

# **Performance, Managerial Skill, and Factor Exposures in Commodity Trading Advisors and Managed Futures Funds**



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Sureyya Burcu Avci



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*Performance, Managerial Skill, and Factor Exposures in Commodity  
Trading Advisors and Managed Futures Funds*

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# ABSTRACT

Understanding risk is important. Prior to 2008, as the yields on safe assets hit rock bottom, investors began to focus on an alphabet soup of more complex instruments. These complex securities were rated AAA and appeared as safe as U.S. Treasuries, but with much higher yields. The 2008 financial crisis revealed, however, that higher yields on these instruments came with higher risk, albeit too late for these investors. This study seeks to understand the risk–return tradeoff, managerial skill, and factor exposures on the risk–return tradeoff in two financial instruments that have been limitedly investigated: commodity trading advisors (CTAs) and managed futures funds (MFFs).

This study begins by documenting the differences between CTAs/MFFs and hedge funds and mutual funds, starting with the legal and operational differences. Next, it conducts a performance analysis, which indicates that CTAs and MFFs, as standalone investment vehicles, provide returns that are higher than the average market returns in bear markets, while carrying lower risk. The strong standing of CTAs and MFFs in bear markets earn them their reputation as “downside risk protectors.” CTAs and MFFs are profitable individual assets but adding these funds to classical asset portfolios enhances portfolio performance significantly. This feature makes them strong hedging assets. As expected, their performance is below that of standard assets in up markets.

Chapter 4 finds 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, the persistence of the Jensen alphas is supported by both parametric and non-parametric tests.

Incentive fees and fund age are found to be positively related to managerial skill, while (somewhat surprisingly) management fees are found to be negatively related to it.

Chapter 5 finds that many financial and macroeconomic factors are statistically unrelated to CTA and MFF performance. However, the value premium (HML) factor and industrial production growth (IPG) are correlated with their performance. HML has a relation effect on one-month-ahead fund returns, whereas IPG has a negative association with them. Nonparametric tests support these results marginally. Overall, 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 advisor, managed futures fund, performance analysis, managerial skill, factor exposure.*

# LIST OF ABBREVIATIONS

<b>AUM</b>	Assets under management
<b>BDTF</b>	Fung and Hsieh bond trend following factor
<b>CFNAI</b>	Chicago FED National Activity Index
<b>CFTC</b>	Commodity Futures Trading Commission
<b>CMA</b>	Fama–French investment factor
<b>CMTF</b>	Fung and Hsieh commodity trend following factor
<b>CRSP</b>	CRSP value-weighted market index
<b>CTA</b>	Commodity trading advisor
<b>DEF</b>	Default spread
<b>DIV</b>	Aggregate dividend yield
<b>EW</b>	Equal-weighted
<b>E(INF)</b>	Expected inflation
<b>FX</b>	Foreign exchange
<b>FXTF</b>	Fung and Hsieh currency trend following factor
<b>GDPPCG: US</b>	Monthly growth rate of real GDP per capita
<b>Gov</b>	Government
<b>HML</b>	Fama–French book-to-market factor
<b>INF</b>	Monthly US inflation rate
<b>IPG</b>	FED FRED Industrial Production Index
<b>IRTF</b>	Fung and Hsieh short-term interest rate trend Following factor
<b>LT</b>	Long-term
<b>MFF</b>	Managed futures funds
<b>MMIFF</b>	Money Market Investor Funding Facility
<b>MOM</b>	Carhart momentum factor
<b>NAV</b>	Net asset value

## Performance, Managerial Skill, and Factor Exposures

<b>NFA</b>	National Futures Association
<b>OTC</b>	Over-the-counter
<b>PRYL</b>	FED FRED Total nonfarm employment
<b><math>R_F</math></b>	One-month treasury securities
<b>RMW</b>	Fama–French operating profitability factor
<b>RREL</b>	Relative T-Bill rate
<b>SEC</b>	Securities Exchange Commission
<b>SKTF</b>	Fung and Hsieh stock index trend following factor
<b>SMB</b>	Fama–French size factor
<b>TED1M</b>	LIBOR 1-month Treasury Bill
<b>TERM</b>	Term spread
<b>UNEMP</b>	US monthly unemployment rate
<b>UNE(INF)</b>	Unexpected inflation
<b>VW</b>	Value-weighted
<b><math>\Delta 10Y</math></b>	Monthly change in TERM
<b><math>\Delta \text{CredSpr}</math></b>	Monthly change in DEF



## CHAPTER 1

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# INTRODUCTION

**M**anaged futures funds (MFFs) are alternative investment vehicles available to investors who wish to participate indirectly in commodity markets (Edwards and Liew, 1999a). The 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 asset price changes by deploying long- and short-strategies and by using leverage, just like hedge funds. Similar to the hedge fund industry, the MFF industry is skill-based. Investment managers buy and sell assets based on their proprietary strategies. Furthermore, MFFs argue that any positive return they generate is the consequence of their individual success (Anson, 2002) since overall correlation with the market portfolio is typically small.

This study examines commodity trading advisors (CTAs) and MFFs from several perspectives. Chapter 1 analyzes the legal definitions of the funds, their investment criteria, and their differences from hedge funds and mutual funds. It finds that CTAs and MFFs stand between hedge funds and mutual funds on the risk spectrum. CTAs are more similar to hedge funds, while MFFs are more similar to mutual funds. The basic difference between CTAs and hedge funds is that CTAs are strictly regulated and monitored by the SEC and CFTC while hedge funds are registered with the SEC. Regulation and monitoring of hedge funds are very limited. Moreover, these funds are more flexible for investors than hedge funds. The difference between mutual funds and MFFs is basically that MFFs invest mostly in derivative markets while many mutual funds do not.

The MFF and CTA data used for this study are drawn from the Lipper TASS hedge fund database. The study's timeframe ranges from January 1994 to December 2014. Though data are available from 1973, the analysis starts 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 in Chapter 2 show that the number of CTAs in the database declines while the total volume of assets under management (AUM) increases over time. Meanwhile, MFFs grow in both number and AUM. Both types of funds attract investment during crisis periods. The average monthly return of a CTA is 0.81% during the life of a fund, its average age is 58 months, its average AUM is \$54 million, its average annual management fee is 2% of assets, and its incentive fee is 20% of returns. On the other hand, the average monthly return of an MFF is 0.23% during the life of a fund, its average age is 71 months, its average AUM is \$107 million, its average annual management fee is 1.85% of assets, and its incentive fee is 17.3% of returns.

The analyses 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. The annual average returns of active and inactive funds are computed in the database. The difference in returns between the 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 the fund is registered prefer backfilling the earlier pre-registration returns. Therefore, backfilling causes spurious higher returns. As a general approach, the data going back 12 months from the registration period is cleansed to eliminate backfilled returns. The results show that CTAs suffer a 3.05% and MFFs a 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 funds' return history

when making investment decisions, Funds with a return history shorter than 12 months are eliminated. Multi-period sampling bias is 0.21% for CTAs and 0.34% for MFFs.

Having cleansed our database of potential biases, CTAs and MFFs are analyzed as standalone investment vehicles as well as portfolio assets in Chapter 3. Four performance measures are used in the analysis: 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 for the full sample period. Their performance is compared with those of stock markets, the corporate bond market, long-term government bond market, and foreign exchange (FX) market. Next, CTAs and MFFs are evaluated as portfolio assets. Their contribution to standard asset portfolios enhances portfolio performance measures significantly. They optimize performance measures when they account for around 15% to 55% of a portfolio.

Performance analysis is a rough measure because many assets behave differently in up and down markets due to their differences in risk. To better understand a broad measure of risk, the same analysis is repeated by dividing the full sample period into up- and down-market (or bull and bear market) periods. The results show that the yields of CTAs and MFFs are much better than those of standard assets in down markets. Their performance is astonishing, both as standalone 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 markets 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 is to compute Jensen alphas and then measure persistency in them. Persistent alphas are an indicator of successful fund managers. Chapter 4 computes Jensen alphas by using four- and 11-factor models.

Around 10% of all funds have positive and significant alphas. Alphas are correlated positively with fund age and incentive fees and, somewhat surprisingly, negatively with management fees. Parametric and nonparametric methods are used to measure persistency. The results indicate 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. Thus, flow analysis works as a robustness test for the initial managerial skill analysis. The results show that fund flows indeed chase higher returns. However, the opposite is not true: No reliable relationship is observed between current flows and future returns. There is no guarantee that a fund will realize higher profits after receiving higher inflows. Therefore, flows are not a good predictor of future fund returns. The only exception to this finding is highly successful and highly unsuccessful funds. Highly successful funds attract higher flows and perform better once they receive them. By contrast, investment flows run away from highly unsuccessful funds, and these funds perform worse in the next period.

Last, CTA and MFF performance in the analysis period can be explained by well-known risk factors in Chapter 5. Parametric and nonparametric tests show that value premium (HML) and industrial 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 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 returns, perhaps due to the negative correlation between industrial growth and derivatives.

The rest of the book is organized as follows. This chapter presents an industry overview and reviews the literature. Chapter 2 describes the study's data, summary statistics, and potential data biases. Chapter 3 conducts a performance analysis of CTAs and MFFs. Chapter 4 analyzes managerial skill and persistency in fund returns. Chapter 5 explores the factor exposures for the performance of CTAs and MFFs. Finally, Chapter 6 concludes.

## 1.1. INDUSTRY OVERVIEW

The first funds were established to reduce investment risk when there was little understanding of the mathematics behind it, before Harry Markowitz improved his portfolio selection theory (1952). The industry flourished in both Europe and the United States, ultimately making it necessary to analyze the building blocks of fund portfolios. Understanding the nature of funds requires one to revise the definitions of asset classes, asset allocation, and diversification.

We can define asset classes as a set of assets with fundamental economic similarities and characteristics that make them distinct (Greer, 1997). Greer divides asset classes into three groups: capital assets, consumable/transformable (C/T) assets, and store of value (SOV) assets. Capital assets are those whose value is dependent on the ongoing value of a company. Stocks and bonds are typical capital assets. C/T assets are consumable, but also transformable, assets that have economic value without requiring binding to another asset. Physical commodities are a typical example. The transformation mechanism of these assets is commodity futures. Since the value of these assets is not bound to discount rates, they depend on commodity prices; they might be very good diversification tools. SOV assets store value; they do not generate income and are not consumed. A good example is fine arts. The author argues that C/T and SOV assets have very low, or even negative, correlations with capital assets and thus should be included in portfolios to increase diversification.

Sharpe (1992) defines asset allocation as the allocation of an investor's portfolio among a number of major asset classes. This study uses a factor model to compute the exposure of factors to various asset classes. The asset classes in his study comprise only capital assets (mainly stocks and bonds). SEC (2014) uses the same definition of asset allocation and categorizes asset classes into three types: stocks, bonds, and cash. We could extend Sharpe's study by using the asset classes (C/T and SOV) recently defined by Greer (1997).

Markowitz (1952) shows that 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 within a large portfolio (Berk and DeMarzo, 2007). Diversification is achieved by investing different assets within only one asset class (Campbell, 2007), but it is stronger if the investment is allocated across different asset classes (Jensen et al., 2002; Lintner, 1983). Diversification is important for long-term investors. Researchers are looking for the most efficient methods of diversification. For example, Campbell and Viceira (1998, 2002, p. 2) find that investing in long-term indexed capital assets is best, while Lintner (1983) suggests that managed futures should be included in portfolios.

Another view divides asset allocation into two groups: strategic and tactical (Anson, 2004). Strategic asset allocation is long-term and primarily involves capital assets. It targets higher expected returns as well as lowered risk. Diversification is the basic method of mitigating risk. Tactical asset management has a shorter-term horizon. It aims to benefit from current market conditions; therefore, one asset may temporarily be preferred over another due to its speculative returns. Reducing risk is not the main target. Alternative asset classes may 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).

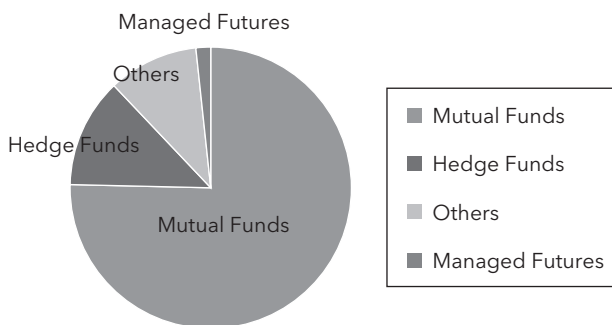
What is the expanding nature of an asset class? Anson (2002, p. 6) discovers this attribute in portfolios composed of different asset classes. Different asset classes not only provide diversification but also increase exposure to other industries to increase returns. The best means of achieving this 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 the returns available in metal markets and also reduce risk due to the negatively correlated assets in the portfolio. Thus, futures and futures funds can be used as both individual assets and portfolio assets because they provide low risk and increased return. Because features of asset classes are important to understand the risks, we should summarize the characteristics of mutual funds, hedge funds, and managed futures funds as different asset classes prior to starting analyzing their performance.

### 1.1.1. 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-market instruments. There are many types of mutual funds. The types are usually determined according to the assets in which they invest. Funds can have different strategies, such as real estate, international, and specialty funds. However, their basic investment assets are usually stocks and bonds. Mutual funds disclose their investment strategies and objectives, investments, risk, and performance, fees along with many other information (Shetty, 2007; Robinson et al., 2010).

Mutual funds are the oldest fund type; they are also the most widely known among many investor groups. Therefore, the word “funds” refers to mutual funds, rather than other types of funds, for many people. Despite the advantages of other fund types, investments in mutual funds account for the largest share of the funds market. Mutual funds’ AUM totaled about \$15 trillion at year-end in 2013 (2014 Investment Company Factbook). The estimated magnitudes of all fund types at the end of 2013 can be found in Figure 1.

The figure clearly shows that mutual funds account for almost 75% of the total industry. The “Others” category in Figure 1 is comprised of exchange traded funds, closed-end funds, and unit investment trusts.



**Figure 1.** AUM of Fund Types as of December 31, 2013.

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

Mutual funds emerged in the second half of the 18th century in Europe as an outcome of mercantilism. After the discovery of new continents, Europeans were not only enriched by the gold and silver that flew from the new lands, but they also found new markets in which to sell their high-tech products. New companies were founded to trade in new lands, and the stocks and bonds of these companies were seized by all types of investors. A lack of immediate information about company operations and the transparency of company books was accompanied by positive investor expectations. Monetary growth played into speculators' hands, and the prices of stocks and bonds jumped up and down constantly. Speculation in stock markets was followed by several crises (Fridson et al., 1996; Kindleberger, 2008, Section 3 and 4). Given the communication technologies of the time, the transoceanic trade was very risky for small investors, who started looking for assets that were more stable than stocks and bonds. As a consequence, the first mutual fund emerged in the 1770s. The primary purpose of mutual funds was to arrange a diversified investment basket for small investor (Rouwenhorst, 2004).

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

The difference between open- and closed-end companies is explained in the 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 describes mutual funds as we know them, yet many mutual funds are open-end companies. These funds are not traded in public



exchanges. Investors wanting to buy shares buy them from the fund or from the fund's broker; if investors want to sell shares, they sell them to the fund or to the fund's broker (Investment Company Act of 1940, Sec. 22). Aside from limitations or restrictions imposed by the fund charter and economic conditions, the funds may issue as many shares as they wish. Selling shares back to the issuer is called "redemption." A fund may have to sell some of its assets to shrink its net asset value (NAV) to the circulating value of the shares. The investor yield can be computed as the difference between the sales and purchase prices and any fee charged by the fund and the broker.

Closed-end companies are defined in the 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 predetermined number of shares, which 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 among investors as open-end funds are. This study refers to open-end funds as "mutual funds."

The relationship between funds and derivatives is an important issue for this study. Can mutual funds invest in derivatives? No direct restriction in securities laws prohibits investment in derivatives. However, mutual funds were excluded 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 a "short-short rule" (Internal Revenue Service Code Section 851 (b)(3)) on mutual funds, which prohibited mutual funds from collecting more than 30% of their revenues from the sale of securities held for fewer than three months. Many derivatives, such as futures and options, have maturities of less than three months. The purpose of the Short-Short Rule is to promote mutual funds as long-term investment vehicles (Barnhart, 1997; Koski and Pontiff, 1999). The Short-Short Rule