reporting to data vendors is a voluntary activity. Therefore, it is probable that only successful funds report to data vendors. The average overall return of the funds reporting to data vendors might be upward biased compared to the all industry. However, it is not possible to compute the selection bias because there is no such source that provides the performances of not-reporting funds. Aiken et al. (2013) measure selection bias using a novel set of hedge funds that have never reported to any database. They find significant difference between reporting and non-reporting funds. Agarwal et al. (2013) use a complete list of hedge fund companies and measure selection bias. Returns of reporting funds are higher than non-reporting funds when they use characteristic-based benchmarks. However, the difference is not significant when they use alternative choices of performance measures. They note that selection of reporting requires a trade-off between costs and benefits. Benefits do not always outweigh costs; so even successful funds do not choose to report. Fung and Hsieh (1997) suggest that not only less successful hedge funds but also very successful hedge funds may prefer not reporting to data vendors. We do not know if this is case for CTAs. There is no known example of very successful CTAs and MFFs, however we hope that it is also true for CTA industry and the level of selection bias is at the minimum.

Multi-Period Sampling Bias

While source of survivorship and backfill biases is data vendors, the source of multi-period sampling bias is investors. Investors usually ask for a minimum of 24 or 36 months of return history from funds before investing in. Funds that have less than 24 months of past record are rarely invested. Therefore, inclusion of funds that have less than 24 months to the study would be misleading.

Following Ackerman et al. (1999), we exclude funds that report less than 24 months from our study. Please note that the exclusion took place after deleting the first 12 months of returns to compute back-fill bias. We lost 150 funds and left with 2132 funds in total (1129 CTAs, and 1003 MFFs). The results can be found in Table 6 Panel C. Multi-period sampling bias for the whole sample is 0,30% per year; it is 0.21% for CTAs and 0.34% for MFFs.

Because having less than five observations cause probems in running regression analysis, we eliminated the funds having less than 5 observations after counting for all biases. Eventually, we are left with 1939 funds, of which 936 are CTAs and 1003 are MFFs.

After introducing data and defining variables in this chapter, we start empirical analysis in Chapters 3-5. Chapter 3 focuses on performance analysis of CTAs and MFFs, Chapter 4 concentrates on managerial skill of fund managers, and Chapter 5 searches for factor exposures of the funds.

CHAPTER 3

PERFORMANCE ANALYSIS

Profitability of CTAs and MFFs has been a matter of discussion for a long time. Earlier literature is confusing about the performance of CTAs and MFFs as individual assets. Some studies find that these assets are profitable investment vehicles whereas some studies claim that they are almost always underperformed by other asset classes. Moreover, some studies find that this asset class is a profitable one as both individual asset type and also as a portfolio asset type while some others argue that this asset class is not successful as an individual asset class; however, it is successful in portfolios. The advocators of this group indicate that CTAs and MFFs do not improve portfolio assets significantly but they reduce portfolio volatility significantly and cause much higher Sharpe ratios. In this paper, we analyze CTAs and MFFs as both standalone investment vehicles, and portfolio assets. After reporting the results for the whole period, we also divide the sampling period into two as bull markets and bear markets. The purpose of the last analysis is to find out if CTAs and MFFs perform better in one of these market conditions.

3.1. CTAs and MFFs as STANDALONE INVESTMENT VEHICLES

The purpose of this section is to assess CTAs and MFFs as standalone investment vehicles. In order to analyze CTAs and MFFs as standalone investment vehicles, we form two portfolios to evaluate these asset classes: Equal-weighted and value-weighted CTA and MFF portfolios. Table 8 displays the rankings of equal-weighted (EW) and value-weighted (VW) CTAs and managed future indices as stand-alone investment vehicles. Equal-weighted indices are equal weighted averages of monthly fund returns whereas value-weighted indices are averages of monthly returns weighted by assets under management for that month. After forming the indices, we compute Sharpe ratio, Roy's criterion, Kataoka's criterion, and Sortino ratio for both indices. We also compare the results of both indices with standard asset classes.

Sharpe Ratio Ranking of Funds

Sharpe Ratio is the best known reward-to-risk ratio. It is computed as the excess return of a fund's return over a risk-free rate divided by the standard deviation of the fund. Sharpe ratio denotes the excess return of a fund for a certain unit of volatility. As Sharpe ratio increases, the fund generates more excess return for a certain level of risk.

$$SR = \frac{E(Ri) - Rf}{\sigma i}$$

As Table 8 displays, during January 1994-December 2014 period, EW-all funds and VW-all funds have a Sharpe ratio of 0.59 and 0.54, respectively. Sharpe ratio is 0.59 for VW-CTAs and 0.56 for EW-CTAs. VW-MFFs generated a Sharpe ratio of 0.50 while EW-MFFs generated a Sharpe ratio of 0.46. EW-CTA and MFF portfolio has the highest Sharpe ratio. Sharpe ratios of CTA indices rank as the second and the third. VW-CTA and MFF portfolio has the fourth highest Sharpe ratio. This list is followed by VW-MFFs, CRSP and EW-MFFs. Other standard asset classes take the lowest ranks in the list. This classification makes CTAs the most profitable assets given a certain amount of risk.

Table 8: Rankings of EW and VW Fund Investment Style Indices as Standalone Investments

	Sharpe Ratio	Sharpe Ratio Ranking	Roy's Criterion	Roy's Criterion Ranking	Kataoka's Criterion	Kataoka's Criterion Ranking	Sortino Ratio	Sortino Ratio Ranking
EW_All CTAs and MFFs	0.59	1	0.34	4	-6.79	2	1.31	2
VW_All CTAs and MFFs	0.54	4	0.31	5	-8.63	6	1.03	4
VW_CTAs	0.59	2	0.35	2	-7.91	4	1.06	3
EW_CTAs	0.56	3	0.40	1	-12.53	8	2.17	1
VW_MFFs	0.50	5	0.28	6	-9.92	7	0.93	5
EW_MFFs	0.46	7	0.20	8	-7.79	3	0.91	6
Standard Assets								
Market (CRSP)	*0.49*	6	*0.34*	3	*-15.03*	10	*0.67*	7
US Small Stock	*0.34*	9	*0.22*	7	*-22.74*	12	*0.47*	9
Emerging Market	*0.23*	10	*0.08*	10	*-18.61*	11	*0.30*	10
LT Gov Bond	*0.41*	8	*0.08*	9	*-5.81*	1	*0.65*	8
Corp Bond	*-0.21*	11	*-0.61*	11	*-8.25*	5	*-0.28*	11
DXY Crncy	*-0.34*	12	*-0.63*	12	*-13.19*	9	*-0.55*	12

Roy's Criterion Ranking of Funds

Roy's Criterion is one of the best known safety-first investment criteria. Safety-first investment criteria for the choice among alternatives are concerned with the risk of failing to achieve a certain minimum target or secure safety margins. Roy's criterion sets a minimum required return for a given level of volatility. It seeks to minimize the probability that a disaster will occur (Bigman, 1996). It considers the best asset or portfolio as the one that has the smallest probability of producing a return below some specified lower return level (Edwards and Çağlayan, 2001). We adopted 5% minimum target in this study. Roy's criterion is calculated as the excess returns of funds over the minimum target divided by the standard deviation of funds. The higher the Roy's criterion, the more desirable the fund is.

$$\text{Roy's} = \frac{E(Ri) - 5\%}{\sigma i}$$

Table 8 shows that EW-CTA index has the highest Roy's criteria. CTAs have the highest ranks among all asset classes. CTA and MFF indices follow CTAs only. MFFs are ranked as 6^{th} and 8^{th} among all indices. According to these results, CTAs has the lowest probability to produce a return less than 5% among all asset classes. CTAs follow stock market, which makes them quite secure against sudden drops in returns. Other standard assets rank very low Roy Criterion ranking.

Kataoka's Criterion Ranking of Funds

Kataoka's Criterion is another best known safety-first investment criterion. Kataoka's criterion requires a predetermination of probability of disaster. It considers the best asset or portfolio that maximizes the minimum target ratio given the probability level. In this study, the probability level is assumed to be 5%. Kataoka's criterion is computed as 1,645 times standard deviation of a fund is subtracted from its average monthly return. This value maximizes the minimum target ratio. This is quite a conservative criterion in risk taking behavior. So, the higher the Kataoka's criterion is, the more desirable the fund is.

Kataoka's= $E(Ri) - 1{,}645.\sigma i$

Table 8 shows that, Kataoka's criterion for LT government bonds ranks the first among all asset classes. E(Ri) represents expected monthly return for each fund. CTA and MFF indices follow long-term government bonds. They rank between 2^{nd} and 8^{th}. Other standard asset classes rank the lowest; only corporate bonds rank around CTA and MFF indices.

Sortino Ratio Ranking of Funds

Sortino Ratio is a new, alternative measure of risk-to-reward ratio in hedge fund studies. Many assets, including hedge funds or mutual funds do not indicate normal distribution properties. They have skewed returns. Sharpe ratio is believed not to be a good measure for skewed returns, since it assumes symmetry. Sortino ratio was developed based on Sortino and Price (1994) that argues there must be a minimal acceptable return (MAR) to accomplish some goals. Returns below this level are unfavorable outcomes. Therefore, returns below this level are assumed to be risk-related (Chaudry and Johnson, 2008). These returns can be thought of correspondents of negative values in standard deviation. Extracting positive values from standard deviation is a measure of downside risk. In this study, we define downside risk as downside standard deviation, which is the standard deviation of returns lower than risk-free rate. We calculate Sortino ratio as the excess monthly fund returns over risk-free rate divided by downside standard deviation.

$$\text{SoR}=\frac{E(Ri)-Rf}{\sigma i^{-}}$$

Table 8 shows Sortino ratios for assets under analysis. Like Sharpe ratio and Roy's criterion, CTAs and MFFs rank the highest among all asset classes. CTAs have higher Sortino ratios than MFFs. This would make CTAs the lowest risk-assets among all, CTAs prove to be the most resistant asset against downside risk. MFFs follow CTAs and standard asset classes rank the lowest.

CTAs and MFFs are not normally distributed as Table 5 shows. They have non-normal skewness and kurtosis; however, they are not left-tail skewed. Therefore, we believe it is not necessary for CTAs and MFFs to compute downside risk measures other than Sortino ratio. Atilgan et al. (2013) shows that almost all downside risk measures indicate the same results for hedge funds. If a hedge fund style is found to be riskier than the other using one downside risk measure, another risk measure assures the results. Therefore, we believe that it is enough to use Sortino ratio as a downside risk measure.

In a nutshell, Table 8 compares the ranking of optimization ratios (Sharpe, Roy's, Kataoka's and Sortino) among EW- and VW-CTAs and MFFs with the ranking of standard assets in the market. In terms of all optimization ratios, CTAs provide the best reward-to-risk ratios among all asset classes while MFFs show a medium-high level reward-to-risk ratio. Stock market, long-term government bonds, and corporate bonds market may provide better results than MFFs for safety-first investment criteria. This analysis shows that CTAs and MFFs perform better than many standard asset classes, yet they are also risky assets.

Table 9 shows the correlation coefficients among CTAs, managed futures and standard asset indices and inflation indices. The correlation among VW-CTAs and VW-MFFs is 96%. Correlation indices among all CTA and MFF indices are high; the lowest coefficient is 52%, which is between value-weighted and equal-weighted CTAs. Correlation between managed futures funds and standard assets is very low, close to zero. Long-term government bond index has the highest correlation coefficients with managed futures funds among all standard assets. The coefficients vary around 10%-15%. On the other hand, foreign exchange market proxy (DXY Currncy index) has negative correlation coefficients with managed futures funds. DXY currency has negative correlation coefficients with all standard assets as well. As Irwin and Brorsen (1985), Chong and Miffre (2010), and Christopherson et al (2004), and Kat and Oomen (2006) state, the power of the managed futures as standalone and portfolio assets may lie under the low correlation between standard assets and managed futures. Our results support these findings: The low correlation between managed futures funds and standard assets may make managed futures funds good performers in down markets.

Another important relationship is observed between managed futures funds and inflation. Do CTAs and MFFs hedge against inflationary risk? Gorton and Rouwenhorst (2005), Kat and Oomen (2006), and Erb and Harvey (2006) comment that there is negative correlation between standard assets and commodity futures, which depends on different behavior over the business cycle. This behavior causes a positive correlation between inflation and futures (Kat and Oomen, 2006; Erb and Harvey, 2006). Edwards and Park (1996) handled the same argument for managed futures industry. In order to test the relationship between inflation and other assets, we follow Gorton and Rouwenhorst (2005) and Kat and Oomen (2006). We compute the correlation coefficient between CTAs and MFFs and nominal inflation. Since expected inflation is already incorporated in current prices of the assets, we need to test the correlation between asset returns and unexpected inflation (Gorton and Rouwenhorst, 2005). Following Fama and Schwert (1977) and Schwert (1981), we subtract 1-month Treasury bill rate from nominal inflation to obtain unexpected inflation. The short-term T-bill rate is a proxy for expected inflation rate in the future. We also compute the change in expected inflation by assuming today's inflation as the best predictor for future inflation as implied in the random walk model.

$$\text{Unexp (INF)}_t = \text{INF}_t - \text{T-Bill}_t$$

$$\text{Exp (INF)}_t = \text{INF}_t - \text{INF}_{t-1}$$

The last three columns of Table 9 show the correlation coefficients among nominal, expected, and unexpected inflation and asset classes. The correlation coefficients of almost all CTA and MFF indices with nominal and expected inflation are usually negative and very close to zero. This behavior is the same as standard asset indices; they have very low correlation with inflation. This outcome cannot support the hypothesis that argues managed futures can hedge against inflationary pressures. Bernard and Frecka (1987) argue that common stocks have hedging power against inflation, especially small stocks, but not international stocks. On the other hand, bonds cannot hedge against inflation, as expected, due to their nominal payoff structure. Correlation coefficients show that managed futures funds are similar to bonds in their relationship with inflation. Chong and Miffre (2010) argue that futures provide diversification for short-term periods but their diversification power decays when they are used along with treasury bills and government bonds. The negative correlation between managed futures funds and inflation is similar to the negative correlation between bonds and inflation. Our results are in line with these statements.

Another point to note is that coefficients for nominal and expected inflation is usually negative, whereas coefficients for unexpected inflation are usually positive. These results suggest that CTAs and MFFs do not hedge against nominal and expected inflation, but they can hedge against inflationary shocks that come as random shocks.

Table 9: Correlation Table for EW and VW CTA and MFF Indices and Stock and Bond Indices

	EW All CTAs and MFFs	EW CTAs	EW MFFs	VW All CTAs and MFFs	VW CTAs	VW MFFs	CRSP	US Small Stock Index	Emerging Market Index	LT Gov Bond Index	Corp Bond Index	DXY Crncy Index	INF	E(INF)	UNE(INF)
EW All CTAs and MFFs	1	0.83	0.93	0.90	0.84	0.90	0.02	0.01	0.07	0.10	0.10	-0.24	-0.05	-0.05	0.05
EW CTAs		1	0.57	0.55	0.52	0.54	0.02	0.02	0.05	0.01	0.00	-0.13	-0.06	-0.06	0.02
EW MFFs			1	0.96	0.89	0.97	0.02	0.01	0.08	0.14	0.16	-0.28	-0.03	-0.03	0.07
VW All CTAs and MFFs				1	0.96	0.98	-0.05	-0.05	0.00	0.13	0.11	-0.18	-0.07	-0.07	0.03
VW CTAs					1	0.89	-0.08	-0.07	-0.05	0.15	0.09	-0.11	-0.11	-0.11	-0.01
VW MFFs						1	-0.03	-0.03	0.03	0.12	0.11	-0.21	-0.04	-0.04	0.05
CRSP							1	0.88	0.95	-0.02	0.22	-0.24	0.01	0.01	-0.01
US Small Stock Index								1	0.81	0.04	0.18	-0.26	0.01	0.01	0.00
Emerging Market Index									1	0.01	0.26	-0.39	0.02	0.02	0.01
LT Gov Bond Index										1	0.07	-0.05	-0.13	-0.13	-0.05
Corp Bond Index											1	-0.33	-0.08	-0.20	0.52
DXY Crncy Index												1	-0.08	-0.08	-0.10
INF													1	1.00	0.52
E(INF)														1	0.52
UNE(INF)															1

3.2. CTAs and MFFs as PORTFOLIO ASSETS

This section examines CTAs and managed futures as portfolio assets along with indices representing stock and bond markets. The rank of portfolios is determined by the increase in the ratio of optimization. Optimization ratios are Sharpe ratio, Roy's criterion, Kataoka's Criterion, and Sortino ratio. We maximize optimization ratio of the portfolios by changing the weights of indices in the portfolios. Then, we add CTAs, MFFs separately and together to the portfolio to observe the increase in the optimization ratio. Table 10 displays the optimized portfolios with respect to four criteria.

Table 10 is organized as follows: Portfolios of standard asset classes are presented in the first column of each panel. Thus, the first portfolio does not contain CTAs and MFFs. We add EW-all funds to the portfolio in the second column; we add EW-CTAs to the portfolio in the third column; we add EW-MFFs to the portfolio in the fourth column; and we add EW-CTAs and EW-MFFs separately to the portfolio in the fifth column. We repeat the same ordering for the VW-CTAs and MFFs in the right hand-side panel. The difference between the second and the fifth columns is that column two does not distinguish between CTAs and MFFs and represent a mixture of these two funds; however, column five distinguishes between the funds and add each of their indices separately to the portfolio. Since the results of these two columns are different, we can say that characteristics of CTAs and MFFs are different even though they have many features in common.

Optimization with respect to Sharpe Ratio

Addition of EW-CTA and MFF indices to an optimal stock and bond portfolio can be observed in Table 10-Panel A. 1. Optimal asset portfolio without managed futures consists of

35% of CRSP, and 65 % of LT government bonds. The Sharpe ratio of this portfolio is 0.65. When we add EW-all funds index, the index gains a weight of 42% as we can see in column 2. In this new portfolio, the weight of CRSP is 22% and the weight of long-term government bond is 36%; Sharpe ratio of this portfolio increases by 30.5% and reaches to 0.85. When we add CTA index only, it gains a weight of 30%, and if we add only MFF index, it gets a weight of 35% as columns 3 and 4 exhibit. Sharpe ratios increase to 0.85 and 0.76, respectively. If we add CTA and MFF indices separately and simultaneously to the portfolio, CTA index gets 24% weight and MFF index gets 10% weight as column 5 shows. We can interpret the results as such: Long-term government bonds are the most preferable asset of a portfolio of standard asset classes as their reward-to-risk ratios are the highest when there are no managed futures funds in the portfolio. CRSP is the second preferred asset in a portfolio in the absence of managed futures funds. When added into a portfolio, both CTAs and managed futures increase Sharpe ratio of the portfolios. CTAs contribute more than MFFs to increase the Sharpe ratio. When added together to a portfolio, CTAs overweight the effect of MFFs; but results are stronger when these two fund types are added together.

Table 10-Panel A.2 shows the same analysis for VW-CTA and MFF indices. When we add VW-all funds, they gain a weight of 37%. If we add CTAs only, they gain a weight of 41%, and if we add MFFs only, they gain a weight of 33% only. When we add both funds into the portfolio separately, MFF do not gain any share as CTAs outperform their diversification power. The enhancements of Sharpe ratios in the last row are between 23% and 33%. The results are similar to Panel A.1 of Table 10; Sharpe ratios increase around 0,85 in either case.

Table 10: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio

Panel A: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio Based on Sharpe Ratio											
A.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio						**A.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio**					
CRSP	0.35	0.22	0.24	0.25	0.23	**CRSP**	0.35	0.25	0.25	0.26	0.25
Russel2000	0.00	0.00	0.00	0.00	0.00	**Russel2000**	0.00	0.00	0.00	0.00	0.00
MSCIWorld	0.00	0.00	0.00	0.00	0.00	**MSCIWorld**	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.65	0.36	0.46	0.41	0.42	**LTGovtBond**	0.65	0.38	0.34	0.41	0.34
CorpBond	0.00	0.00	0.00	0.00	0.00	**CorpBond**	0.00	0.00	0.00	0.00	0.00
DXY Currency	0.00	0.00	0.00	0.00	0.00	**DXY Currency**	0.00	0.00	0.00	0.00	0.00
EW_All CTAs and MFFs		0.42				**VW_All CTAs and MFFs**		0.37			
EW_CTAs			0.30		0.24	**VW_CTAs**			0.41		0.41
EW_MFFs				0.35	0.10	**VW_MFFs**				0.33	0.00
Sharpe Ratio	0.65	0.85	0.85	0.76	0.86	**Sharpe Ratio**	0.65	0.83	0.87	0.80	0.87
% increase in Sharpe Ratio of Optimal Portfolio		30.5%	30.6%	17.3%	31.6%	**% increase in Sharpe Ratio of Optimal Portfolio**		27.4%	33.2%	23.0%	33.2%

Optimization with respect to Roy's Criterion

Table 10-Panel B shows the optimal portfolio structures with respect to Roy's criterion. When we optimize our portfolios with respect to Roy's criterion, CRSP gets a 65% weight, and long-term government bonds get a 35% share in the portfolio. The Roy's criterion of this portfolio is 0.35. When we add EW-funds in the portfolio, as displayed in Panel B.1, Roy's criterion improves concordantly to 0,48. Addition of all funds gains a share of 55%, addition of CTAs only gains a share of 45%, and addition of MFFs only gains a share of 41%. When C to TAs and MFFs are added separately and at the same time to the portfolio, CTAs outperform MFFs, therefore there is no need to add them together in a portfolio. The improvements in Roy's criterion are also remarkable. For example, addition of CTAs improves the criterion by 48.3%.

When we run the same analysis using VW-CTA and MFF indices as in Panel B.2, we find very similar results. CTAs and MFFs together take a share of 52%. CTAs take a weight of 57% while MFFs take a share of 47% in the portfolio. Addition of CTA and MFF portfolios separately and simultaneously outweigh the effects of MFFs. Addition of CTAs improves Roy's criterion by 45,6%. CTAs and MFFs are good diversifiers, and the diversification power of CTAs is stronger than that of MFFs. This result shows that managed futures funds, especially CTAs are effective safety-first investment assets.

Table 10: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio (Continued)

Panel B: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio Based on Roy's Criterion											
B.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio						**B.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio**					
CRSP	0.65	0.34	0.36	0.43	0.36	**CRSP**	0.65	0.38	0.37	0.40	0.37
Russel2000	0.00	0.00	0.00	0.00	0.00	**Russel2000**	0.00	0.00	0.00	0.00	0.00
MSCIWorld	0.00	0.00	0.00	0.00	0.00	**MSCIWorld**	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.35	0.11	0.19	0.16	0.19	**LTGovtBond**	0.35	0.10	0.06	0.13	0.06
CorpBond	0.00	0.00	0.00	0.00	0.00	**CorpBond**	0.00	0.00	0.00	0.00	0.00
DXY Currency	0.00	0.00	0.00	0.00	0.00	**DXY Currency**	0.00	0.00	0.00	0.00	0.00
EW_All CTAs and MFFs		0,55				**VW_All CTAs and MFFs**		0.52			
EW_CTAs			0,45		0,45	**VW_CTAs**			0.57		0.57
EW_MFFs				0,41	0,00	**VW_MFFs**				0.47	0.00
Roy's Criterion	0,35	0,48	0,53	0,40	0,53	**Roy's Criterion**	0.35	0.48	0.52	0.46	0.52
% increase in Roy's Criterion of Optimal Portfolio		35,7%	48,3%	13,0%	48,3%	**% increase in Roy's Criterion of Optimal Portfolio**		35.2%	45.6%	28.9%	45.6%

Optimization with Respect to Kataoka's Criterion

As Table 10-Panel C.1 displays, when we optimize portfolios with respect to Kataoka' s criterion, CRSP gets a share of 13%, long-term government bonds get a share of 38%, DXY currency gets a 21%, and corporate bonds get a share of 28% in the portfolio. Kataoka's criterion leads more diversification, yet it is a safety-first investment criterion like Roy's criterion. The Kataoka's criterion for this portfolio is -2.34. When we add EW-CTA indices to this portfolio as in Panel C.1, Kataoka's criterion increases substantially. Addition of all funds increases Kataoka's criterion to -1.00. Inclusion of CTA and MFF indices increase Kataoka's criterion to -1,31 and -1,33, respectively. When CTA and MFF portfolios are included separately, Kataoka's criterion rises up to -1.08. CTAs and MFF indices gain shares around 15% to 26% within the asset portfolios.

Table 10-Panel C.2 displays the same analysis conducted by using VW-CTA and MFF indices. The results are somewhat similar to earlier sections of this table. The inclusion of indices and the improvements of Kataoka's criterion are slightly weaker than the inclusion of EW-indices. When all funds are included together, they gain a share of 21%, that increases Kataoka's criterion by 46.4%. Addition of CTAs only increases Kataoka's criterion by 49,1%.

Table 10: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio (Continued)

Panel C: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio Based on Kataoka's Criterion											
C.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio						**C.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio**					
CRSP	013	0.12	0.12	0.12	0.12	**CRSP**	0.13	0.14	0.14	0.13	0.14
Russel2000	0.00	0.00	0.00	0.00	0.00	**Russel2000**	0.00	0.00	0.00	0.00	0.00
MSCIWorld	0.00	0.00	0.00	0.00	0.00	**MSCIWorld**	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.38	0.28	0.34	0.28	0.30	**LTGovtBond**	0.38	0.30	0.30	0.31	0.30
CorpBond	0.28	0.13	0.19	0.14	0.14	**CorpBond**	0.28	0.15	0.14	0.16	0.14
DXY Currency	0.21	0.20	0.19	0.22	0.20	**DXY Currency**	0.21	0.20	0.19	0.21	0.19
EW_All CTAs and MFFs		0.26				**VW_All CTAs and MFFs**		0.21			
EW_CTAs			0.15		0.09	**VW_CTAs**			0.23		0.21
EW_MFFs				0.23	0.14	**VW_MFFs**				0.19	0.02
Kataoka's Criterion	-2.34	-1.00	-1.31	-1.33	-1.08	**Kataoka's Criterion**	-2.34	-1.25	-1.19	-1.37	-1.19
% increase in Kataoka's Criterion of Optimal Portfolio		57.4%	44.0%	43.2%	54.0%	**% increase in Kataoka's Criterion of Optimal Portfolio**		46.4%	49.1%	41.4%	49.2%

Optimization with Respect to Sortino Ratio

When we optimize portfolios with respect to Sortino ratio as in Table 10-Panel D, the portfolio gets a CRSP weight of 29% and long-term government bonds of 71%. The Sortino ratio of this portfolio is 0.96. When we add EW-CTA and MFF indices, they increase the Sortino ratio tremendously to 1,71. Inclusion of CTAs increase Sortino ratio by 169% to 2,59; and inclusion of MFFs increase Sortino ratio by 38.7% to 1,34. CTA and MFF indices gain 41%-63% shares in portfolios.

Inclusion of VW-CTAs and MFFs enhances Sortino ratio by 45,1% to 1,40. When we add VW-CTAs only Sortino ratio increases to 1,55 and when we add MFFs only, Sortino ratio increases to 1,32. Inclusion of CTAs and MFFs separately and simultaneously gains weight to CTAs for 51%.

In line with the percentage increases in safety-first investment criteria, the percentage increase of Sortino ratio indicates an attribution of powerful downside risk protection of CTAs and MFFs. This feature is more powerful for CTAs. However, MFFs are also important tools in diversifying downside risk away from portfolios.

Table 10: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio (Continued)

Panel D: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio Based on Sortino

D.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio						**D.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio**					
CRSP	0.29	0.22	0.10	0.26	0.18	**CRSP**	0.29	0.17	0.22	0.21	0.19
Russel2000	0.00	0.00	0.05	0.00	0.02	**Russel2000**	0.00	0.01	0.04	0.00	0.06
MSCIWorld	0.00	0.00	0.02	0.00	0.00	**MSCIWorld**	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.71	0.19	0.16	0.26	0.15	**LTGovtBond**	0.71	0.26	0.21	0.50	0.21
CorpBond	0.00	0.00	0.00	0.00	0.01	**CorpBond**	0.00	0.03	0.00	0.00	0.00
DXY Currency	0.00	0.08	0.04	0.06	0.06	**DXY Currency**	0.00	0.11	0.01	0.00	0.06
EW_All CTAs and MFFs		0.50				**VW_All CTAs and MFFs**		0.42			
EW_CTAs			0.63		0.63	**VW_CTAs**			0.51		0.51
EW_MFFs				0.41	0.00	**VW_MFFs**				0.28	0.00
Sortino Ratio	0.96	1.71	2.59	1.34	2.59	**Sortino Ratio**	0.96	1.40	1.55	1.32	1.55
% increase in Sortino Ratio of Optimal Portfolio		77.8%	169.0%	38.7%	169.0%	**% increase in Sortino Ratio of Optimal Portfolio**		45.1%	60.6%	37.2%	60.6%

3.3 BULL AND BEAR MARKET ANALYSIS

The purpose of this section is to analyze CTAs and MFFs in bear and bull markets and to reveal if they are real downside risk protectors. CTAs and MFFs are known to be good downside protectors (Edwards and Liew, 1999a; Liang,2003; Christopherson et al., 2004; Bhardwaj et al., 2008; Till and Eagleeye, 2011). Therefore, the emphasis will be on bear markets.

We define bear markets as markets where the VW-CRSP return is lower than -1%; and bull markets as the markets where the VW-CRSP return is greater than 1%. Under this definition, we have 144 bull months and 79 bear months in our data frame. Table 11 shows the average annual returns, Sharpe ratios and correlations with standard asset classes for EW- and VW-CTA and MFF indices in bull and bear markets when CTAs and MFFs are analyzed as standalone investment vehicles.

The left hand side of Table 11 shows results for standalone investment analysis in bear markets. For brevity, we rank assets only with respect to Sharpe ratio. Column 3 shows that CTAs gain the highest rankings among all asset classes with respect to Sharpe ratio criterion. MFFs rank 5^{th} and 5^{th} among 12 indices. Only DXY currency among standard assets is doing better than VW-MFFs. Managed futures funds are performing better than all other asset classes in bear markets. The most important attribute of managed futures funds is that they have negative correlations with other assets in bear markets. VW-CTAs have -47%, VW-MFFs have -42% correlation with the market index. These correlation coefficients make managed futures funds great downside risk protection assets.

The right hand side of Table 11 shows the results for bull markets. In bull markets, managed futures are doing very badly. Only DXY currency index is performing worse than managed futures funds. Stock and fixed income indices are ranked the best among all assets.

Correlation coefficients of CTAs and MFFs with the market are around 0. The outcome is that managed futures funds are not profitable individual assets in up markets.

Table 11: Rankings of EW and VW Fund Investment Style Indices as Standalone Investments in Bull and Bear Markets

	BEAR MARKETS				***BULL MARKETS***			
	Average Annual Excess Return	**Sharpe Ratio**	**SR Ranking**	**Correlation with Market**	**Average Annual Excess Return**	**Sharpe Ratio**	**SR Ranking**	**Correlation with Market**
EW_All Funds	1.94	0.22	3	-0.39	8.71	0.90	6	0.04
VW_All Funds	2.26	0.20	4	-0.44	8.33	0.81	8	-0.05
EW_CTAs	5.44	0.70	1	-0.46	11.08	0.64	11	0.09
VW_CTAs	3.59	0.33	2	-0.47	7.66	0.78	10	-0.06
EW_MFFs	*-0.18*	*-0.02*	7	*-0.37*	*7.85*	*0.88*	7	0.00
VW_MFFs	1.19	*0.10*	5	*-0.42*	*8.99*	*0.81*	9	*-0.04*
Standard Assets								
Market (CRSP)	-57.37	-5.13	12	1.00	50.67	6.70	1	1.00
US Small Stock	-67.99	-4.51	10	0.80	55.74	4.73	3	0.59
Emerging Market	-56.03	-4.59	11	0.92	42.89	4.98	2	0.83
LT Gov Bond	-0.43	-0.06	8	0.01	9.30	1.32	5	-0.07
Corp Bond	*-7.82*	*-1.23*	9	*0.27*	*7.64*	*1.39*	4	*0.16*
DXY Currency	*0.00*	*0.00*	6	*-0.26*	*0.00*	*0.00*	12	*-0.16*

Table 12 displays portfolio analysis in bull and bear markets. We use the same structure that we employ in Table 10. This time, we optimize portfolio weights only with respect to Sharpe ratio for simplicity. Panel A.1. of Table 12 shows the optimal portfolio in bear markets with and without EW-managed futures funds. In the absence of managed futures funds, corporate bond index gains 55% and foreign exchange market index gains 45% weights. Sharpe ratio of this portfolio is 0,34. Addition of EW-CTAs and MFFs would improve portfolio's Sharpe ratio to 0,46. Addition of CTAs only improves the Sharpe ratio to 0,82 by a 141% increase. Addition of VW-CTAs and MFFs enhance portfolio Sharpe ratio to 0,43. Addition of CTAs and MFFs improve Sharpe ratio to 0.50 and 0,38, respectively. This result is a spectacular outcome that documents the success of CTAs in down markets.

Panel B of Table 12 shows the same analysis for bull markets. CRSP, Russell2000, long-term government bonds, corporate bonds, and DXY currency take shares in the optimal portfolio in the absence of managed futures funds. The Sharpe ratio of this portfolio is 5.83. Addition of EW- and VW-CTAs and MFFs enhance portfolio Sharpe ratios slightly by less than 2% for each CTA and MFF category. The results support earlier findings in that CTAs and MFFs perform poorly in up-markets. They can take small portions in portfolios to provide diversification, but their overall performance cannot exert this level of success.

Table 12: Addition of EW and VW Fund Indices into an Optimal Stock and Bond Portfolio in Bear and Bull Markets

BEAR MARKETS

Panel A: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio in Bear Markets

A.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio

CRSP	0.00	0.00	0.00	0.00	0.00
Russel2000	0.00	0.00	0.00	0.00	0.00
MSCIWorld	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.00	0.00	0.00	0.00	0.00
CorpBond	0.55	0.33	0.23	0.49	0.23
DXY Currency	0.45	0.38	0.26	0.44	0.26
EW_All CTAs and MFFs		0.29			
EW_CTAs			0.50		0.50
EW_MFFs				0.07	0.00
Sharpe Ratio	0.34	0.46	0.82	0.34	0.82
% increase in Sharpe Ratio of Optimal Portfolio		34.95%	141.42%	1.70%	141.42%

A.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio

CRSP	0.00	0.00	0.00	0.00	0.00
Russel2000	0.00	0.00	0.00	0.00	0.00
MSCIWorld	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.00	0.00	0.00	0.00	0.00
CorpBond	0.55	0.40	0.37	0.44	0.37
DXY Currency	0.45	0.40	0.36	0.42	0.36
VW_All CTAs and MFFs		0.21			
VW_CTAs			0.27		0.27
VW_MFFs				0.14	0.00
Sharpe Ratio	0.34	0.43	0.50	0.38	0.50
% increase in Sharpe Ratio of Optimal Portfolio		26.97%	48.13%	11.78%	48.13%

BULL MARKETS

Panel B: Addition of EW and VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio in Bull Markets

B.1. Addition of EW CTA and MFF Indices into an Optimal Stock and Bond Portfolio

CRSP	0.86	0.77	0.85	0.74	0.74
Russel2000	0.12	0.11	0.12	0.10	0.10
MSCIWorld	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.00	0.00	0.00	0.00	0.00
CorpBond	0.00	0.00	0.00	0.00	0.00
DXY Currency	0.02	0.04	0.02	0.05	0.05
EW_All CTAs and MFFs		0.08			
EW_CTAs			0.01		0.00
EW_MFFs				0.11	0.11
Sharpe Ratio	5.83	5.87	5.83	5.90	5.90
% increase in Sharpe Ratio of Optimal Portfolio		0.73%	0.02%	1.17%	1.17%

B.2. Addition of VW CTA and MFF Indices into an Optimal Stock and Bond Portfolio

CRSP	0.86	0.74	0.74	0.75	0.74
Russel2000	0.12	0.10	0.10	0.10	0.10
MSCIWorld	0.00	0.00	0.00	0.00	0.00
LTGovtBond	0.00	0.00	0.00	0.00	0.00
CorpBond	0.00	0.00	0.00	0.00	0.00
DXY Currency	0.02	0.04	0.03	0.04	0.03
VW_All CTAs and MFFs		0.12			
VW_CTAs			0.12		0.12
VW_MFFs				0.10	0.01
Sharpe Ratio	5.83	5.93	5.94	5.92	5.94
% increase in Sharpe Ratio of Optimal Portfolio		1.84%	1.85%	1.58%	1.86%

This chapter examines performance of CTAs and MFFs. The analysis shows that CTAs and MFFs are well- performing individual assets according to Sharpe ratio, Roy’s criterion, Kataoka’s criterion, ans Sortino ratio. Similar results are obtained from portfolio analysis. CTAs and MFFs enhance portfolio Sharpe ratios significantly. Moreover, these funds perform successfully in bear markets while they operate poorly in bull markets. Next we search the sources of successful performance. Next chapter is analyzing if fund returns are due to managerial skill.

CHAPTER 4

MANAGERIAL SKILL

This section measures managerial skill, persistency of returns, and cash flows into and from funds during the analysis period. All the analyses are handled together since they are related to each other somehow. Managerial skill is expected to induce persistency in fund returns; persistency is expected to be followed by systematic cash inflows.

We measure managerial skill by using a two-step approach. The first step is the "regression or Jensen alphas" as widely used to measure the abnormal returns a fund earns over a benchmark. It is assumed that the abnormal returns come from the ability of the manager to generate extra cash flows (Jensen, 1968). The second step is persistency. If abnormal returns are persistent over time, we may assume that there is managerial skill at work, rather than chance (Edwards and Çağlayan, 2001).

4.1. JENSEN ALPHAS

To estimate Jensen alphas, we use two multifactor models. We employ multiple regression analysis of the factors in each model on individual excess returns. We compute excess returns by subtracting a 1-month Treasury bill rate from individual returns. After running the regressions, we create a series of intercept (alphas) of each regression and check if the average alphas are significantly different from 0. The models we used are:

1. 4-factor model of Fama-French (1993), and Carhart (1997): CRSP, HML, SMB, MOM.

2. 11-factor Model of Fama-French (1993), Carhart (1997), and Fung and Shieh (2001,2004): CRSP, HML, SMB, MOM, Δ10Y, ΔCredSpr, BDTF, FXTF, CMTF, IRTF, SKTF.

By employing the two models, we computed two sets of alphas. The 4- factor model is a standard model used in many analysis. Therefore, we add this model to the analysis. However, we know that CTA and MFF returns have a u-shape distribution similar to hedge funds. Therefore, we need to add some non-linear hedge fund factors to represent this distribution (BDTF, FXTF, CMTF, IRTF, and SKTF). We believe the 11-factor model represents the industry better. We distinguished between positive and significant alphas and all other alphas. Regression results of fund characteristics on alphas and fund characteristics for CTAs and MFFs are summarized in Table 13. As Table 13 suggests, the number of funds with positive and significant alphas is 207 for both 4- and 11-factor models. These numbers correspond to about 11% of all funds. Annualized average values of alphas, size and age are substantially higher for significant alpha funds than for other funds. However, there is not a remarkable difference between management fee and incentive fee of successful and other funds. The results are consistent for the two models; however, this table is only suggestive about the characteristics of the funds.

Table 13: Managerial Skill: Alphas of CTAs and MFFs and Fund Characteristics

	4 Factor Alpha	11 Factor Alpha
Number of Funds	1938	1868
Number of Funds w/ Positive Significant Alphas	207	207
% of Funds w/ Positive Significant Alphas	0.11	0.11
Annualized Average of Positive Significant Alphas (%)	1.55	1.55
Annualized Average of All Other Funds' Alphas (%)	-0.12	-0.05
Average Size of Funds w/ Positive Significant Alphas (million $s)	188.83	188.83
Average Size of All Other Funds (million $s)	79.78	62.20
Average Age of Funds with Positive Significant Alphas	111.83	111.46
Average Age of All Other Funds	63.11	66.66
Average Mgmt Fee of Funds w/ Positive Significant Alphas	1.80	1.80
Average Mgmt Fee of All Other Funds	2.01	1.96
Median Mgmt Fee of Funds w/ Positive Significant Alphas	2.00	2.00
Median Mgmt Fee of All Other Funds	2.00	2.00
Average Incentive Fee of Funds w/ Positive Significant Alphas	21.35	21.35
Average Incentive Fee of All Other Funds	18.39	18.41
Median Incentive Fee of Funds w/ Positive Significant Alphas	20.00	20.00
Median Incentive Fee of All Other Funds	20.00	20.00

To understand the effects of fund characteristics on fund success, we regress the fund characteristics on alphas. Regression results are presented in Table 14. The fund characteristics are incentive fee, management fee, size, and age. Table 14-Panel A demonstrates that incentive fee and age have a positive relationship with fund alpha; management fee has a negative relationship with fund alpha.

Table 14: Cross Section Regression of CTA and MFF Alphas on Fund Characteristics

Panel A: αi,t= δi + λ1,t. INCFEEt + λ2,t. MANFEEt + λ3,t. SIZEt + λ4,t. AGEt +υt		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.41***	-0.28**
	(-2.79)	(-2.08)
Incentive Fee	0.02***	0.02***
	(3.46)	(3.36)
Management Fee	-0.12***	-0.09***
	(-3.55)	(-2.79)
Average Size	0.00	0.00
	(-0.55)	(-0.47)
Age	0.00***	0.00***
	(6.95)	(5.67)
Panel B: αi,t= δi + λ1,t. INCFEEMEDIUMt. D1 + λ2,t. INCFEEHIGH. D2+ λ3,t.MANFEEHIGHt + λ4,t. MANFEEMEDIUMt + λ5,t. SIZEt + λ6,t.AGEt +υt		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.42***	-0.24*
	(-3.06)	(-1.87)
Incentive Fee Medium	0.02***	0.01***
	(3.78)	(3.03)
Incentive Fee High	0.02**	0.02**
	(2.45)	(2.38)
Management Fee Medium	0.24	0.12
	(0.61)	(0.34)
Management Fee High	-0.09***	-0.06**
	(-2.58)	(-1.97)
Average Size	0.00	0.00
	(-0.53)	(-0.47)
Age	0.00***	0.00***
	(6.95)	(5.73)

Incentive fee and management fee are two very important characteristics of CTAs and MFFs. Our analysis shows that they have contradicting effects. The former enhances fund performance while the latter mitigates it. Table 13 does not exhibit much of a difference in management fee and incentive fee between positive and significant alpha funds and other funds. Thus, we expect the sensitivity of these funds to be very high.

To test the sensitivity of incentive fee and management fee, we divide incentive fee and management fee values into three parts as low, medium, and high. We use medium and high management fee as independent factors in the regressions, so that we are able to compare the results and tell the difference between high and low management fees. We used slope dummies for the medium and high management fees as two different regressors as in Table 14-Panel B.

Results show that both high and medium incentive fee are significant on alpha level. We interpret this as follows: Alpha level is highly sensitive to incentive fee. High and low incentive fee is a significant factor in determination of alpha. On the other hand, only high management fee is significant on alpha. That means, as long as management fee is low or at industry average, it does not have any effect on alpha; however, if it is higher than industry average, it significantly reduces fund success. Fund alpha is sensitive to high level of management fee only.

To distinguish the differences between CTAs and MFFs, we repeat the same analysis for CTAs and MFFs only. Table 15 exhibits the alphas and fund characteristics computed by using multifactor models for CTAs. Number and percentage of positive and significant alphas are different for the two factor models. 11% of all funds are positive and significant for the 4-factor model whereas 12% of all funds are positive and significant for the 11-factor model. Fund alphas, size, and age have different averages for positive significant alpha funds and other funds.

Table 15: Managerial Skill: Alphas of CTAs and Fund Characteristics

	4 Factor Alpha	11 Factor Alpha
Number of Funds	936	870
Number of Funds w/ Positive Significant Alphas	105	105
% of Funds w/ Positive Significant Alphas	0.11	0.12
Annualized Average of Positive Significant Alphas (%)	1.82	1.82
Annualized Average of All Other Funds' Alphas (%)	-0.15	-0.02
Average Size of Funds w/ Positive Significant Alphas (million $s)	232.61	253.39
Average Size of All Other Funds (million $s)	31.70	39.92
Average Age of Funds with Positive Significant Alphas	102.69	104.33
Average Age of All Other Funds	54.03	62.84
Average Mgmt Fee of Funds w/ Positive Significant Alphas	1.85	1.85
Average Mgmt Fee of All Other Funds	2.12	2.04
Median Mgmt Fee of Funds w/ Positive Significant Alphas	2.00	2.00
Median Mgmt Fee of All Other Funds	2.00	2.00
Average Incentive Fee of Funds w/ Positive Significant Alphas	21.21	21.21
Average Incentive Fee of All Other Funds	20.09	20.21
Median Incentive Fee of Funds w/ Positive Significant Alphas	20.00	20.00
Median Incentive Fee of All Other Funds	20.00	20.00

Table 16 repeats Table 14 for CTAs only. Panel A shows that only management fee is significant for CTAs in both models. None of the other variables have relationship with fund success. Panel B repeats the same results by dividing management fee into three parts as low, medium, and high. We use medium and high management fee as independent factors in the regressions, so that we are able to compare the results and tell the difference between high and low management fees. We used slope dummies for the medium and high management fees as two different regressors as in Table 16-Panel B. High level management fee is significant in the 4-factor model, and both of medium and high management fee are significant for the 11-factor model. This suggests that high level of management fee is highly significant in fund alphas. The higher the management fee is, the lower the fund alpha.

Table 16: Cross Section Regression of CTA Alphas on Fund Characteristics

Panel A: αi,t= δi + λ1,t. INCFEEt + λ2,t. MANFEEt + λ3,t. SIZEt + λ4,t. AGEt +υt		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.35	-0.06
	(-0.95)	(-0.18)
Incentive Fee	0.03*	0.02
	(1.70)	(1.23)
Management Fee	-0.21***	-0.17***
	(-3.66)	(-3.02)
Average Size	0.00	0.00
	(-0.65)	(-0.60)
Age	0.01***	0.00***
	(4.75)	(3.57)
Panel B: αi,t= δi + λ1,t. INCFEEMEDIUMt. D1 + λ2,t. INCFEEHIGH. D2+ λ3,t.MANFEEHIGHt + λ4,t. MANFEEMEDIUMt + λ5,t. SIZEt + λ6,t.AGEt +υt		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.15	0.28
	(-0.53)	(1.04)
Incentive Fee Medium	0.02*	0.01
	(1.81)	(0.64)
Incentive Fee High	0.01	0.01
	(1.01)	(0.44)
Management Fee Medium	-0.22**	-0.24***
	(-2.22)	(-2.57)
Management Fee High	-0.19***	-0.17***
	(-3.23)	(-2.99)
Average Size	0.00	0.00
	(0.00)	(-0.56)
Age	0.01***	0.00***
	(4.71)	(3.49)

Table 17 displays fund characteristics for positive significant alpha funds and other funds for MFFs only. Around 10% of all funds for both models has positive significant alphas. We observe that annualized alpha and age are higher for positive significant alpha funds and other funds. On the other hand, size is not a distinguishable characteristic on funds. To check the validity of this observation, we regress fund characteristics on regression alphas and form Table 18.

Table 17: Managerial Skill: Alphas of MFFs and Fund Characteristics

	4 Factor Alpha	11 Factor Alpha
Number of Funds	1002	998
Number of Funds w/ Positive Significant Alphas	102	102
% of Funds w/ Positive Significant Alphas	0.10	0.10
Annualized Average of Positive Significant Alphas (%)	1.27	1.27
Annualized Average of All Other Funds' Alphas (%)	-0.08	-0.07
Average Size of Funds w/ Positive Significant Alphas (million $s)	86.99	155.86
Average Size of All Other Funds (million $s)	106.00	115.21
Average Age of Funds with Positive Significant Alphas	121.25	118.79
Average Age of All Other Funds	71.48	69.93
Average Mgmt Fee of Funds w/ Positive Significant Alphas	1.74	1.74
Average Mgmt Fee of All Other Funds	1.87	1.88
Median Mgmt Fee of Funds w/ Positive Significant Alphas	2.00	2.00
Median Mgmt Fee of All Other Funds	2.00	2.00
Average Incentive Fee of Funds w/ Positive Significant Alphas	21.49	21.49
Average Incentive Fee of All Other Funds	16.77	16.83
Median Incentive Fee of Funds w/ Positive Significant Alphas	20.00	20.00
Median Incentive Fee of All Other Funds	20.00	20.00

Tables 18-Panel A suggests that incentive fee and age are highly significant for determination of fund alpha, but management fee does not have any effect. Panel B suggests that alpha is highly sensitive to incentive fee: Both medium and high level of incentive fee are significant in determination of fund alpha.

Table 18: Cross Section Regression of MFF Alphas on Fund Characteristics

Panel A: $\alpha_{i,t} = \delta_i + \lambda_{1,t}.\ INCFEE_t + \lambda_{2,t}.\ MANFEE_t + \lambda_{3,t}.\ SIZE_t + \lambda_{4,t}.\ AGE_t + \upsilon_t$		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.48***	-0.41***
	(-3.70)	(-3.18)
Incentive Fee	0.02***	0.02***
	(3.00)	(3.00)
Management Fee	-0.02	-0.02
	(-0.46)	(-0.60)
Average Size	0.00	0.00
	(0.68)	(0.76)
Age	0.00***	0.00***
	(5.44)	(4.93)
Panel B: $\alpha_{i,t} = \delta_i + \lambda_{1,t}.\ INCFEEMEDIUM_t.\ D1 + \lambda_{2,t}.\ INCFEEHIGH.\ D2 + \lambda_{3,t}.MANFEEHIGH_t + \lambda_{4,t}.\ MANFEEMEDIUM_t + \lambda_{5,t}.\ SIZE_t + \lambda_{6,t}.AGE_t + \upsilon_t$		
	4 Factor Alpha	**11 Factor Alpha**
Constant	-0.51***	-0.44***
	(-3.75)	(-3.30)
Incentive Fee Medium	0.02***	0.02***
	(3.15)	(3.30)
Incentive Fee High	0.02***	0.02***
	(2.76)	(2.85)
Management Fee Medium	0.03	0.01
	(0.22)	(0.07)
Management Fee High	0.01	0.00
	(0.22)	(0.05)
Average Size	0.00	0.00
	(0.62)	(0.72)
Age	0.00***	0.00***
	(5.48)	(5.03)

In a nutshell, both models support the fact that age is a significant factor in determination of fund alphas in both type of funds. CTA alphas are sensitive to management fee, and MFF alphas are sensitive to incentive fee. Incentive and management fees are effective on fund alphas when we examine all funds together. Management fee has a negative effect; and incentive fee has a positive effect on fund alphas.

4.2. PERSISTENCY

In order to call a fund manager successful, we need to prove that the manager is successful over time. One-time success can be due to for other factors such as luck. But persistence in high returns will be defined as success. This fact leads us to check the persistency of returns. We are looking for persistency in high or low returns. In other words, do successful funds in a certain month continue to be successful in the coming months? Or less successful funds become more successful in time? Can the success of a fund in a month be generalized to longer horizons?

We measure persistency of returns using parametric and a nonparametric tests. We employ a regression analysis as a parametric persistency test. In this test, we regress one-period-ahead returns on the current period's returns on a yearly and monthly frequency by using the below equation:

$$R_{i,t}-Rf_{,t}=\alpha+\beta.(R_{i,t-1} - Rf_{,t})$$

Table 19 shows the results for monthly and annual frequency for all funds, CTAs only, and MFFs only. All regression results are significant at a 10% level in monthly frequency for all fund groups. We can say that there is marginal persistence in managerial success in monthly returns. However, annual returns show that there is strong persistence in only CTA returns. Since all of our analysis is conducted in monthly frequency, the results are relevant to our study. On the other hand, annual results show that there is strong persistence in CTA returns but there is no persistence in MFF returns.

Table 19: Cross Section Regression of Excess Returns of CTAs and MFFs on Past Excess Returns

		Monthly Returns	Annual Returns
All Funds	**Average**	0.03*	0.02
	Newey West T-Stat	(1.83)	(0.42)
CTAs	**Average**	0.03*	0.13**
	Newey West T-Stat	(1.68)	(2.47)
MFFs	**Average**	0.03*	0.00
	Newey West T-Stat	(1.68)	(-0.09)

Regression results should be interpreted with caution because there is estimation error in independent variables even though we clean the database from survivorship bias (Carpenter and Lynch, 1999). In order to strengthen these results, we also run winner and loser two-way contingency tests as a non-parametric test.

Winner and loser contingency analysis is a nonparametric test that measures whether winners in a certain period continues to be winners in subsequent periods, and whether losers in certain period continues to be losers in subsequent periods. We call winners as funds as funds whose current return is greater than industry median return. The persistence is measured by a CPR ratio. The higher the CPR, the more persistent are the returns. CPR ratio is tested by a Z-statistics (Agarwal and Naik, 2000).

We use winner/ loser contingency tests to measure the differences of persistence among years. Table 20 shows the results for all funds. The CPR ratio for all funds is 1,43 with a Z-score of 9,58. This result indicates persistence in annual frequency. Table 21 shows the results of winner/ loser contingency tests for CTAs only. The Z-score for the CPR value is 6.97, which indicates persistence. Table 22 shows the winner/ loser contingency test for MFFs only. The Z-score is 6.44, which indicates persistence for MFFs as well. As a result, 2-way contingency test indicates persistence in all funds.

Table 20: Winner and Loser Two-Way Contingency Test for All Funds

Year	WW	WL	LW	LL	CPR	Z-Statistics
1995	140	161	156	145	0.81	-1.30
1996	183	163	109	236	2.43	5.62
1997	179	159	108	230	2.40	5.48
1998	175	169	118	226	1.98	4.37
1999	164	193	144	213	1.26	1.51
2000	166	190	153	202	1.15	0.95
2001	194	195	140	248	1.76	3.87
2002	199	214	173	239	1.28	1.79
2003	249	197	150	295	2.49	6.58
2004	218	251	189	280	1.29	1.91
2005	232	235	174	293	1.66	3.82
2006	187	263	173	277	1.14	0.95
2007	190	185	115	259	2.31	5.50
2008	61	244	81	224	0.69	-1.91
2009	77	66	96	64	0.78	-1.08
2010	71	103	55	31	0.39	-3.47
2011	39	87	27	84	1.39	1.13
2012	25	41	38	103	1.65	1.59
2013	47	16	65	38	1.72	1.53
2014	18	94	9	30	0.64	-0.98
Total	2814	3226	2273	3717	1.43	9.58
Percentage	23.4%	26.8%	18.9%	30.9%		

Table 21: Winner and Loser Two-Way Contingency Test for CTAs

Year	WW	WL	LW	LL	CPR	Z-Statistics
1995	99	107	90	92	0.95	-0.27
1996	107	115	59	160	2.52	4.56
1997	102	87	65	147	2.65	4.68
1998	78	113	53	142	1.85	2.82
1999	83	78	92	129	1.49	1.92
2000	80	114	56	103	1.29	1.15
2001	88	70	78	104	1.68	2.36
2002	81	118	63	84	0.92	-0.40
2003	71	97	32	161	3.68	5.24
2004	49	65	94	140	1.12	0.50
2005	73	82	75	94	1.12	0.49
2006	54	102	31	103	1.76	2.13
2007	30	56	49	86	0.94	-0.21
2008	19	60	26	61	0.74	-0.84
2009	29	16	28	30	1.94	1.63
2010	27	31	15	18	1.05	0.10
2011	14	28	7	29	2.07	1.37
2012	9	12	15	29	1.45	0.68
2013	17	7	13	14	2.62	1.63
2014	6	24	3	14	1.17	0.20
Total	1116	1382	944	1740	1.49	6.97
Percentage	9.3%	11.5%	7.8%	14.5%		

Table 22: Winner and Loser Two-Way Contingency Test for MFFs

Year	WW	WL	LW	LL	CPR	Z-Statistics
1995	41	54	66	53	0.61	-1.78
1996	76	48	50	76	2.41	3.39
1997	77	72	43	83	2.06	2.91
1998	97	56	65	84	2.24	3.42
1999	81	115	52	84	1.14	0.57
2000	86	76	97	99	1.15	0.68
2001	106	125	62	144	1.97	3.37
2002	118	96	110	155	1.73	2.96
2003	178	100	118	134	2.02	3.96
2004	169	186	95	140	1.34	1.72
2005	159	153	99	199	2.09	4.41
2006	133	161	142	174	1.01	0.07
2007	160	129	66	173	3.25	6.31
2008	42	184	55	163	0.68	-1.69
2009	48	50	68	34	0.48	-2.52
2010	44	72	40	13	0.20	-4.34
2011	25	59	20	55	1.17	0.43
2012	16	29	23	74	1.78	1.46
2013	30	9	52	24	1.54	0.95
2014	12	70	6	16	0.46	-1.37
Total	1698	1844	1329	1977	1.37	6.44
Percentage	14.1%	15.3%	11.0%	16.4%		

As a second non-parametric test, we run portfolio analysis for all funds, CTAs only and MFFs only. We perform quintile portfolio analyses every month (and year) by sorting funds according to fund's current return. We compute next-month (and next-year) return averages and t-statistics of each quintiles. Quintile 1 contains the funds with the lowest current return; quintile 5 contains the funds with the highest current return. Then, we take the Q5-Q1 difference for next month (year) returns and compute the t-statistic to test if the difference is different from 0. If the difference is significantly different from 0, we would conclude that returns are persistent.

Table 23: Portfolio Analysis of One-Period-Ahead Future Returns

		Monthly Returns	Annual Returns
All Funds	**Average**	**3.93*** **	**1.72*** **
	Newey West T-Stat	**(15.41)**	**(9.42)**
CTAs	**Average**	**3.85*** **	**1.76*** **
	Newey West T-Stat	**(15.25)**	**(9.98)**
MFFs	**Average**	**3.75*** **	**1.62*** **
	Newey West T-Stat	**(16.33)**	**(8.14)**

The results of portfolio analysis are presented in Table 23. The results show very strong persistence in both monthly and annual returns. As a result, we can cautiously conclude that there is persistence in CTA and MFF returns.

4.3. FUND FLOWS

Another way of measuring managerial skill can go through analyzing cash flows into the industry. Investors may invest in an asset for several reasons. However, if there is persistent flow over years, we can interpret at least part of this success as managerial skill. We measure the significance of flow in three ways.

Firstly, we test if the flow into a fund affects the return of the fund the next year. In order words, do returns follow flow? To test this hypothesis, we simply use the second step of Fama-MacBeth (1973) regressions. The regression is:

$$R_{i,t+1}=\alpha_i+\beta_i.\ F_{i,t}+\varepsilon_t$$

R and F represent return and flow of fund i. The regression results run separately for all funds, CTAs, and MFFs can be found in Table 24 Panel-A. T-statistics is insignificant for all fund groups. Flow has a positive relationship with 1-year-ahead returns for all funds and CTAs but it has a negative relation with 1-month-ahead returns for MFFs. However, all relationships between flow and 1-month-ahead returns are statistically insignificant. Thus we can conclude that a fund that attracted cash for a period will likely not generate better returns in upcoming periods.

Table 24: Univariate Fama-MacBeth Cross Section Regressions on One-Month Ahead Returns and Past Month's Flow

	$Return_{t+1}=\alpha+\beta Flow_t$		$Flow_{t+1}=\alpha+\beta Return_t$	
All Funds	**Average**	0.00	**Average**	**131,120.41*** **
	NW T-Stat	(-0.85)	**NW T-Stat**	**(2.57)**
CTAs	**Average**	-0.01	**Average**	**210,570.99*** **
	NW T-Stat	(-0.86)	**NW T-Stat**	**(3.18)**
MFFs	**Average**	0.00	**Average**	**56,977.10* **
	NW T-Stat	(0.18)	**NW T-Stat**	**(1.74)**

Second, we test if a return of a year affects the flow of the coming year. We measure if flow follows return. To test it, we run the following regression:

$$F_{i,t+1}=\alpha_i+\beta_i.\ R_{i,t}+\varepsilon_t$$

Table 24 Panel-B presents the results. All funds and CTAs deduce highly significant and positive results. This result is marginally lower for MFF database. So, flow follows higher returns. That is quite a surprising result. By combining the results of the two regressions, we can say that successful funds attract flow; but if a fund gets inflows in a certain month, it does not increase returns any more in future months protect its success any more.

Third, we want to see how significantly successful and unsuccessful funds behave. We determine positive and significant as well as negative and significant alpha funds using 4- and 11-factor models. Then, we run the two regressions above only for positive and significant and negative and significant funds to check if successful funds get positive flow and unsuccessful funds lose investment. The results for all funds can be found in Table 25. The first panel of the table tests the first hypothesis: Does return follow flow? Positive alpha funds receive flows, and negative alpha funds lose flows. Thus, we can conclude that return follows flow. Successful funds have higher returns and unsuccessful funds mitigate returns. Panel B of Table 25 asks whether flow follows return. The answer is no for positive alpha funds. There is a negative but insignificant relationship between one-month-ahead flow and current-month-return. On the other hand, there is a significant relationship between return and flow for unsuccessful funds. As returns go down, flow runs away from unsuccessful funds.

Table 25: Univariate Fama-MacBeth Cross Section Regressions on One-Month Ahead Returns and Past Month's Flow on Positive and Negative Significant Alpha CTAs and MFFs

Panel A: $Return_{t+1}=\alpha+\beta Flow_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	**1.36*****	**-1.48*****	**1.36*****	**-1.24*****
Newey West T Stat	**(10.09)**	**(-12.98)**	**(10.09)**	**(-13.06)**
Panel B: $Flow_{t+1}=\alpha+\beta Return_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	-54,519.30	**-1,623,623.74*****	-54,519.30	**-1,939,592.59*****
Newey West T-Stat	(-0.13)	**(-3.07)**	(-0.13)	**(-3.20)**

We repeat the same test for CTAs only. The results are presented in Table 26. The results in Panel A are in line with Panel A of Table 25. The result is that return follows flow for highly successful and highly unsuccessful funds. Panel B shows that flow does not follow return for highly successful funds but flow follows return for highly unsuccessful funds. However, the latter result is true for only 11-factor model.

Table 26: Univariate Fama-MacBeth Cross Section Regressions on One-Month Ahead Returns and Past Month's Flow on Positive and Negative Significant Alpha CTAs

$Return_{t+1}=\alpha+\beta Flow_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	**1.53*** **	**-1.82*** **	**1.53*** **	**-1.41*** **
Newey West T-Stat	**(6.26)**	**(-8.36)**	**(6.26)**	**(-7.01)**
$Flow_{t+1}=\alpha+\beta Return_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	654,587.53	-267,572.86	654,587.53	**-453,142.96*** **
Newey West T Stat	(0.87)	(-1.29)	(0.87)	**(-3.06)**

Table 27 repeats the same analysis for MFFs only. Panel A is in line with Panel A of Tables 25 and 26: Return follows flow for top- and bottom-performer funds. However, Panel B displays a contradicting result to earlier tables: Flow runs away from return for MFFs. This outcome should be interpreted carefully by taking other factors into account.

Table 27: Univariate Fama-MacBeth Cross Section Regressions on One-Month Ahead Returns and Past Month's Flow on Positive and Negative Significant Alpha MFFs

$Return_{t+1}=\alpha+\beta Flow_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	**1.18*** **	**-1.20*** **	**1.18*** **	**-1.14*** **
Newey West T-Stat	**(11.45)**	**(-12.30)**	**(11.45)**	**(-12.60)**
$Flow_{t+1}=\alpha+\beta Return_t$				
	4-Factor		**11-Factor**	
	Positive Alpha Funds	**Negative Alpha Funds**	**Positive Alpha Funds**	**Negative Alpha Funds**
Average	**-784,482.22*** **	**-2,728,036.31*** **	**-784,482.22*** **	**-2,840,950.35*** **
Newey West T-Stat	**(-2.53)**	**(-2.93)**	**(-2.53)**	**(-2.97)**

All in all, the results for highly successful and unsuccessful funds suggest that return follows flow. If a fund receives inflows in a certain month, it is expected that its expected returns will increase in next month. Similarly, if a fund, loses investment in a certain month, it is expected that its returns will drop in next month. Thus, flow can be predictive factor for future returns. On the other hand, flow follows return for highly successful and highly unsuccessful CTAs, but this is not true for highly successful and unsuccessful MFFs. It seems that MFF investors have other decision criteria for their investments rather than prior returns.

The results from Table 24 contradict with the results in Tables 25-27: Return does not follow flow, but flow follows return for all funds. A possible reason is that highly successful and highly unsuccessful fund investors have other decision making criteria or priorities that would make their investments different from all other investors.

This chapter seeks managerial skill in CTA and MFF success. The first step to compute managerial skill is to find Jensen alphas. We use 4-factor and 11-factor models to compute alphas. About 10%-12% of all funds has positive and significant alphas. Positive significant alphas have positive correlation with age and incentive fee, and negative correlation with management fee. The second step is to compute persistency in retruns. Both parametric and non-parametric tests show that monthly fund returns are persistent. Lastly, analysis shows that fund flows cannot be used to predict future fund returns.

CHAPTER 5

FACTOR EXPOSURES TO CTAs AND MFFs

It is hard to predict behaviors of complex investment vehicles. Yet, it is a crucial question for an investor to ask what factors affect CTA and MFF performance. There is a vast literature in hedge funds on risk exposures. However, important risk factors for CTAs and MFFs have never been investigated. This section examines several risk factors to find if any of them can be used to predict future CTA and MFF returns.

In order to find financial and macroeconomic factors affecting CTA and MFF performance, we select 22 variables used in earlier research. These variables are defined in Table 6. Table 6 shows the time series mean, median, standard deviation, minimum and maximum percentage returns of the 24 financial and macroeconomic factors used in this study. The financial factors are as follows: (1) CRSP-Rf: Value-weighted CRSP market index return net of 1-month US T-bill rate; (2) SMB: Fama-French (1993) size factor; (3) HML: Fama-French (1993) book-to-market factor; (4) RMW: Fama-French (2017) operating profitability factor; (5) CMA: Fama-French (2017) investment factor; (6) MOM: Carhart (1997) momentum factor; (7) Δ10Y: Fung-Hsieh (2004) long-term interest rate factor; (8) ΔCredSpr: Fung-Hsieh (2004) credit risk factor; (9) BDTF: Fung-Hsieh (2001) bond trend following factor; (10) FXTF: Fung-Hsieh (2001) currency trend following factor; (11): CMTF: Fung-Hsieh (2001) commodity trend following factor; (12) IRTF: Fung-Hsieh (2001) short-term interest rate trend following factor; (13) SKTF: Fung-Hsieh (2001) stock index trend following factor.

The macroeconomic factors are as follows: (1) TERM: Term spread, measured as the difference between yields on 10-year and 3-month treasury securities; (2) DEF: Default spread measured as the difference between yields on BAA rated and AAA-rated corporate bonds; (3)

DIV: Aggregate dividend yield on the S&P 500 index; (4) INF: Monthly inflation rate based on the US consumer price index; (5) RREL: Relative T-bill rate, measured as the difference between 3-month T-bill rate and its 12 month moving average backward average; (6) UNEMP: The US monthly unemployment rate, measured as the number of unemployed persons as a percentage of labor force; (7) CFNAI: Chicago FED national activity index; (8) TED1M: TED spread, an indicator of credit risk and perceived soundness of the banking system, measured as the difference between 1-month LIBOR and 3-month T-bill rates; (9) GDPPCG: US monthly growth rate of real GDP per capita; (10) IPG Growth: Louisiana FED industrial production index; (11) PYRL: Louisiana FED total nonfarm employment.

5.1. PARAMETRIC TESTS

5.1.1. Univariate Fama-MacBeth Regressions

To determine the significant factors on CTA and MFF performance, we run time-series regressions on a 12-, 18-, 24-, 30-, and 36-month rolling window basis for each factor one by one on individual excess fund returns, and compute the regression slope coefficients (betas). The analysis period is January 1997-December 2014. The first rolling window returns were used to compute betas for the period starting on January 1997. Excess fund returns are computed by subtracting 1-month Treasury-bill rate from individual returns. The regression equation, in which β is estimated on an individual basis for each factor, can be seen below.

$$R_{i,t}=\alpha_{i,t} + \beta^{F}_{i,t}.F_t + \varepsilon_{i,t}$$

As a second step, we regress betas on one-period ahead individual excess fund returns. The analysis period of this regression is January 1997-December 2014. In this regression, we estimate λs, which are the factor exposures on future fund returns. The average and t-statistics of λs provide us the significance levels of factor betas on future fund returns. The cross-sectional regression equation can be seen below.

$$R_{i,t+1}=\omega_t + \lambda_t.\ \beta^F_{i,t} + \varepsilon_{i,t+1}$$

In all of our regressions, we use rolling windows to be able to eliminate periodic trends in the time series. Table 28 exhibits Fama-MacBeth second step regression coefficients. Results suggest that most of the variables are insignificant in all rolling window series. Only HML, GDPPCG, and IPG are significant factors for most of the rolling windows. HML has a positive relationship with future returns of the funds. However, we observe a negative relationship between future fund returns and IPG.

Table 28: Univariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Univariate Risk Factor Beta for CTAs and MFFs

12-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.12	-0.06	0.20	0.10	0.07	0.07	0.00	0.00	-0.01	0.00	0.00	-0.02
T-Stat	0.60	-0.47	1.32	0.78	0.66	0.30	-0.39	0.27	-0.94	-0.33	0.53	-1.36
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.04	-0.01	0.00	-0.03	0.01	0.00	-0.02	**0.04***	0.00	**-0.05***	0.00
T-Stat	-0.83	-1.82	-1.04	0.06	-1.59	0.80	0.00	-0.61	**1.72**	-1.44	**-1.65**	-0.50
18-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.05	-0.01	**0.40****	0.13	0.12	0.08	-0.01	0.00	0.00	0.00	0.00	-0.02
T-Stat	0.21	-0.05	**2.27**	0.90	0.93	0.27	-0.60	0.17	-0.41	0.44	0.49	-1.47
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.05	-0.01	0.00	-0.01	0.02	0.00	-0.03	0.01	**0.00***	**-0.08****	0.00
T-Stat	-1.00	-1.41	-0.72	-0.04	-0.78	1.00	0.18	-0.76	0.41	**-1.62**	**-2.13**	0.23
24-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.09	-0.06	**0.38***	0.16	0.14	0.08	-0.02	0.00	0.00	0.01	0.01	-0.02
T-Stat	0.39	-0.29	**1.73**	1.00	0.95	0.24	-1.19	0.38	0.43	1.36	0.94	-0.91
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.05	-0.02	0.00	-0.03	0.03	0.00	-0.06	0.01	**0.00****	**-0.12****	0.00
T-Stat	-0.60	-0.97	-0.80	-0.08	-1.47	0.73	0.16	-1.29	0.24	**-2.21**	**-2.94**	0.23
30-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	-0.06	-0.15	0.34	0.20	0.14	0.19	-0.02	0.01	0.00	0.01	0.01	-0.01
T-Stat	-0.26	-0.67	1.43	1.19	0.85	0.48	-1.21	0.60	0.46	1.27	1.31	-0.39
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.04	-0.03	-0.02	-0.04	0.03	0.00	-0.03	0.01	**0.00****	-0.04	0.01
T-Stat	-0.01	-0.69	-1.44	-0.81	-1.60	0.79	0.02	-0.59	0.17	**-1.99**	-0.93	1.14
36-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	-0.05	-0.11	0.41	0.20	0.16	0.11	-0.02	0.01	0.00	0.01	**0.02****	-0.01
T-Stat	-0.18	-0.41	1.51	1.00	0.94	0.27	-1.16	0.47	0.30	0.86	**2.04**	-0.60
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.03	-0.02	0.00	-0.04	0.02	0.00	-0.06	0.03	0.00	-0.05	0.01
T-Stat	-0.44	-0.50	-0.77	0.01	-1.46	0.37	-0.12	-1.04	0.39	-1.12	-1.04	1.00

Table 29 shows the second step regression coefficients and t-statistics for only CTAs: HML is not a significant factor for CTAs but GDPPCG and IPG are the significant factors in many rolling windows. GDPPCG and IPG have a negative relationship with future CTA returns.

Table 30 shows the second step regression coefficients and t-statistics for only MFFs: Similar to CTAs, HML is not a significant factor for MFFs but GDPPCG and IPG are the significant factors in many rolling window tests. GDPPCG and IPG have a negative relationship with future MFF returns.

Table 29: Univariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Univariate Risk Factor Beta for CTAs only

12-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.15	-0.18	0.14	0.09	0.09	0.13	-0.01	0.01	-0.01	-0.01	0.00	-0.01
T-Stat	0.76	-1.22	0.85	0.69	0.80	0.50	-0.99	0.79	-1.49	-0.65	0.67	-1.05
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	**-0.05***	-0.01	0.00	-0.02	0.01	0.00	-0.03	0.05	**0.00***	**-0.06****	0.00
T-Stat	-0.91	**-1.86**	-1.65	-0.15	-1.25	0.77	-1.56	-0.77	2.17	**-1.86**	**-2.40**	-0.78
18-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.12	-0.09	0.20	0.13	0.07	0.18	-0.01	0.01	0.00	0.00	0.01	-0.01
T-Stat	0.53	-0.54	1.12	0.84	0.50	0.61	-1.08	0.62	-0.51	0.40	0.64	-0.88
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.04	-0.02	0.00	-0.02	0.02	0.00	-0.02	0.03	**0.00***	**-0.05***	0.00
T-Stat	-0.74	-1.19	-1.44	-0.31	-1.03	1.04	-0.86	-0.52	1.11	**-1.76**	**-1.67**	-0.08
24-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.16	-0.06	0.32	0.14	0.14	0.18	-0.02	0.00	0.00	0.01	0.01	0.00
T-Stat	0.62	-0.26	1.50	0.83	0.85	0.50	-1.07	0.27	0.28	1.25	0.88	-0.23
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.05	-0.02	-0.01	-0.02	0.04	0.00	-0.05	0.05	**0.00***	**-0.09****	0.01
T-Stat	-0.02	-0.92	-1.42	-0.38	-0.98	1.18	-0.15	-1.08	0.97	**-1.79**	**-2.11**	0.76
30-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.12	-0.25	0.34	0.12	0.12	0.16	-0.01	0.00	0.00	0.01	0.01	-0.01
T-Stat	0.43	-0.98	1.38	0.62	0.65	0.41	-0.81	0.33	0.09	1.10	1.27	-0.55
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.04	-0.03	-0.02	-0.04	0.03	0.00	-0.03	0.01	**0.00****	-0.04	0.01
T-Stat	0.21	-0.69	-1.44	-0.81	-1.60	0.79	0.02	-0.59	0.17	**-1.99**	-0.93	1.14
36-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.07	-0.20	0.33	0.20	0.13	0.04	-0.02	0.00	0.00	0.01	0.02*	-0.01
T-Stat	0.21	-0.74	1.15	0.90	0.67	0.09	-1.06	0.15	-0.34	0.72	1.94	-0.46
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.04	-0.02	0.00	-0.01	0.01	0.00	-0.03	0.04	0.00	-0.05	0.01
T-Stat	-0.06	-0.58	-0.75	-0.11	-0.40	0.12	-0.50	-0.57	0.61	-1.10	-0.87	0.55

Table 30: Univariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Univariate Risk Factor Beta for MFFs only

12-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.10	0.09	0.23	0.07	0.05	-0.13	0.00	0.00	0.00	0.00	0.01	-0.03
T-Stat	0.42	0.50	1.24	0.51	0.39	-0.47	0.06	0.04	-0.40	0.33	0.71	-1.57
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.03	-0.01	0.00	-0.03	0.01	0.00	0.00	0.03	0.00	-0.02	0.00
T-Stat	-0.64	-1.00	-0.76	-0.36	-1.48	0.37	0.81	-0.07	1.02	-0.95	-0.40	0.65
18-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	-0.03	0.11	0.47	0.10	0.12	-0.19	-0.01	0.00	0.00	0.01	0.01	-0.03
T-Stat	-0.11	0.52	2.13	0.61	0.78	-0.51	-0.63	0.07	0.01	0.55	0.55	-1.50
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.06	-0.01	0.00	-0.01	0.02	0.00	-0.01	0.00	0.00	-0.05	0.00
T-Stat	-0.97	-1.36	-0.60	-0.06	-0.55	0.70	0.32	-0.22	-0.04	-1.14	-1.12	0.55
24-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	0.03	0.03	0.38	0.08	0.12	-0.09	-0.02	0.00	0.01	0.01	0.01	-0.02
T-Stat	0.14	0.13	1.37	0.44	0.65	-0.22	-1.00	0.24	0.91	1.18	0.88	-1.13
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.07	-0.01	0.00	-0.04	0.01	0.00	-0.06	-0.01	**0.00***	**-0.12***	0.00
T-Stat	-0.79	-1.18	-0.58	-0.19	-1.52	0.34	0.04	-0.95	-0.15	**-1.77**	**-2.19**	0.16
30-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	-0.17	0.00	0.29	0.14	0.12	0.07	-0.02	0.01	0.01	0.01	0.01	0.00
T-Stat	-0.67	-0.01	0.98	0.73	0.62	0.14	-1.05	0.52	1.02	1.09	1.16	-0.22
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	0.00	-0.08	-0.03	-0.02	-0.05	0.04	0.00	-0.01	0.00	**0.00***	-0.02	0.02
T-Stat	-0.35	-1.04	-1.18	-0.59	-1.95	0.81	-0.09	-0.08	0.05	**-1.62**	-0.26	1.25
36-Month Rolling Window												
	β^{CRSP_Rf}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	β^{MOM}	$\beta^{\Delta CrdSpr}$	$\beta^{\Delta 10Y}$	β^{BDTF}	β^{FXTF}	β^{CMTF}	β^{IRTF}
Average	-0.10	0.09	0.45	0.09	0.18	0.05	-0.02	0.01	0.01	0.01	**0.02***	-0.01
T-Stat	-0.37	0.28	1.37	0.40	0.90	0.10	-0.78	0.36	0.93	0.60	**1.67**	-0.38
	β^{SKTF}	β^{TERM}	β^{DEF}	β^{DIV}	β^{INF}	β^{RREL}	β^{UNEMP}	β^{CFNAI}	β^{TED1M}	β^{GDPPCG}	β^{IPG}	β^{PYRL}
Average	-0.01	-0.07	-0.03	0.00	-0.05	0.04	0.00	-0.07	0.03	0.00	-0.05	0.02
T-Stat	-0.64	-0.85	-0.80	-0.02	-1.67	0.60	-0.17	-0.81	0.39	-1.12	-1.04	1.33

The general path of all tables is that factors are not significant for 12-month and 36-month rolling windows, but some variables are significant for medium length-rolling windows. Therefore, we believe 18-month or 24-month rolling windows are good lengths for predicting CTA and MFF returns and the factors affecting fund returns.

5.1.2. Multivariate Fama-MacBeth Regressions

The results of univariate regressions reveal HML, GDPPCG, and IPG as significant factors on future fund returns. In order to strengthen our results, we run bivariate and multivariate cross-sectional regressions of these factors in the second part.

As a first step, we run bivariate and multivariate time series regressions of HML, GDPPCG, and IPG factors using 24-month rolling windows in order to find multiple factor betas.

$$R_{i,t}=\alpha_{i,t} + \beta^{HML}{}_{i,t}.HML_t + \beta^{IPG}{}_{i,t}.IPG_t + \beta^{GDPPCG}{}_{i,t}.GDPPCG_t + \varepsilon_{i,t}$$

Using multiple-factor betas, we apply univariate cross-sectional regressions of factor betas on one-month-ahead fund returns.

$$R_{i,t+1}=\omega_t + \lambda_t.\ \beta^{F}{}_{i,t} + \varepsilon_{i,t+1}$$

The results can be found in Table 31. HML is significant at 5% level and it has a positive relationship with future fund returns. IPG is significant at 1% level and it has a negative relationship with future fund returns.

Table 31: Multivariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Multivariate Risk Factor Beta for CTAs and MFFs

Rt+1=λ+γ1.β1t+ γ2.β2t+ γ3.β3t+ εt+1				
HML	**0.48****	**0.50****		**0.48****
	(1.99)	**(2.07)**		**(2.05)**
IPG	**-0.13*****		**-0.09****	0.00
	(-2.89)		**(-2.34)**	(0.39)
GDPPCG		0.00	0.00	0.00
		(-1.31)	(-0.48)	(0.39)

Using multiple-factor betas, we secondly apply multiple cross-sectional regressions of factor betas on one-month-ahead fund returns.

Table 32: Multivariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Multivariate Risk Factor Beta for CTAs only

Rt+1=λ+γ1.β1t+ γ2.β2t+ γ3.β3t+ εt+1				
HML	0.35	0.39		0.30
	(1.50)	(1.61)		(1.33)
IPG	**-0.08***		-0.05	-0.03
	(-1.88)		(-1.24)	(-0.91)
GDPPCG		0.00	0.00	0.00
		(-1.13)	(-0.15)	(0.06)

Table 33: Multivariate Fama-MacBeth Cross Section Regressions of One-Month Ahead Returns on Past Month's Multivariate Risk Factor Beta for MFFs only

Rt+1=λ+γ1.β1t+ γ2.β2t+ γ3.β3t+ εt+1				
HML	**0.55***	**0.54***		**0.56****
	(1.87)	**(1.82)**		**(1.96)**
IPG	**-0.14****		**-0.10****	**-0.10****
	(-2.49)		**(-2.00)**	**(-2.05)**
GDPPCG		0.00	0.00	0.00
		(-1.20)	(-0.78)	(0.14)

Table 32 and Table 33 display the same results for CTAs and MFFs only. Tables show that CTAs and MFFs have a positive relationship with HML beta and a negative relationship with IPG beta even after controlled with the other factor.

5.1.3. Multivariate Fama-MacBeth Regressions Using Control Variables

Univariate and multivariate regressions show that HML and IPG are significant factors in forecasting future managed futures funds returns. As a last check, we add control variables in our analysis. The control variables are lagged return, flow, incentive fee, management fee, age, and minimum investment. We run the below regression for all funds, for abbreviation.

$$R_{i,t+1}=\omega_t + \lambda_{1,t}.\ \beta^{HML}_{i,t} + \lambda_{2,t}.\ \beta^{IPG}_{i,t} + + \lambda_{3,t}.\ LagRet_{i,t} + \lambda_{4,t}.\ Flow_{i,t} + \lambda_{5,t}.\ IncFee_{i,t} + \lambda_{6,t}.\ ManFee_{i,t} + \lambda_{7,t}.\ Age_{i,t} + \lambda_{8,t}.\ MinInv_{i,t} + \varepsilon_{i,t+1.}$$

As Table 34 shows the regression coefficients and Newey West T-statistics. HML beta an IPG beta are still significant even after adding control variables to the multivariate regressions. Moreover, lagged return, incentive fee, and age are also significant in predicting one-month-ahead fund returns.

Table 34: Multivariate Fama-MacBeth Cross Section Regressions of the One-Month-Ahead Returns on Past Month's Multivariate Risk Factor Beta

Returns (t+1)	Alpha	HML Beta	IPG Beta	Lagged Return	Flow	Incentive Fee	Management Fee	Age	Minimum Investment
Coefficient	**-0.67****	**-0.10****	**0.40***	**0.04***	0.00	**0.04****	-0.03	**0.00*****	0.00
Newey-West T-Stat	**(-2.33)**	**(-2.22)**	**(1.81)**	**(1.87)**	(-1.36)	**(2.55)**	(-0.66)	**(4.50)**	(0.62)

To conclude, we can say that, HML and IP growth are the common factors that explain the variability in cross section of returns of CTAs and MFFs. HML has a positive relationship with excess future returns of funds; HML increases future fund returns. This fact indicates that CTAs investments are similar to value stocks (but not growth stocks). (HML is the difference between the returns of high and low book-to-market ratio stocks. Fama and French (1992 find a positive relationship between stock returns and HML factor, similar to these funds). (Fama and French (1992, 1993)). We believe that strong positive relationship with HML factor is a sign of profitability of managed futures in cyclic periods (managed futures profit structure is similar to stocks). IP Growth has a negative relationship with CTA and MFF returns. Çağlayan and Ulutaş (2014) found a negative relationship between hedge funds and IP growth. However, the relationship is insignificant in their paper. IPG is not a stock market or even a financial indicator. It is a production factor variable. It is expected that managed futures move independently from stock markets because commodities are exposed to production factors. Therefore, the sources of commodity returns are not related to financial assets' sources of returns. The negative relationship can be a reason of hedging efforts: As IPG falls down, investors may demand more managed futures for hedging purposes.

5.2. NONPARAMETRIC TESTS

A nonparametric portfolio test can be used as an alternative to Parametric Fama-MacBeth tests. In a portfolio analysis, we form quintile portfolios every month according to HML and IPG betas, and then we compute average next-month return and alpha differences between the highest and the lowest quintiles to find a pattern. Alphas of funds are computed by using a 4-factor and an 11-factor model. In the first stage, we form univariate portfolios; in the second stage, we form bivariate portfolios; and in the last stage, we break the data into parts and run the same analysis for subsections.

5.2.1. Univariate Portfolio Analysis

We perform quintile portfolio analyses every month by sorting funds according to HML beta (β^{HML}) and IPG beta (β^{IPG}), separately. We compute next-month returns, 4-factor alphas, and

11-factor alphas of each quintile. The analysis period is January 1997-December 2014. β^{HML} and β^{IPG} were computed 24-month rolling window regressions. Quintile 1 contains the funds with the lowest β^{HML} or β^{IPG}; quintile 5 contains the funds with the highest β^{HML} or β^{IPG}. Table 35 Panel A reports the average β^{HML}, average next-month returns, 4-factor model alphas, and 11-factor alphas for the five quintiles. Table 35 Panel B reports the same variables for β^{IPG}.

In Table 35 Panel A, next month average returns fluctuate but does not really increase as β^{HML} increases; however, alphas increase in β^{HML}. Q5-Q1 difference for next month returns is 0,29% with a t-statistics of 1,20. This difference is 0.09% and for four-factor and eleven-factor alphas with statistically significant t-statistics, respectively. We can say that 4-factor and 11-factor models cannot fully explain the variability in future fund returns. Therefore, the table suggests that the return difference between high HML and low HML beta funds is positive but not significant.

The last two lines show the sensitivity of extreme values. High β^{HML} return and average return of other quintiles is significant, suggesting that the outperformance of Q5 is much stronger than the underperformance of Q1. The last row shows the difference between average of the second, third, fourth, and the fifth quintiles and the first quintile. The insignificant return difference suggests that underperformance of the lowest quintile is not very deep.

In Table 35 Panel B, next month average returns decrease as β^{IPG} increases; the decrease is monotonic and Q5-Q1difference is significant at 10% level for next month returns. Unlike returns, 4-factor and 11-factor alphas increase in β^{IPG}. The increase is not monotonic, it is rather U-shaped, and the difference between the highest and the lowest quintiles is not significant in conventional terms. The last two rows show that the return difference between the highest and the lowest quintiles is due to the underperformance of the lowest quintiles. However, it is the other way around for alphas: The differences are originated from the highest quintile's outperformance of the other quintiles.

Table 35: Univariate Portfolios of CTAs and MFFs Sorted by βHML and βIPG

Panel A: Quintile portfolios of MFFs sorted by βHML				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βHML	-0.58	0.28	0.35	0.37
2	-0.12	0.24	0.23	0.24
3	0.07	0.17	0.24	0.24
4	0.26	0.19	0.28	0.28
High βHML	0.73	0.27	0.44	0.46
High βHML Return – Low βHML Return		0.29	**0.09*****	**0.09*****
NW T-Statistic		(1.20)	**(4.25)**	**(4.43)**
High βHML Return – Average Return of Rest of Quintiles		**0.36****	**0.17*****	**0.18*****
NW T-Statistic		**(2.06)**	**(12.81)**	**(13.89)**
Average Return of Rest of Quintiles–Low βHML Return		0.01	**-0.06*****	**-0.06*****
NW T-Statistic		(0.05)	**(-3.73)**	**(-3.98)**

Panel B: Quintile portfolios of MFFs sorted by βIPG				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βIPG	-2.91	0.60	0.34	0.35
2	-0.84	0.26	0.19	0.20
3	0.02	0.20	0.24	0.25
4	0.94	0.16	0.30	0.30
High βIPG	3.03	0.23	0.47	0.48
High βIPG Return – Low βIPG Return		**-0.38***	**0.13*****	**0.13*****
NW T-Statistic		**(-1.72)**	**(4.88)**	**(4.89)**
High βIPG Return – Average Return of Rest of Quintiles		-0.08	**0.20*****	**0.21*****
NW T-Statistic		(-0.52)	**(11.73)**	**(11.75)**
Average Return of Rest of Quintiles–Low βIPG Return		**-0.39*****	**-0.04****	**-0.04****
NW T-Statistic		**(-2.63)**	**(-1.98)**	**(-2.09)**

Table 36 reports the same results only for CTAs. Panel A of the table shows the quintile portfolios sorted in according to β^{HML}. This table shows that return difference between high and low β^{HML} funds is significant at 10% level. Next month returns and alphas increase in β^{HML}. The Q5-Q1 differences for alphas are all significant, suggesting that there is a relationship between β^{HML} and next month returns, and fund alphas. The last two rows show that the outperformance of the highest quintile is significant for next month returns. However, outperformance of the highest quintile and underperformance of the lowest quintile are both significant for 4-factor and 11-factor alphas.

Panel B of the Table 36 displays the quintile portfolios sorted in according to β^{IPG}. Next month average returns decrease in β^{IPG} and the difference between high and low β^{IPG} funds is significant at 10% level. Next month alphas increase in β^{IPG} and the differences are highly significant. The last two columns show that return difference is originated by the underperformance of the lowest quintile while alpha difference is originated by the outperformance of the highest quintile.

Table 36: Univariate Portfolios of CTAs Sorted by βHML and βIPG

Panel A: Quintile portfolios of MFFs sorted by βHML				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βHML	-0.57	0.20	0.49	0.51
2	-0.12	0.27	0.38	0.39
3	0.05	0.24	0.35	0.36
4	0.24	0.30	0.40	0.41
High βHML	0.72	0.62	0.52	0.54
High βHML Return – Low βHML Return		**0.42***	0.03	0.03
NW T-Statistic		**(1.87)**	(1.45)	(1.57)
High βHML Return – Average Return of Rest of Quintiles		**0.37****	**0.12*****	**0.12*****
NW T-Statistic		**(2.20)**	**(8.48)**	**(9.39)**
Average Return of Rest of Quintiles–Low βHML Return		0.16	**-0.08*****	**-0.09*****
NW T-Statistic		(1.09)	**(-6.19)**	**(-6.56)**

Panel B: Quintile portfolios of MFFs sorted by βIPG				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βIPG	-2.88	0.60	0.44	0.46
2	-0.86	0.35	0.35	0.36
3	0.00	0.22	0.36	0.37
4	0.87	0.21	0.40	0.41
High βIPG	2.84	0.27	0.58	0.60
High βIPG Return – Low βIPG Return		**-0.33***	**0.14*****	**0.14*****
NW T-Statistic		**(-1.66)**	**(5.29)**	**(5.34)**
High βIPG Return – Average Return of Rest of Quintiles		-0.08	**0.19*****	**0.20*****
NW T-Statistic		(-0.55)	**(10.81)**	**(10.92)**
Average Return of Rest of Quintiles–Low βIPG Return		**-0.34****	-0.02	-0.02
NW T-Statistic		**(-2.35)**	(-1.12)	(-1.13)

Table 37 reports the same results only for MFFs. Panel A of Table 37 shows the quintile portfolios sorted in according to β^{HML}. Both, return and alphas increase in β^{HML} quintiles. The difference between the highest and the lowest returns is not significant whereas the difference between highest and the lowest alphas is significant. The significance in alpha differences is due to the outperformance of the highest quintile.

Panel B of Table 37 displays the quintile portfolios sorted in according to β^{IPG}. Next month average returns decrease in β^{IPG} and next month alphas increase in β^{IPG}. Q5-Q1 difference in returns is insignificant. Q5-Q1 difference in alphas is significant. The last two lines show that the significance is originated from the outperformance of the highest quintile.

Univariate portfolio analysis only marginally supports that β^{HML} and $^{\beta IPG}$ have predictive power on future CTA and MFF returns.

Table 37: Univariate Portfolios of MFFs Sorted by βHML and βIPG

Panel A: Quintile portfolios of MFFs sorted by βHML				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βHML	-0.59	0.38	0.24	0.25
2	-0.12	0.25	0.11	0.11
3	0.08	0.13	0.17	0.18
4	0.27	0.15	0.19	0.19
High βHML	0.74	0.49	0.42	0.43
High βHML Return – Low βHML Return		0.11	**0.18*****	**0.18*****
NW T-Statistic		(0.37)	**(5.55)**	**(5.93)**
High βHML Return – Average Return of Rest of Quintiles		0.27	**0.24*****	**0.25*****
NW T-Statistic		(1.33)	**(14.46)**	**(15.15)**
Average Return of Rest of Quintiles–Low βHML Return		-0.13	-0.02	-0.02
NW T-Statistic		(-0.62)	(-0.85)	(-0.82)

Panel B: Quintile portfolios of MFFs sorted by βIPG				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**Next-month 4-factor alphas**	**Next-month 11-factor alphas**
Low βIPG	-3.05	0.61	0.23	0.24
2	-0.92	0.19	0.08	0.08
3	-0.04	0.16	0.16	0.16
4	0.92	0.20	0.24	0.24
High βIPG	2.69	0.26	0.38	0.38
High βIPG Return – Low βIPG Return		-0.35	**0.15*****	**0.14*****
NW T-Statistic		(-1.44)	**(5.16)**	**(5.05)**
High βIPG Return – Average Return of Rest of Quintiles		-0.03	**0.21*****	**0.20*****
NW T-Statistic		(-0.18)	**(11.98)**	**(12.03)**
Average Return of Rest of Quintiles–Low βIPG Return		**-0.41****	-0.02	-0.03
NW T-Statistic		**(-2.39)**	(-0.85)	(-1.13)

5.2.2. Bivariate Portfolio Analysis

We perform quintile portfolio analyses every month by sorting funds according to HML beta (β^{HML}) and IPG beta (β^{IPG}), dependently. We sort funds firstly in HML beta and then we sort every quintile in IPG beta. As a second step, we firstly sort funds in IPG beta and then we sort every IPG quintile in HML beta. Thus, we have 25 groups of funds after every dependent sorting. We compute next-month returns, 4-factor alphas, and 11-factor alphas of each sub-quintile. The analysis period is January 1994-December 2014. β^{HML} and β^{IPG} were computed 24-month rolling window regressions. Quintile 1,1 contains the funds with the lowest β^{HML} and β^{IPG}; quintile 5,5 contains the funds with the highest β^{HML} and β^{IPG}. Table 38 Panel A reports the average β^{HML}, average next-month returns, 4-factor model alphas, and 11-factor alphas for the sub-quintiles firstly sorted in β^{IPG} and then β^{HML}. Table 38 Panel B reports the same variables for the sub-quintiles firstly sorted for β^{HML} and β^{IPG}.

Table 38 Panel A suggests that next month average returns increase in β^{HML} when first sorted in β^{IPG}. High β^{HML} –low β^{HML} difference is significant with an average value of 0,48 %, which is significant at 5% level. Next month 4-factor alphas provide an insignificant difference for high β^{HML} –low β^{HML} difference. The last two-rows of Table 38-Panel A shows that the insignificance is due to a high value of the lowest quintile β^{HML}. Average return of rest of quintiles –low β^{HML} return is negative and significant. However, next month 11-factor alphas are positive and significant.

Table 38 Panel B shows the results of sub-quintiles firstly sorted for HML and then sorted for IPG. The results are not similar to Panel A results. Next month returns are negatively related to β^{IPG}; 4- and 11-factor alphas are positively related to average β^{IPG} sorted quintiles. Yet, none is significant. The last 2 rows suggest that the lowest β^{IPG} sub-quintile is very high for next month returns; and the highest β^{IPG} quintile for 4- and 11-factor alphas have very high values.

Table 38: Bivariate Portfolios of CTAs and MFFs Sorted into βHML and βIPG

Panel A: Quintile portfolios of CTAs and MFFs sorted into βHML sub-quintiles after sorted into βIPG				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βHML	-0.47	0.15	0.72	0.98
2	-0.09	0.28	0.63	0.84
3	0.08	0.38	0.62	0.84
4	0.25	0.33	0.66	0.92
High βHML	0.65	0.64	0.74	1.06
High βHML Return – Low βHML Return		**0.48****	0.01	**0.08**
NW T-Statistic		**(1.98)**	(0.45)	**(1.80)***
High βHML Return – Average Return of Rest of Quintiles		**0.35****	**0.08*****	**0.08**
NW T-Statistic		**(2.10)**	**(3.72)**	**(6.13)*****
Average Return of Rest of Quintiles–Low βHML Return		**0.25***	**-0.06*****	**0.17**
NW T-Statistic		**(1.66)**	**(-2.90)**	**(6.13)*****
Panel B: Quintile portfolios of CTAs and MFFs sorted into βIPG sub-quintiles after sorted into βHML				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βIPG	-2.53	0.64	0.70	0.95
2	-0.78	0.34	0.63	0.89
3	0.00	0.25	0.62	0.86
4	0.75	0.23	0.65	0.90
High βIPG	2.49	0.33	0.76	1.04
High βIPG Return – Low βIPG Return		-0.31	0.06	0.09
NW T-Statistic		(-1.59)	(1.17)	(1.36)
High βIPG Return – Average Return of Rest of Quintiles		-0.04	**0.11*****	**0.14*****
NW T-Statistic		(-0.26)	**(3.17)**	**(3.19)**
Average Return of Rest of Quintiles–Low βIPG Return		**-0.35*****	-0.03	-0.03
NW T-Statistic		**(-2.86)**	(-090)	(-0.70)

Table 39 displays the same results for CTAs only. The results are weaker but similar to the results of all funds. According to Panel A, next-month average returns are positively and significantly correlated to β^{HML}. This outcome is bone by the highest β^{HML} quintile for the next month return. 4- and 11-factor alphas are not significantly related but they have a positive relationship with β^{HML}. The last rows show that both the highest and the lowest quintiles contain high values so that they offset H5-H1 difference and make it insignificant. Panel B suggests no significant relation with β^{IPG} and next month returns, 4-factor, and 11-factor alphas.

Table 40 displays the same results for MFFs only. Panel A presents that next month returns are not significantly related to β^{HML} but only 11-factor alphas have a significant relationship with β^{HML}. Panel B shows no significant relationship between β^{IPG} and independent variables.

Bivariate portfolio analysis supports the results of univariate portfolio analysis by marginally allowing $\beta^{HML\ and}\ \beta^{IPG}$ to have predictive power over one-month-ahead CTA and MFF returns. Interpreting parametric and nonparametric test results altogether, one should be very cautious to use these factors to predict future fund returns.

Table 39: Bivariate Portfolios of CTAs Sorted into βHML and βIPG

Panel A: Quintile portfolios of CTAs sorted into βHML sub-quintiles after sorted into βIPG				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βHML	-0.45	0.20	0.80	0.98
2	-0.09	0.19	0.66	0.81
3	0.06	0.27	0.64	0.79
4	0.22	0.31	0.68	0.86
High βHML	0.59	0.63	0.81	1.00
High βHML Return – Low βHML Return		**0.44****	0.01	0.02
NW T-Statistic		**(2.28)**	(0.30)	(0.38)
High βHML Return – Average Return of Rest of Quintiles		**0.39*****	**0.11*****	**0.14**
NW T-Statistic		**(2.75)**	**(6.76)**	**(5.25)*****
Average Return of Rest of Quintiles–Low βHML Return		0.15	**-0.10*****	**-0.12*****
NW T-Statistic		(1.17)	**(-4.69)**	**(-3.75)**
Panel B: Quintile portfolios of CTAs sorted into βIPG sub-quintiles after sorted into βHML				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βIPG	-2.30	0.47	0.76	0.92
2	-0.69	0.29	0.67	0.84
3	0.01	0.29	0.66	0.81
4	0.71	0.28	0.69	0.86
High βIPG	2.32	0.28	0.82	1.00
High βIPG Return – Low βIPG Return		-0.20	0.06	0.08
NW T-Statistic		(-1.08)	(1.24)	(1.31)
High βIPG Return – Average Return of Rest of Quintiles		-0.06	**0.13*****	**0.14*****
NW T-Statistic		(-0.43)	**(3.93)**	**(3.27)**
Average Return of Rest of Quintiles–Low βIPG Return		-0.19	-0.05	-0.04
NW T-Statistic		(-0.62)	(-1.61)	(-1.12)

Table 40: Bivariate Portfolios of MFFs Sorted into βHML and βIPG

Panel A: Quintile portfolios of MFFs sorted into βHML sub-quintiles after sorted into βIPG				
Quintiles	**Average βHML in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βHML	-0.48	0.19	0.64	0.95
2	-0.08	0.35	0.60	0.87
3	0.09	0.42	0.61	0.87
4	0.26	0.36	0.63	0.95
High βHML	0.67	0.68	0.72	1.13
High βHML Return – Low βHML Return		0.50	0.08	**0.18*****
NW T-Statistic		(1.55)	(1.59)	**(2.83)**
High βHML Return – Average Return of Rest of Quintiles		**0.35***	**0.10*****	**0.22*****
NW T-Statistic		**(1.69)**	**(2.91)**	**(5.95)**
Average Return of Rest of Quintiles–Low βHML Return		0.27	**0.00**	**0.00**
NW T-Statistic		(1.26)	**(0.12)**	**(0.08)**
Panel B: Quintile portfolios of MFFs sorted into βIPG sub-quintiles after sorted into βHML				
Quintiles	**Average βIPG in each quintile**	**Next-month average returns**	**4-factor alphas**	**11-factor alphas**
Low βIPG	-2.54	0.69	0.65	0.97
2	-0.86	0.46	0.59	0.89
3	-0.05	0.23	0.62	0.90
4	0.73	0.27	0.62	0.93
High βIPG	2.56	0.38	0.73	1.08
High βIPG Return – Low βIPG Return		-0.31	0.08	0.10
NW T-Statistic		(-1.39)	(1.48)	(1.55)
High βIPG Return – Average Return of Rest of Quintiles		-0.03	**0.11*****	**0.15*****
NW T-Statistic		(-1.19)	**(2.93)**	**(3.48)**
Average Return of Rest of Quintiles–Low βIPG Return		**-0.35****	-0.01	**0.15*****
NW T-Statistic		**(-2.31)**	(-0.19)	**(3,42)**

This chapter analyzes factor exposures to CTA and MFF returns. Univariate and multivariate analysis reveal a positive relation between HML and future fund returns, negative relation between IPG and future retruns. Nonparametric tests support the analysis partially. We can argue that HML and IPG are the significant factors affecting future fudn returns.

CHAPTER 6

CONCLUSION

Commodity trading advisors (CTAs) and managed futures (MFFs) are alternative investment vehicles, which are similar to hedge funds and mutual funds. CTAs are indeed very similar to hedge funds. They are in a skill-based industry, they require a minimum investment amount, they market themselves as ‘absolute investment funds’ like hedge funds. They also use leverage and short-positions like hedge funds do. However, CTAs are supervised by CFTC. They are more transparent and flexible to their investors. On the other hand, MFFs are very similar to mutual funds. The only difference between an MFF and a mutual fund is that MFFs invest mostly in derivatives, whereas mutual funds usually don’t invest in derivatives.

The similarities between CTAs, MFFs, hedge funds, and mutual funds cause hedge funds and mutual funds industry overweigh CTA and MFF industry. CTAs and MFFs lack required amount of research. This study investigates the industry deeply and contributes to the industry in several ways. First, it provides a comprehensive risk-return analysis. The results are strong and provides deep knowledge about the industry. Second, it shows that CTA an MFF managers are indeed skilled managers. Third, it shows that CTAs and MFFs are exposed to value premium (HML) and industrial production growth (IPG) factors. These factors can be used to predict future fund returns.

This study finds that CTAs and MFFs are successful standalone investment vehicles in the whole sample period (January 1994-December 2014). Their performance is higher than standard asset classes like stocks, bonds, and foreign exchange trading tools. Moreover, these funds are also successful when invested in standard asset portfolios. They have diversification power, they increase portfolio performance significantly.

The most important attribution of these funds come from their negative correlation with standard assets. The negative correlation is especially high in down markets. CTAs and MFFs perform significantly better than standard assets in down markets. Therefore, they are excellent standalone investment vehicles, and they are very valuable portfolio assets. On the other hand, their performance is low in up markets.

CTAs and MFFs owe their success not only market conditions but also managerial skill. Managerial skill is persistent in the industry and it is related to longer life of a fund, higher incentive fee, and lower management fee of a fund. Fund flows do not provide any information about the whole industry, and thus cannot be used as a predictive factor in future fund returns. But, fund flows are a significant determinant of fund returns for highly successful and highly unsuccessful funds.

This study finds that CTAs and MFFs are exposed to value premium (HML) and industrial production growth (IPG) factors. HML has a positive relationship with the future fund returns while IPG has a negative relationship with future fund returns. In that, investments in CTAs and MFFs can be similar to investments in value stocks. On the other hand, CTAs and MFFs invest densely in commodity markets and derivatives. The negative correlation between commodity markets and industrial production may cause IPG to have a negative exposure on CTAs and MFFs. One caveat is that nonparametric tests marginally support these findings.

This dissertation focuses on performance, managerial skill, and risk factor exposures on CTAs and MFFs. Results provide information about the industry. Future research should focus on other risk factors affecting CTAs and MFFs. Moreover, many other alternative assets require more research to enhance portfolio performance.

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